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Enhancing market access of demand response through generation forecast updates

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Abstract—Advances in communication infrastructure and electric appliances have enabled demand side participation in power system operation. However, the full potential of demand flexibility is yet to be exploited. Existing demand response programs require flexibility in a set time frame from the electricity consumers in reaction to economic incentives. For a more detailed qualitative analysis of consumer flexibility, not only price but also notice time are imperative parameters. The former has been studied in numerous references whereas the latter has not yet been examined in depth. This paper presents a market model of demand response that enhances an efficient use of flexible consumers by hourly updates. The consequences of flexible electricity consumers are studied in a Real Time Pricing model with continuous forecast updates, where elasticity is subject to notice time. A case study is presented using data from Sweden. We conclude that current demand response programs are not optimally designed to integrate consumer flexibility that changes with the notice time.

Index Terms—demand side management, power system simulation, power system economics, smart grids, wind energy integration.

I. INTRODUCTION

Power systems with a large share of inherently intermittent renewable energy sources require new approaches to system operation. Demand response is seen as one option to contribute to maintaining power balance in a future energy system with large amounts of volatile renewable energy generation. The study of the flexibility of electricity consumers is an essential key to exploring the current and future potential of demand response (DR) for power system services.

Research on the capacity of demand side management has received growing attention in power systems research and a continuously growing body of academic literature has evolved on a variety of different DR programs. In [1] a summary is presented and a classification of DR programs is proposed. However, the classification mainly depends on the purpose of its application and can be done in several ways. The Federal Energy Regulatory Commission defines a DR program in [2] as ”a company or utility’s service/product/compilation of all effective rate schedules, general terms and conditions and standard forms related to demand response and/or advanced metering infrastructure services and classification thereof”. Common DR program classifications are based on

- price- or incentive-based approaches [1].
- ability to be dispatched [3].
- load management purpose based [4].
- type of control architecture [5].
- market level [6].
- time of notification [7].

With respect to this study, the most purposeful way of classifying DR programs is to cluster them by the time when the information for providing a certain service is exchanged. Fig. 1 shows the time frame of existing DR programs as classified in [7].

For balancing the power system, many markets such as Nordpool [10] offer energy suppliers to submit bids in consecutive markets with different time periods until the delivery hour. DR programs, on the other hand, are designed for a specific notice time, that is commonly fixed [1]. This means that the participation of the demand side is limited by the market structure. Demand flexibility is bound to a program specific notice time which may or may not be optimal.

The root causes for imbalances are errors in load forecasting, volatile renewable energy forecasting, and unscheduled power plant outages. An inherent feature of forecasts of both load and volatile production is that they statistically improve over time. The closer the delivery hour is approached, the smaller the statistic forecast error becomes.

A qualitative illustration of the wind power forecast root mean square error over the forecast horizon is shown in Fig. 2. The figure also illustrates the time frame of electricity markets in Nordpool. The day-ahead market closes at 12:00. The intra-day market is a continuous market and starts at 14:00 for the...
following day and ends 1 hour before the delivery hour, when the balancing market starts [11].

Statistically, the forecasts become better the closer they approach real operation. In practice however, this does not happen in each case. This means that the flexibility need for a given delivery hour will be different, depending on when the need is identified, i.e. different notice times. Consequently, it becomes important to consider the notice period in the stages of DR events as shown in Fig. 3. We suggest to include notice period in the definition of a demand response event, since this may impact the quantity of response. Especially for appliances such as electric heaters with coupled thermal inertia the notice period can be a decisive parameter.

It has been hypothesized that the flexibility of residential electricity consumers varies with notice time [7, 8]. On the other hand, forecasts of wind power production become statistically better the closer they approach the delivery hour. The question is thus, which consequences notice time has on consumer participation. In order to formulate and model this problem, we propose DR model, where consumers are updated on the price changes due to statistically improving wind power forecasts. The contributions of this paper are the following:

- We present a modeling framework to analyse the capability of DR whose elasticity is subject to notice time.
- We extend the definition of the elasticity matrix for DR modeling by the parameter notice period.
- We integrate the time horizon of wind forecasts and demand flexibility into the iterative market clearing.

