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Demand response approaches for real-time renewable energy integration
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Study of Price Elasticity's Predictability for Special Low Voltage Consumers

Pierfrancesco Corsi [a], Pedro Faria[b], Zita Vale[b]

[a] *UNIPD – Università di Padova, Province of Padua, Itália*
[b] *IPP – Polytechnic of Porto, Porto, Portugal*

Abstract

Demand Response programs have been assuming lot of importance in the simulations for electric systems in the last years. Their evolution brought to the need of new models able to consider the power consumption profile for every category of user; moreover, in order to better match energy consumptions and productions, highly precise forecasts of loads' profiles will be needed. This goal can be achieved also thanks to the definition of the elasticity factor. This paper proposes a way to obtain the elasticity price value for the BTE type of user together with an interpolation able to predict it. It will be discussed about the importance of having a real-time elasticity value able to vary according to specific factors, as for example user's habits during the weekends or weekdays and weather forecasts.

Keywords: demand response, price elasticy, elasticity forecasting, smart grid

1. Introduction

Demand Response represents a way both for final consumers and transmission system operator to optimize power fluxes during the all day by a technical and an economical point of view. It allows users to respond to electric market offers managing their power consumptions. Load shifting allows for the transfer of load from less to more attractive periods (e.g. lower energy tariffs when dynamic pricing is considered) [1], [2].

It may be interesting analysing demand response from a generation point of view, in fact load shifting represents a useful way to move load from periods where the generation availability is lacking to others when it is abundant (e.g. photovoltaic energy is only available during the day).

There are different categories of electric consumers according to their power consumption: domestic, commercial and industrial. For each one of these consumer's perspective, energy management systems can bring economic advantages: in order to get them several adaptive features are needed but they increase the consumer's comfort and reduce energy expenditure with an efficient strategy [3], [4].

According to [5] industrial and large commercial loads have generally been considered better candidates for DR programs as each individual customer can provide more response. Elasticity is a parameter that characterizes every user as it expresses how much is willing to change its power absorption in response to price changes. Two types of elasticities are defined, in order to better describe the behaviour of the final user in response to price variations: short-run elasticity and long-run elasticity. Short-run elasticity describes the consumer response during the first year since the variable of concern changed while the long-run one takes into account a larger amount of time. According to [6] this distinction allows to observe how consumers' adaptation changes over time. In particular it shows that short-run elasticity describes the price-response from the system with its current infrastructure and equipment while long-run one considers investments that can be made in response to higher prices. In [7] it is also said that reduction in electricity consumptions in response to prices, particularly by residential consumers, is relatively inelastic in the short term. It means that even high price increases produce fairly small changes in electricity usage. Large consumers as industrial ones, on the other hand, are relatively price sensitive.

Elasticity parameter can be a characterization for every type of consumer because each costumer can have different consumption's profile. That brings to the need of define an elasticity value for each user, able to change in time according to factors as the day of the week or weather forecast. This could be helpful for the transmission system operator to better manage real time power fluxes.

In this paper the BTE user type will be analysed in order to demonstrate that is possible to predict elasticity value basing on historical data thanks to interpolating functions. This work intends to explain how the values are obtained and how good are the approximations, referring to MAPE method.

2. Analytical approach for elasticity's predictability

It is possible to predict users' elasticities from graphs of relative price variations in function of relative absorbed power's variations. Indeed, elasticity formula is given by equation (1):

$$\boldsymbol{e} = \frac{\Delta \boldsymbol{Q}/\boldsymbol{Q}}{\Delta \boldsymbol{P}/\boldsymbol{P}} \tag{1}$$

Where Q represents the absorbed power, ΔQ its variation (after and before Demand Response), P represents the price and ΔP its variation (after and before Demand Response).

