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Stochastic Short-term Incentive-based Demand Response Scheduling of Load-serving Entities

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***Abstract*—In competitive electricity markets it is necessary for a profit-seeking load-serving entity (LSE) to optimally adjust the financial incentives offering the end users that buy electricity at regulated rates to reduce the consumption during high market prices. The LSE in this model manages the demand response (DR) by offering financial incentives to retail customers, in order to maximize its expected profit and reduce the risk of market power experience. The stochastic formulation is implemented into a test system where a number of loads are supplied through LSEs.**

***Index Terms*—Day-ahead market, demand response, demand-side bidding, load-serving entities, stochastic programming.**

I. NOMENCLATURE

Indices:

t	Time periods.
s	Scenarios.
b	Buses.
c	Consumers.
j	LSEs.
f	Fixed loads.
r	Responsive loads.

Parameters:

N_c	Number of consumers.
N_s	Number of scenarios.
ω_s	Weight of scenarios s.
l	Load demand forecast (MW).
l^{base}	Baseline consumption (MW).
LMP_b	Locational marginal price at bus b (€/MWh).
R_c	Utility rate that consumer c is charged for electrical energy consumption in time period t (€/MWh).
ME_b	Maximum daily curtailment for electrical energy consumption at bus b (MWh).
D_c^{Min}	Minimum curtailable load of consumer c (MW).
$FI_c^{Min/Max}$	Minimum/maximum financial incentive for consumer c (€/MW).

Variables:

x	Binary decision variable for the curtailment state of loads.
P_j^{D+1}	Expected payoff of the LSE j in the DAM (€).
FI	Financial incentive for DR in DAM (€/h)
Δl	Demand reduction (MW).
DR	The demand response that receives the financial incentives (MW).

Sets:

Ω_j	Buses that the LSE j serves loads in them.
Ω_j^b	Consumers served by the LSE j located at bus b.

II. INTRODUCTION

A. *Motivation*

The end-users in a competitive market prefer the contracts with a broad selection of plans from the retailers consisting innovative products and services for everyday energy needs preferably at lower retail prices. In a full retail competition the consumers have the right to choose their own suppliers. Customers of restructured power markets might prefer buying electricity from LSEs rather than procuring it directly from the wholesale market [1]. LSEs fill the gap between the retail customers who are not conscious of short-term price changes and the wholesale electricity market by offering DR programs for customers and stimulating the end-users to the fluctuations of electricity price. DR is a price-based or incentive-based program or tariff to motivate changes in electricity consumption in response to changes in price. It benefits the system by shaving the peak load and reducing the transmission congestion with reshaping the load profile [2].

Energy trading in a day-ahead market (DAM) is very risky, due to the stochastic nature of energy prices, balancing prices, energy availability, and demand [3]. The success of DR programs greatly depends on how pricing signals are sent for retail customers and the choices that these customers are faced

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with among price and reliability differentiated products [4]. One of the main barriers for expanded implementation of DR programs in restructured electricity market is the disagreement on choosing the entity that should be in charge of promoting DR resources [4]. Market rules should be clearly defined for DR regardless of the entity that is in charge of it, whether it is the load serving entity or an independent DR provider.

DR providers participate in electricity market as mediums between the independent system operator (ISO) and the retail customers; they aggregate and manage customer responses to the offered programs of an ISO [5]. An ISO receives bid-quantity offers from generation companies (GENCO) and DR providers [5]. In many electricity markets LSEs carry the responsibility of DR providers. Apart from the benefits for the whole system, profit seeking LSEs can earn higher payoff through DR programs. PJM and NYISO have launched programs to allow the active participation of customers by DR programs either through a curtailment service provider or through the customers' LSEs [6]. These entities act as an aggregator for customer loads and provide the load data for the ISO [2].

The LSE in an electricity market secures the energy and transmission service to serve the electrical demand and energy requirements of end-use customers [3]. The LSEs benefit from the DR programs when the wholesale electricity price is high. Implementation of DR programs reduces the load that should be served and avoids the need for power purchase at high prices [7]. The main objective of LSEs in restructured electricity markets is to maximize the total expected payoff while keeping the risks within acceptable level [3]. LSEs frequently provide customers with various hedge contracts when launching a real-time pricing program [8].