The rest of the paper is organized as follows. Section II outlines a market framework for DR based on Real Time Pricing. This market model with additional updates allows for the analysis of notice time using update intervals. The demand model is presented in Section III using an elasticity matrix. A case study is investigated in Section IV. In Section V the results of the case study are discussed and Section VI gives a conclusion of this paper.

II. Market Framework

It is obvious that for the system operator, a program with very quick decision before the target hour, such as Direct Control (cf. Fig. 1), is optimal, since the most accurate wind power forecast is available only then, i.e. on the short forecast horizon. From the consumer point of view however, a repetitive predetermined tariff, such as in Time of Use programs, is the most comfortable option if not automated. A trade-off can be seen in a market framework that starts on the day ahead, but offers the capability to change consumption until the delivery hour.

Such a market sequence allows for modeling consumer flexibility in different notice periods. The response of flexible demand is then depending on

- the flexibility need, arising from wind power forecast deviations on a shortening forecast horizon,
- the flexibility incentive, arising from the following price change, and
- the flexibility capability originating from a notice time dependent elasticity.

All of the above are time dependent parameters that impact the system imbalance. We assume a perfect demand forecast with deterministic consumption. The forecast horizon of wind power production and the notice period $T_n$ of price sensitive demand with respect to a specific deployment period, i.e. delivery hour can be seen as equivalent time periods, cf. Fig. 2.

A. Continuously Updated Real Time Pricing Program

It can be concluded from Fig. 1 that Demand Bidding (DB) and Real Time Pricing (RTP) allow for flexible economic scheduling starting on the day-ahead (DA). A DR study using DB was conducted in [7]. In order to examine consumer flexibility with respect to notice time, a continuously updated Real Time Pricing (CU-RTP) approach is developed in this study.

The conceptual framework proposed here is similar to [7], where new bids and offers are traded in several update intervals. Here, it is assumed that market participants are updated on new forecasts every hour. The market equilibrium for a given delivery hour (DH) is determined through an iterative market clearing algorithm. The initial market equilibrium for each hour is found by aggregating supply bids of generation units, wind power bids based on the producers’ forecast, and load forecasts. Consumers are modeled with self and cross elasticities to react to this RTP price and change their consumption pattern according to the price change.

We assume perfect competition and information in an organized market whose purpose is to discover the price of electricity for the upcoming time intervals. The balance of supply and demand sets the initial DA price as follows:

- Generators offer bids of volumes at a certain price.
- The bids are ranked in terms of their price.
Bids are taken in this order until the forecasted demand is satisfied.

The proposed CU-RTP model is illustrated in Fig. 4 starting at 12:00 DA for delivery hours DH1 to DH24 on the consecutive day. At this initial notice time \( t_{n,0} = 12:00 \), the notice period \( T_{n,0}(DH_1) = 12 \) hours for delivery hour DH1 and \( T_{n,0}(DH_{24}) = 35 \) hours for DH24. Every hour, an updated wind power forecast \( W_{f,t_n} \) results in a new predicted imbalance of energy and rescheduling of flexible generation \( (G_{f,t_n}) \) and consumption \( (D_{t_n}) \) units.

For the market operator, knowledge of wind power forecasts, marginal cost of flexible generation and price elasticity of demand is required in order to obtain the market equilibrium.

**B. Market Participants**

**Wind power generation** is modeled as a generator with zero marginal cost that may in addition receive subsidies of some form. Wind power suppliers are thus bidding their forecasted production volume \( W_f \) at a price \( c_W \leq 0 \).

**Flexible generation** is modeled as a generator with a linear marginal cost curve of the form

\[
E_G = c_{G_0} + a_G \cdot G 
\]  

where \( c_G \) is the marginal cost of production at production volume \( G \), \( c_{G_0} \) is the minimal cost and \( a_G \) is the slope of the linear utility function. Eq. (1) contains no notice time dependent parameters.