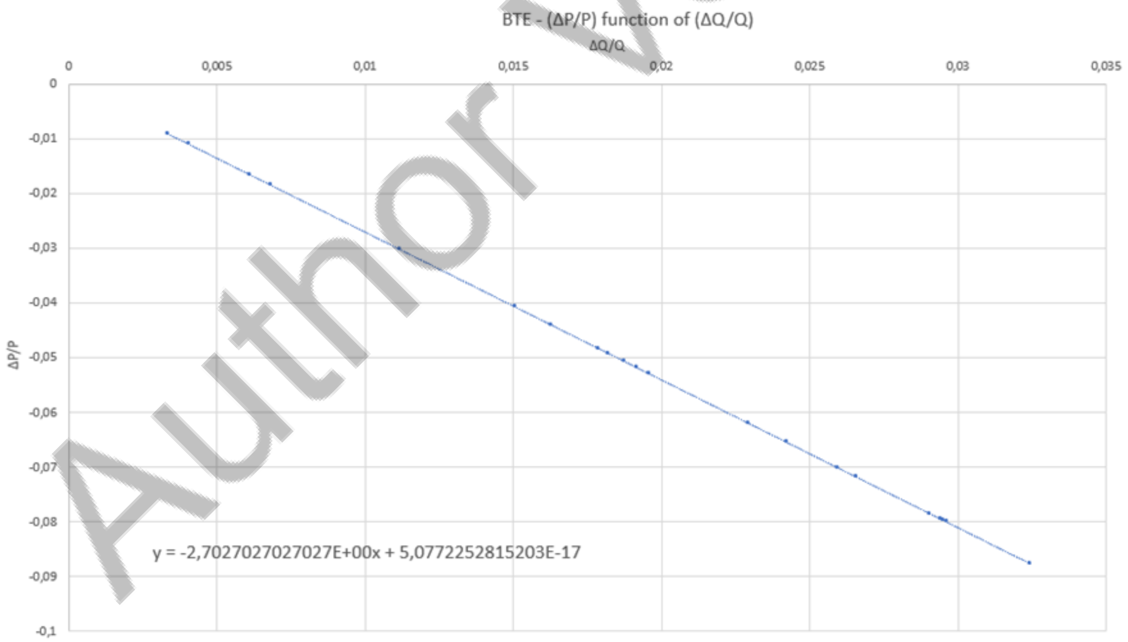

Fig. 1: Graph of ΔP/P in function of ΔQ/Q for BTE user type.

In Fig.1 it is shown how relative price variation is related to relative power absorption. The study was made using (DATA ORIGIN) as input data, assuming for the BTE consumer type the e=0,37 elasticity value. A linear interpolation line was adopted, whose equation is represented in the corner of Fig.1.

The angular coefficient represents the slope of the line, given by the equation (2).

$$slope = \frac{\Delta P}{P} \Big/ \frac{\Delta Q}{Q} \tag{2}$$

Therefore, elasticity value is given by the reciprocal of the slope. Calculations brought a value of e=0,37 that perfectly matches the one given as input data. It means that linear interpolation can be a good method to predict elasticities' values.

Other types of interpolations are possible, such as polynomial (quadratic or cubic) and logarithmic. In order to see how much each interpolation is good the MAPE (3) was used. MAPE stands for "mean absolute percentage error" and according to [8] is one of the most widely used measure of forecast accuracy in businesses and organizations.

3. Results

$$MAPE = \frac{100\%}{n} \sum_{t=1}^{n} \frac{|At - Ft|}{At} \tag{3}$$

Equation (3) gives a value that express the accuracy of the interpolation referring to the input data. This value can be [9] less than 10, between 10 and 20, between 20 and 50 or over 50: it means that have been used a highly accurate forecasting, a good forecasting, a reasonable one and an inaccurate one respectively. That is because (3) equation considers the actual values (called "At") and the forecast values (called "Ft") both averaged on the total number n of elements. MAPE error has been computed for BTE user type for the case of linear, quadratic and cubic interpolation.

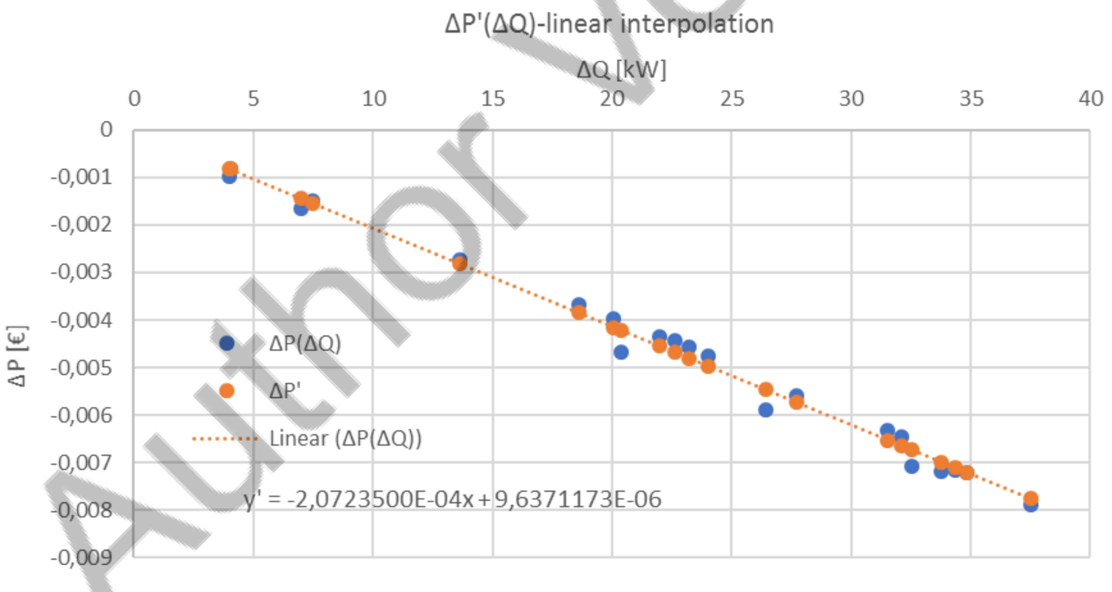

Fig. 2: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on interpolation line.