B. *Literature review and contributions*

The coupon incentive-based DR model in [9] is suitable for a smart grid where the retail customers are paying a flat electricity rate. It targets the retail customers that can participate in real-time DR programs. A short-term stochastic model from the viewpoint of an ISO that receives the bids from DR providers is proposed in [5] focusing more on reserve scheduling of wholesale electricity markets. The hourly stochastic security-constrained unit commitment model of [2] is designed for market clearing; it incorporates DR programs in a market with both fixed and responsive loads. In this model the DR bids are submitted from the retail customers/load aggregators to the ISO, in order to be included in the market clearing [2]. In the proposed DAM clearing mechanism of [10], consumers can submit complex bids with specific constraints on their hourly and daily consumptions. DemSi is a decision support system that can be used by a retailer to maximize its payoff concerning DR programs in a distribution system [11].

In [12] an economic model of responsive loads is derived based upon price elasticity of demand and customers' benefit function. Voluntary incentive-based programs such as direct load control and emergency DR programs are considered, in which the ISO only prizes the customers for load reduction, but does not penalize their violence [12].

A financial bilateral contract negotiation process between a GENCO and a LSE in a wholesale electric power market with congestion, managed by locational marginal pricing is modeled in [13]. Customers do not access the wholesale market in [8] and have to procure electricity only through LSEs. In [3] a LSE owns the generating units such as several wind and thermal units while carrying the inherent duty of serving the demand requirements of end-use customers. This broad spectrum of responsibilities for a LSE resembles the duty of a system operator in a centralized power system. In other words the deregulation requires individual market entities with more distinct operational duties. Although this LSE has the chance of self-balancing mechanism, most load serving entities in real-world power systems are expected to just provide the energy requirements of the end-users.

We want to emphasize the uncertainty associated with the operation of LSEs. Our proposed decision support system helps the LSEs while calculating the daily financial incentives of end-use customers that are paying regulated rates for electricity consumption. The iterative procedure between the customers and the LSE in [9] to achieve the optimal amount of incentives for real-time DR is not realistic for residential and commercial customers of conventional power systems without smart infrastructure. This mechanism is represented to overcome the risk of uncertain estimations that the LSE is normally involved. Instead of choosing an iterative procedure, we have used stochastic programming to overcome the uncertainty of estimations.

C. *Paper structure*

In section III, the operation of the main DAM players is introduced. The DR scheduling formulation in section IV is tested on a modified IEEE test system at section V. The final section is assigned to the conclusions of the paper and the direction of our future works in this area.

III. DAY-AHEAD MARKET MODEL

The final part of electrical energy delivery to end-users is done through retailing, usually known as the last step of electricity supply chain. The general definition of a retailer in economic theory is a business that purchases products or services at spot prices in vast quantities directly from the primary sources and sells them to individual end-users in order to maximize its own profit.

The LSEs have the motive for increasing the price elasticity of retail customers by using a financial incentive-based DR. They procure electricity on wholesale electricity markets (e.g., day-ahead, real-time balancing, and ancillary services) or from distributed energy resources (DER), and sell it on a retail market to end users. They buy energy at volatile prices and sell at fixed regulated prices. The bids for purchasing energy from the DAM are submitted based on the expected LMPs at each bus, which is determined by the market operator to serve retail customers in the next day [13]. Direct involvement of retail customers in real-time DR programs requires large scale deployment of smart metering and two way communication system that will be enabled in the coming decades [14].

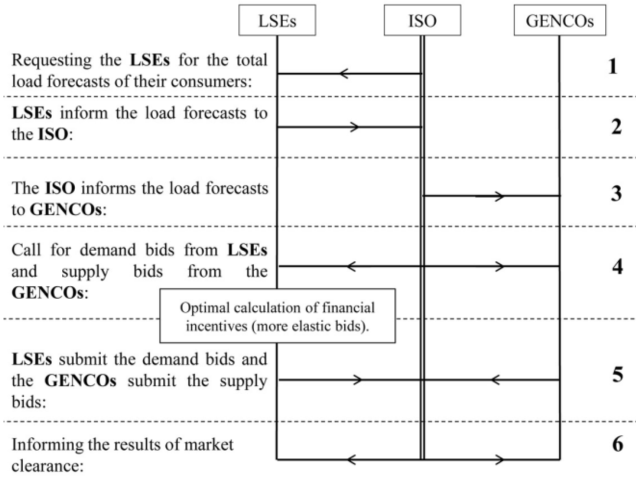

Figure 1. The role of the major players in a DAM (adapted from [15]).

At the end of day, the LSE is charged the price of $LMP_b(t)$ for the cleared demand of time period t of the day ahead. This price is determined by the market operator for bus b through implementing DC-OPF [13]. The LSE submits demand bids with more price elasticity when dealing with retail customers that are more responsive to financial incentives. We have designed the model in this paper for a DAM, but it is possible to calculate the incentives for longer time horizons. The relative role of the major players in a DAM is reflected in fig. 1. The LSE submits the demand bids based on the optimal financial incentives.