**Demand** is modeled as a forecasted demand

\[
D_0 = D_{min} + D_{flex} 
\]  

which is composed of an inelastic part \( D_{min} \) and a flexible part \( D_{flex} \), where \( |D_{flex}| \leq 0.1 \cdot D_0 \). The flexible demand is assumed to respond to a price change \( \Delta \lambda \) with a demand change

\[
\Delta D = \epsilon(T_n) \cdot \frac{D_0}{\lambda_0} \cdot \Delta \lambda, \tag{3}
\]

where \( \epsilon(T_n) \) is the normalised price elasticity of demand with notice period \( T_n \). \( D_0 \) is the reference demand and \( \lambda_0 \) is the reference price for the initial DA equilibrium.

An illustration of the market participant model is shown in Fig. 5 for the equilibrium on the DA spot market at \( t_{n,0} = 12:00 \).

**C. Iterative Market Clearing Algorithm**

The response of consumers to a change of price will in turn affect the market price. In order to model this feedback loop an iterative Market Clearing Algorithm (MCA) as illustrated in Fig. 6 is implemented. Here, we extend the MCA by the time dependency of wind power forecasts and demand elasticity. Upon a forecast update, the MCA determines the new
equilibrium for each delivery hour. The starting point is the forecasted demand \((D_0)\), initially scheduled generation \((G_0)\) and wind power forecast \((W_{f,0})\) at notice time \(t_{n,0} = 12:00\).

According to the required flexible generation, unit commitment (UC) and economic dispatch (ED) determines the new price \(\lambda\). In each iteration, the price change \(\Delta \lambda\) is computed with respect to the initial reference price \(\lambda_0\). Here, the price after rescheduled flexible generation is modeled by the marginal cost curve of Eq. (1).

III. DEMAND ELASTICITY MODEL

The reaction of flexible consumers is modeled by a Price Elasticity Matrix (PEM) as defined in [9] which captures the normalized self \((\epsilon_s)\) and cross \((\epsilon_c)\) price elasticity. The response of demand modeled in a PEM depends on two parameters:

A. the values of self-elasticity and
B. the structure of the price elasticity matrix.

The modeling of the above parameters is detailed in this section.

A. Elasticity Values

We suggest two hypotheses for the trajectory of demand elasticity over notice period. The first assumes that elasticity decreases continuously with shortening notice period, similar to the trajectory of wind power forecast errors. The second is based on the review of [8], which lays out indicators that demand elasticity increases again in the intra-day notice period time frame. The trajectory of both hypotheses are illustrated in Fig. 7.

![Fig. 7. Structure of the Price Elasticity Matrix for various consumer.](image)

The initial value of self-elasticity \(\epsilon_{s,0}\) is set to -0.3 in Fig. 7. \(\epsilon_{s,0}\) is the initial elasticity at \(T_n = 168\) hours ahead, i.e. one week’s notice period. It should be noted, that this discussion is only dealing with values for self-elasticity. Cross-elasticity values are distributed in the elasticity matrix according the pattern described in Section III-B.

1) Hypothesis 1: Here, we hypothesize that consumer elasticity decreases with shortening notice period, i.e. consumers become less flexible and require larger price change to react. The price elasticity of consumers with a notice period \(T_n\) is assumed to decrease continuously with

\[
\epsilon(T_n) = \epsilon_{s,0} \cdot k_1(T_n),
\]

(4)

Here, the factor \(k_1(T_n)\) is used to represent the decreasing elasticity as notice time decreases according to

\[
k_1(T_n) = \sqrt{\frac{T_n}{168}}.
\]

(5)

The assumption for decreasing consumer elasticity is that the flexibility decreases slightly in the long term, but more rapidly in the last hours before the delivery hour. This trajectory corresponds to the trajectory of wind power forecast errors over the forecast horizon as illustrated in Fig. 2. Eq. (5) implies that the elasticity is reduced to half its value at \(T_n = 9\) h as compared to \(T_n = 36\) h.