Fig. 2 shows new values of ΔP, called ΔP', based on interpolation line. Line's equation is written on the left corner of the graph and can be used to estimate ΔP forecast values in function of ΔQ points. MAPE has been calculated for this case: 21 elements were studied and put into equation (3) as n variable. The value is MAPE=4.884 meaning that a highly accurate forecasting has been made.

MAPE calculations have been made also with a quadratic interpolation, shown in Fig. 3. In this case MAPE=4.393, meaning that this interpolation is better than the linear one. Blue points represent measured values and orange ones the new values based on the interpolation function, written on the left corner.

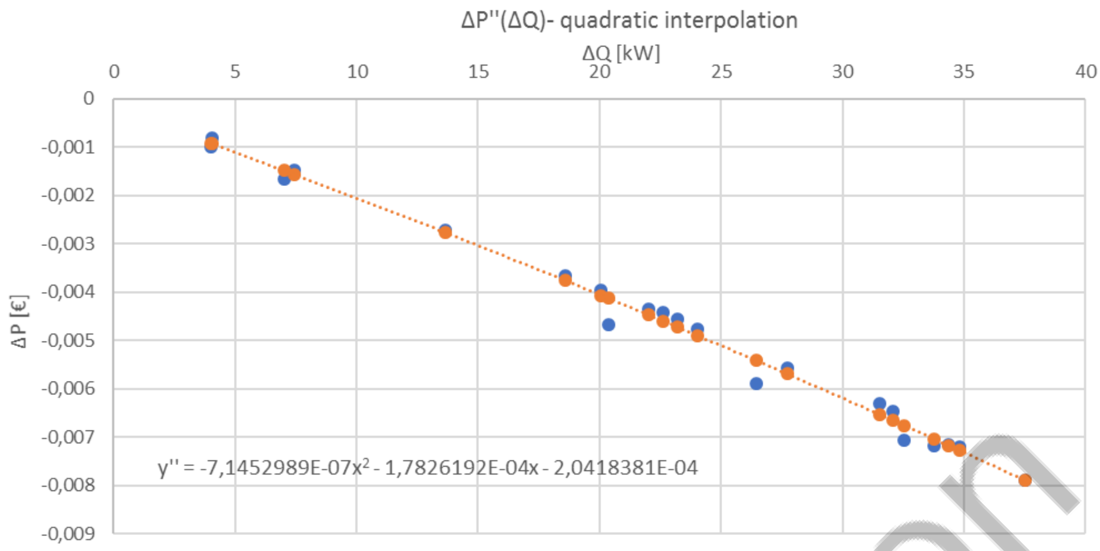

Fig. 3: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on quadratic interpolation.