The electricity price at different buses varies during a day, but the retail customers are more inclined to pay a regulated price for energy. In real-time pricing the clients receive the real-time price data and pay the hourly price for their consumption. The kind of customers that participate in real-time pricing programs varies from one market to another [11]. Southern California Edison (or SCE Corp) that supplies electrical energy for about 14 million people in USA has designed real-time pricing programs for customers with maximum demand greater than 500 kW [15]. The GENCOs have less incentive to bid close to their marginal cost when the demand-side participation is negligible and price spikes may also occur. Increasing the demand-side participation mitigate the price manipulation and market power exercise [2].

IV. FORMULATION OF DR SCHEDULING

In short-term markets the participants are requested to submit their schedules a day before real-time markets [3]. There is always the risk of getting penalized by the ISO if they do not provide what they have decided and agreed in the DAM [3]. Most significant risks faced by a LSE in day-ahead operation arises from the uncertainty regarding to the prices of the cleared demand [13].

The model is designed under the following realistic assumptions: (i) the market operator provides the opportunity to participate in real-time pricing programs for LSEs instead of facing with many small end-users with more tendencies toward staying in fixed price contracts with the utility provider. (ii) The LSEs offer a regulated rate for electricity to retail customers and a voluntary financial incentive-based DR program for demand reduction under the baseline load. (iii) The financial incentive can be different for each customer and each hour.

The main focus here is on the inclusion of uncertainty in the problem faced by LSEs. The LSE j calculates the optimal financial incentives by maximizing its expected payoff for the 24 hours of the day (1).

$$\begin{aligned} P_j^{D+1} = \sum_{s=1}^{N_s} \omega_s \cdot \sum_{b\in\Omega_j} \sum_{t=1}^{24} \Bigg[& \sum_{c\in\Omega_j^b} R_c(t)\cdot\left(l_c^s(t)-\Delta l_c^s(t)\right) \\ & - \sum_{c\in\Omega_j^b} LMP_b^s(t)\cdot\left(l_c^s(t)-\Delta l_c^s(t)\right) \\ & - \sum_{c\in\Omega_j^b} FI_c(t)\cdot DR_c^s(t)\cdot x_c(t)\Bigg]. \end{aligned} \tag{1}$$

The first term in (1) shows the expected income from the energy purchase to retail customers. The second term is the money that the LSE pays in the wholesale market for buying electricity at volatile nodal prices. The total financial incentive that the LSE pays is included in the last term. LSEs can present different offers for clients including DR programs which might lead to different prices for customers located at one bus. The binary variable x is 1 for the time periods that the LSE j finds them beneficial and appropriate for setting financial incentives, and it is 0 for other periods.

The LSE sets the financial incentive for retail customers when the consumption is lower than the baseline load profile. If the customer c consumes energy beneath the baseline during the periods that the LSE has set the financial incentive, it will receive the incentives for each kWh of demand reduction. The LSE can pay this incentive while calculating the periodical electricity bills of the customers. The expected quantity of DR for each customer is calculated from its baseline value. Different techniques are used to calculate the amount of baseline consumption of loads [9], which is beyond the scope of this paper. The amount of demand response that the customers are paid for it is shown in (2). They are paid proportional to the reduced amount from the baseline electricity consumption.

$$DR_c^s(t) = l_c^{base}(t) - (l_c^s(t) - \Delta l_c^s(t)), \qquad \forall c, \forall s, \forall t. \tag{2}$$

Each consumer has a fixed load demand that should be fully satisfied in addition to its responsive load (3) [2].

$$l_c^s(t) = l_{cr}^s(t) + l_{cf}^s(t), \qquad \forall c, \forall s, \forall t. \tag{3}$$

The fixed loads should be satisfied completely and the LSE expects the curtailment within the responsive share of the loads. The expected load curtailment for each consumer must be within a certain range represented by its minimum curtailable load and the responsive load share which is volatile at each hour (4).

$$x_c^s(t)\cdot D_c^{Min} \le \Delta l_c^s(t) \le x_c^s(t)\cdot l_{cr}^s(t), \qquad \forall c, \forall s, \forall t. \tag{4}$$

The LSE considers a limitation over the total demand reduction at each bus during a day (5). If more than one LSE is servicing the loads at one bus, it has to consider the strategies of other LSEs.