2) Hypothesis 2: The second hypothesis is based on the review of [8], where demand elasticity increases again in the intra-day notice period time frame. The findings are based on a review and comparison of DR pilot projects and studies thereof.

The initial price elasticity \(\epsilon_{s,0}\) is defined at a “static” notice period of \(T_n = 168\) h. This elasticity decreases linearly with shortening notice period until it reaches 51% of its initial value at \(T_n = 24\) h. After this, the elasticity is assumed to increase again to 79% of its initial value at \(T_n = 0\) h. This trajectory is represented by the factor \(k_2(T_n)\) as shown in Fig. 7.

\[
\epsilon(T_n) = \epsilon_{s,0} \cdot k_2(T_n)
\]

(6)

The market framework described in Section II starts at 12:00 DA. This implies that the notice period \(T_{n,0}(DH_1) = 12\) hours for delivery hour DH1 and \(T_{n,0}(DH_{24}) = 35\) hours for DH24. Consequently, the elasticity for the first 12 delivery hours would increase directly. On the other hand, the elasticity for the second 12 hours would first decrease and then increase again.

B. Structure of the Price Elasticity Matrix

In this section, the PEM structure is discussed. The idea to use a PEM and suggestions for its structure have been presented in [9]. Consumer response with respect to price changes \(\Delta \lambda\) is reflected by

\[
\Delta D = PEM \cdot \Delta \lambda.
\]

(7)

where \(\Delta D\) is the array of change of demand in the scheduling intervals. If it is assumed that the reorganization of consumption and production does not extend beyond one respective scheduling period (e.g. 24 hours) of \(n\) scheduling intervals, the self- and cross-elasticity coefficients can be arranged in a \(n\) by \(n\) matrix

\[
PEM = \begin{bmatrix}
\epsilon_{11} & \ldots & \epsilon_{1j} & \ldots & \epsilon_{1n} \\
\vdots & & \vdots & & \vdots \\
\epsilon_{i1} & \epsilon_{ii} & \epsilon_{in} \\
\vdots & & \vdots & & \vdots \\
\epsilon_{n1} & \ldots & \epsilon_{nj} & \ldots & \epsilon_{nn}
\end{bmatrix},
\]

(8)
where the diagonal elements $\epsilon_{ii}$ represent the self-elasticities and the off-diagonal elements $\epsilon_{ij}$ correspond to the cross-elasticities.

In Fig. 8 we present three basic categories of flexible consumers. Structure type (α) presents consumers that rearrange their consumption symmetrically before and after the hour of interest. Structure type (β) presents postponing consumers that have different capability to shift their consumption to a later hour. Structure type (γ) presents preproperating consumers that have different capability to shift their consumption to an earlier hour.

![Fig. 8. Structure of the Price Elasticity Matrix for various types of customer reactions, extension based on [9]. (α) Flexible consumer with $c$ values of cross-elasticities. (β) Postponing consumer with $c$ values of cross-elasticities. (γ) Preproperating consumer with $c$ values of cross-elasticities. The length of the horizontal lines represents the number of $c$ values of cross-elasticities, the white spaces represent zero entries.](image)

The ability to shift consumption by $c$ time intervals is modeled by an equal distribution of cross-elasticities along each row. For example the response of a type (α) consumer to shift consumption by $c = 2$ is modeled by $c$ cross-elasticities on the left and on the right of the diagonal with values $\epsilon_{ij} = \frac{k}{c} \forall j \leq i \pm 2$.

The authors of [9] define a PEM that follows $\sum_j \epsilon_{ij} = v_i$ as lossless. However, it should be noted that this relation can only hold if cross-elasticities are redistributed at the rows where they intersect the matrix dimensions.