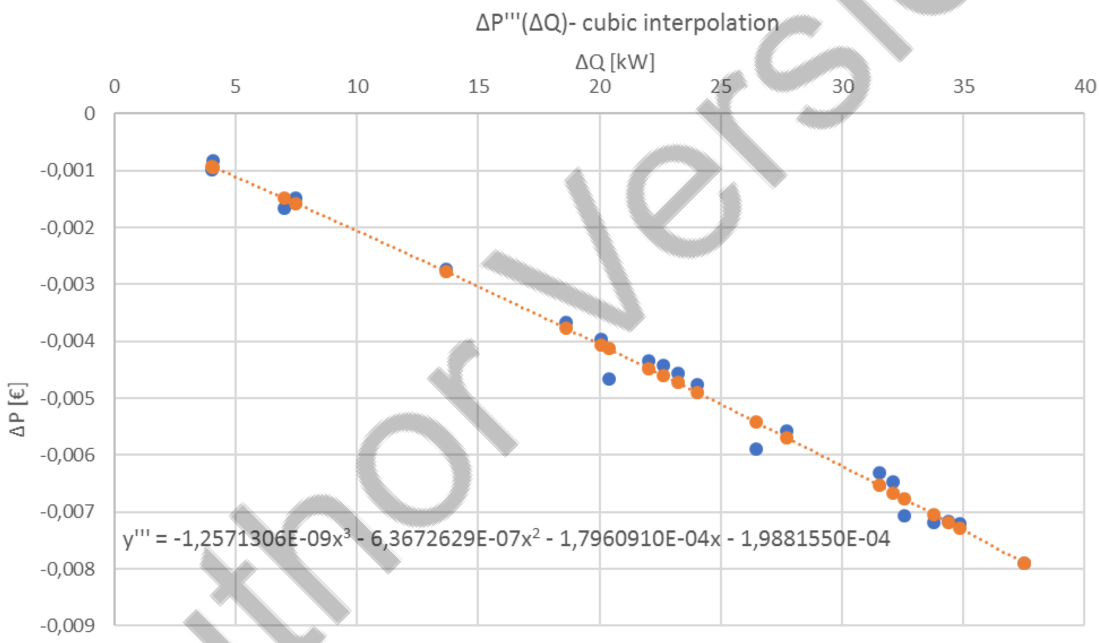

Fig. 4: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on cubic interpolation.

MAPE value in this case is 4.396. A comparison between quadratic and linear case shows that cubic interpolation is not better than the quadratic one.

Logarithmic interpolating function was taken into account, but it resulted to have a MAPE value worse than other methods, precisely 21.137. It is shown if Fig. 5. This means that the other interpolating methods presented (linear, quadratic and cubic) are more indicated. Moreover, if all values along the 24h of a day are collected, it may happen that some of them are related to moments without DR characterized by any ΔQ neither ΔP so logarithmic interpolation wouldn't be able to manage those points in the origin of the axes.

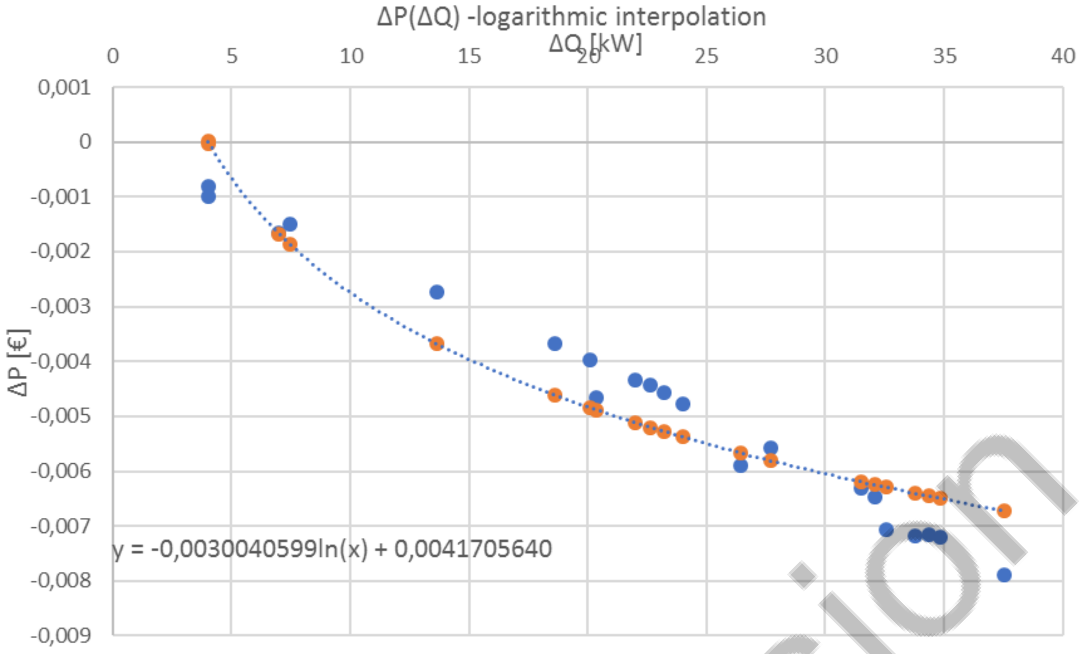

Fig. 5: Graph of ΔP in function of ΔQ (blue points) and forecast points (orange) based on logarithmic interpolation.

4. Conclusions

In this paper it was shown how to obtain the elasticity value of a user by analysing the graph of the relative price variation in function of the relative power absorption. By knowing that value, more accurate forecasts can be done resulting in a better balance between consumption and power offer. This will be handful for transmission system operator that is in charge to keep demand and offer always balanced. In the second part of the paper, a distinction between three types of interpolating functions has been made in order to see which way was more accurate by comparing the MAPE parameter. After excluding the logarithmic interpolation due to its high MAPE, it has been demonstrated that linear, quadratic and cubic functions are able to interpolate points with a good accuracy; in particular, there's not a sensitive difference between the quadratic and the cubic one.

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