$$\sum_{t=1}^{24}\Delta l_b^s(t) \le ME_b, \qquad \forall b, \forall s. \qquad (5)$$

The $f_c(\cdot)$ function in (6) represents the response of consumer c when the financial incentive of $FI_c(t)$ is offered to it [9]. It shows the elasticity of end users to financial incentives. This function is estimated from the historical data and the utility function of the end users.

$$\Delta l_c^s(t) = f_c\left(FI_c(t)\right), \qquad \forall c, \forall s, \forall t. \qquad (6)$$

The financial incentive to cause demand-side participation for consumption reduction should be within the range that stimulates the reduction and the consumers can also afford (7).

$$x_c^s(t)\cdot FI_c^{Min} \le FI_c^s(t) \le x_c^s(t)\cdot FI_c^{Max}, \qquad \forall c, \forall s, \forall t. \qquad (7)$$

V. NUMERICAL STUDIES AND DISCUSSIONS

The IEEE 24-bus reliability test system in [16] is modified for the application of the proposed model (fig. 2). Two LSEs procure energy demand of some loads in this system and submit the demand bids to the ISO to participate in the DAM. These LSEs buy electricity at volatile prices at each node and sells them at regulated rates to the end users. Determining the value of financial incentives before submitting the demand bids is an influential decision for them to increase their expected profit.

There is one consumer at each node, and the LSE at that bus serves all its energy needs for the 24 hours of the day. The regulated rates of electricity stated in the contracts of the two LSEs with their retail customers are shown in fig. 3. In this case study, a linear function has been used to represent the elasticity of the end users to financial incentives of the LSE. The forecasted load of each consumer is shown in fig. 4.

The GAMS/DICOPT system [17] is used to solve the mixed-integer nonlinear programming model within two representation of deterministic and stochastic formulation. The LMPs have been considered as the main source of uncertainty that the LSEs face in the DAM. The hourly LMPs are based on the market reports of Ontario ISO [18]. Fig. 5 shows the LMPs for the deterministic case. In order to assess the effect of uncertain prices at each node of the system, 3 more scenarios in addition to the LMPs in fig. 5 is selected, and equal weights are considered for each scenario.

Fig. 6 shows the amount of financial incentives that the LSEs offer to the retail customers before the start of DAMs. These optimal values are calculated within a deterministic representation of the model. The LSEs submit the demand bids based on these incentives and their expectation of the response of the consumer. In fig. 7 it is shown that the amount of incentives differs significantly when the LSE considers more than one scenario.

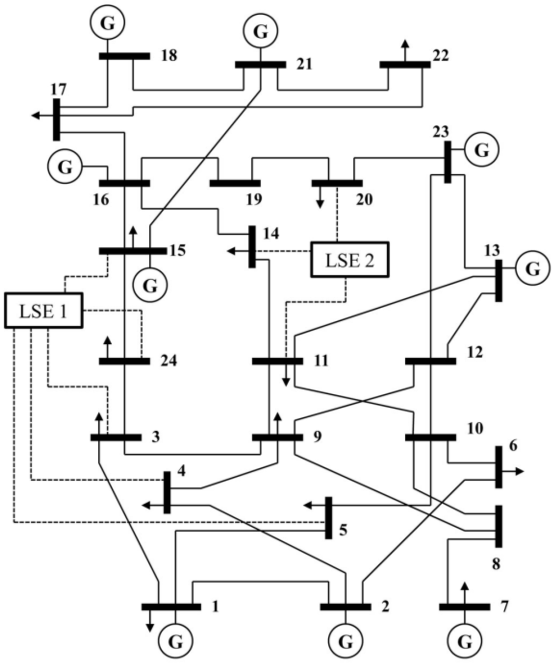

Figure 2. Modified IEEE 24-bus test system.

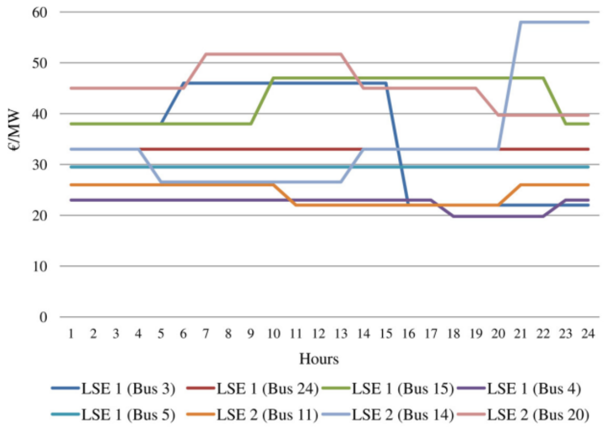

Figure 3. Regulated rates for the retail customers.