This above describes the normalised PEM. At each time step, the rows of PEM are multiplied with the respective notice time dependent factor $k_D (D \in 1, 2)$ and scaling with reference demand and price.

$$PEM_{i,1\ldots,n}(T_n) = PEM_{0,1\ldots,n} \cdot k_D(T_n) \cdot \frac{D_0}{\lambda_0}. \quad (9)$$

The reference demand $D_0$ is the forecasted demand $D_{f,i}$ for delivery hour $DH_i$. The reference price $\lambda_0$ is determined as the arithmetic mean of the DA prices $[\lambda(DH_1) \ldots \lambda(DH_{24})]^T$.

### IV. Case Study

In this section, a number of real forecast and production data is analysed in the developed CU-RTP program. We use accurate load forecasts and consecutive hourly updated wind power forecasts from Nordpool spot market [10] as well as real production and load data. The marginal production cost of flexible power generation is modeled by a linear bid curve with a typical slope of supply bids at Nordpool [10]. The slope of supply bids remains the same and the elasticity of consumers changes with decreasing notice time. The initial self-elasticity is set to $\epsilon_{s,0} = -0.3$.

The results of the simulation are displayed for January 22nd, 2017 as an example with a PEM structure of consumer type (α). In Fig. 9 hypothesis 1 was used and in Fig. 10 hypothesis 2 was applied. The figures show the wind power forecasts, prices, flexible generation and demand when informed at different notice time $t_n$. The dotted black line shows the reference scenario where flexibility is solely provided by generators and no flexible demand is present. The full black line shows the response of demand and generation at $t_{n,35} = 12:00$ DA and in blue the response to a very short notice period is shown.

### V. Discussion

The case study is conducted with the assumption of notice time dependent elasticity. Two hypotheses are tested and yield opposing results. As expected, with hypothesis 1, DR should be informed and integrated as early as possible. With hypothesis 2 however, the results suggest that DR should be integrated on a much shorter time horizon. The volume of DR is larger and it leads to more even electricity prices.

The results are strongly dependent on the choice of hypothesis. The structure of the PEM also plays a role, as it decreases...
consumers of modelling quantification the time analysis on electricity flexibility and of swedish
Fig. 10. Simulation results with hypothesis 2, wind power for January 22nd 2017 in Sweden with notice time $t_{n,0}$ to $t_{n,35}$

the volume of DR the more cross-elasticities are used and can lead to non-convergence of the iterative market clearing.

Flexible consumers are modeled with a linearised and normalized elasticity under two hypotheses. We further assume that the bulk aggregated demand of Sweden can be modeled with generic self and cross price elasticities in an elasticity matrix. Suggestions for values and for the structure of this elasticity matrix are presented and discusses. For a more detailed analysis, price elasticities may need to be separated for industrial, commercial and residential consumer segments.

The presented CU-RTP market framework assumes perfect information and competition. Therefore, the market operator would in practise require information about consumers’ notice time dependent flexibility and generators’ costs. The proposed framework can however be used to analyse the potential capacity of DR in different notice periods.

On the day-ahead (long notice period), wind power forecasts show statistically higher forecast deviations, while in the intra-day frame (short notice period), the wind power forecasts tend to display smaller deviations. This suggests that flexible demand may be more effective when integrated on a shorter notice period, i.e. forecast horizon. Furthermore, the authors of [11] found that 50% of the intra-day volume in Elbas is traded in the last 3:19 h before the delivery hour. This implies that in practise most imbalance in the intra-day market Elbas is settled in time frame a of 2:19 h to 1:00 h before the delivery hour.

VI. CONCLUSION

In this paper, the impacts of flexible electricity consumers are studied, when elasticity is subject to notice time. We present a demand response market model that allows for the study of time dependent parameters that impact the system imbalance: statistically improving wind power forecasts and changing price elasticity of demand. We include the time dependency into the demand model and integrate it into an iterative market clearing algorithm. We conclude that current demand response programs are not optimally designed to integrate consumer flexibility that changes with the notice period.

We further conclude that the need for demand response is higher with a short time horizon which should be considered in market design. In order to judge in which notice period consumers are capable of contributing the most flexibility, more evidence from quantitative DR studies and pilot projects in different time frames is required.

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