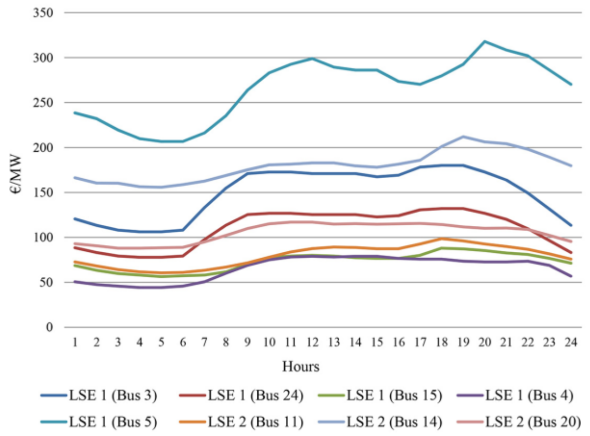

Figure 4. Hourly load forecast of consumers.

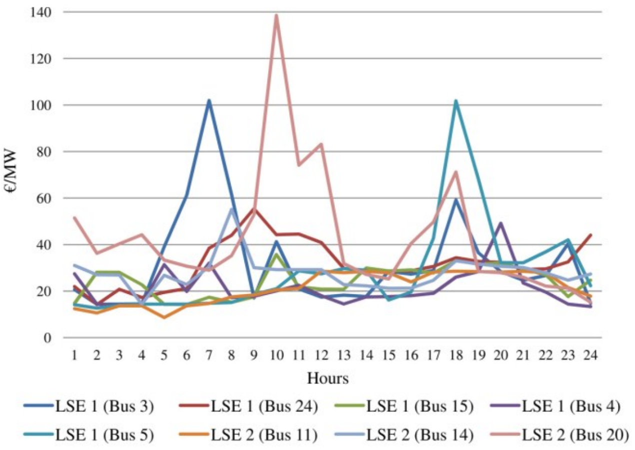

Figure 5. Hourly LMPs forecast at each bus.

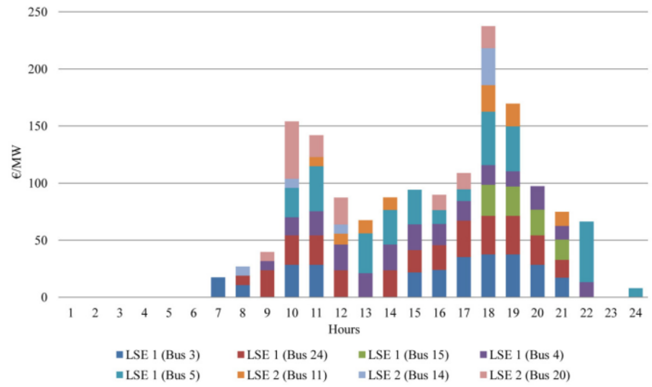

Figure 6. Deterministic calulation of the optimal financial incentives.

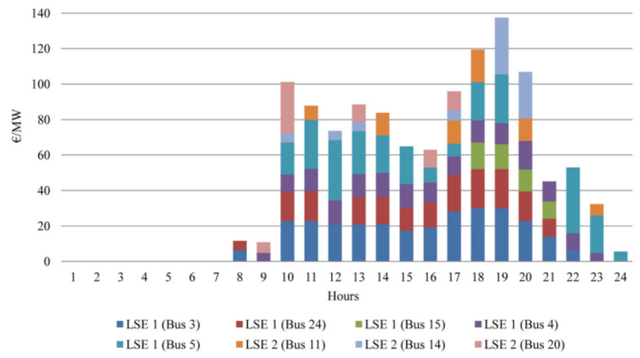

Figure 7. Stochastic calulation of the optimal financial incentives.

VI. CONCLUSIONS AND FUTURE WORKS

In this study the LSEs that face uncertain LMPs in a DAM, optimally calculate the financial incentives to offer to retail customers served by them. Besides benefiting the LSEs, the proposed DR model profits the whole system by decreasing the need for peaking units and reducing the possibility of the occurrence of market power. The results in this paper show how the expected profit of the LSE and the optimal value of financial incentives for the retail customers depend on the uncertain parameters of the competitive electricity markets.

In our future works we will address the problem of optimally calculating the DR financial incentives of LSEs for retail customers in mid-term time horizons. We will develop the model by considering more advanced DR constraints to limit the minimum on/off time and the drop off/pick up rates of the loads at each bus.

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