Available online at www.sciencedirect.com
ScienceDirect
Energy Reports 6 (2020) 127–132
www.elsevier.com/locate/egyr

6th International Conference on Energy and Environment Research, ICEER 2019, 22–25 July, University of Aveiro, Portugal

Effects of elasticity parameter definition for real-time pricing remuneration considering different user types

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

[a] *Università degli studi di Padova, Via Gradenigo 6, Padova 35131, Italy*
[b] *IPP - Polytechnic Institute of Porto, Porto, Portugal*

Received 1 August 2019; accepted 20 August 2019

Abstract

In the last decade Demand Response (DR) programs have been influencing loads' profiles of electric users who participate in these programs. The evolution of the simulations able to study them brought to the possibility of defining new models that can consider power consumption profiles for different types of user (MAT, AT, MT, BTE, BTN-2, BTN-1) but, in order to better match consumption and production energy curves, highly precise predictions of loads' profiles are still needed. This goal can be achieved also thanks to the study of the price elasticity factor. A way to obtain it will be examined in this paper: price and power absorption variations will be considered because it is defined as the ratio of their relative variations before and after DR. This work focuses on the profiles of price variations ΔP with respect to the absorbed power variation ΔQ: users indeed are expected to vary their consumptions according to different values of remunerations. Moreover, different ranges of elasticities have been evaluated in order to study the behavior of ΔP profiles for the more representing users. Finally, effects of a wrong interpolation have been discussed in order to see their consequences on the actual available power.

Peer-review under responsibility of the scientific committee of the 6th International Conference on Energy and Environment Research, ICEER 2019.

Keywords: Demand response; Elasticity definition; Power profiles interpolations

1. Introduction

Demand Response represents either the availability of an end-use consumer to change its electric usage in response to electricity price variations over time or the incentive payments designed to lower electricity consumptions (in high prices situations or when system reliability is jeopardized). Responsiveness and interaction of costumers with the grid can be promoted, giving as a result an improved reliability of the power system and, in the long term, lower peak demand and reduction of overall plant and capital cost investments [1]. Every user type is characterized by its elasticity value that is necessary to define in order to get a better interaction and a full information exchange between smart grid operators and end-consumers. Elasticity is defined as the availability

* Corresponding author.
E-mail address: pnf@isep.ipp.pt (Z. Vale).

https://doi.org/10.1016/j.egyr.2019.08.030

Peer-review under responsibility of the scientific committee of the 6th International Conference on Energy and Environment Research, ICEER 2019.

Nomenclature

DR	Demand Response
RTP	Real Time Price
MAPEMean	Absolute Percentage Error
DNO	Distribution Network Operator

of a user to vary its power absorption after a remuneration: therefore, its definition is supposed to help building scenarios able to consider the impact of the long-term use of RTP remuneration (Real Time Price). Participating in the RTP program means for the consumer to change his consumption pattern with response to real-time electricity price changes [2]. As said in [3], response of consumers to price variation should not be assumed as totally flexible since constraints as maximum load reduction, price caps, load and generation balance are present. Despite that, this paper aims to focus only on elasticity definition, therefore these constraints are not considered. Households' price elasticities can be increased by the energy management technologies available in a "Smart Grid" context, giving as a result positive net welfare effects of RTP and therefore a growth of the business and policy interest in it [4]. It assumes lot of importance having a real-time elasticity value able to vary according to specific factors as user's habits during the week or weekends, weather forecasts [5], time and location [6]: by defining that, a more accurate prevision for each day of the week can be done allowing to use in the most efficient way the available power in the grid for each moment of the day. As said in [7], estimation of reactions to prices will assume lot of importance in calculating volumes of load shifting, since actual methods will not be sufficient for the balancing authorities. Interpolations of data points have been done because they allow to estimate price variations that every user type can afford or not: every regression has been marked with its MAPE (Mean Average Percentage Error) in order to define which interpolation works better. In every user profile MAPE value related to logarithmic interpolation is far greater than other regressions, meaning that this type of interpolation is less reliable. For this reason, logarithmic fit will be shown only for the BTN-1 consumer type. Interpolations have been realized with Microsoft Excel software. In order to plot ΔP values in function of ΔQ, data from [8] were used. Prices before and after DR program have been calculated and the same was done with power absorptions. Starting from each graph, 3 regression lines have been plotted and their equations represented. For each one of them, new ΔP points have been calculated in order to compute MAPEs in relation to the original data set. The same procedure has been made for every interpolation line: linear, quadratic, cubic, logarithmic. To study how ΔP profiles change as elasticity values do, some range of elasticities have been computed. Indeed, if ΔP profiles are reliable then a good long-run estimation can be made. It assumes importance then to consider new possible values of elasticity since the ones used until now are either "set/assumed" [9] and their reliability is limited to simulations.

2. Method

In order to define price remunerations profiles with more accuracy, some scenarios with different ranges of elasticities have been implemented. Some user types have been characterized by a different elasticity range according to their actual availability of joining DR programs. The central value of each interval was defined as in Table 1.

Table 1. Elasticity values ranges for each consumer type.

User	MAT	AT	MT	BTE	BTN-2	BTN-1
e value	0.53	0.45	0.41	0.37	0.33	0.27
range	±0.03	± /	± /	± /	±0.02	±0.02

After computing ΔP values based on new elasticity values, the following increases (positive sign) and decreases (negative sign) have been found (Table 2). Before analyzing the behavior of the interested users, it is worth of notice how it is possible to get the elasticity value from specific graphs. Since elasticity is defined as the ratio of the relative quantity variation over the relative price variation before and after DR (1), elasticity assumes a geometrical meaning in the graphs. A plot that represents a ΔP/P trend over ΔQ/Q is characterized by an angular coefficient that is the

Table 2. Price variations for some consumers with respect to different elasticities values.

MAT						
Elasticities	0.50	0.51	0.52	0.54	0.55	0.56
$\Delta P \times 10^{-7}$	−5.758805064	−5.75880514	−5.752872	1203.6113272	1808.2963933	2412.9815
BTN-2						
Elasticities	0.31	0.32		0.34	0.35	
$\Delta P \times 10^{-7}$	0.0038910596	−0.0022601286		0.000000006587096	9.269918E−8	
BTN-1						
Elasticities	0.25	0.26		0.28	0.29	
$\Delta P \times 10^{-7}$	15 689.687996	18 414.802027		15 689.6879955825	15 689.687996	

reciprocal of the elasticity parameter (2). Fig. 1 shows a representation of the method used to estimate ΔP values.

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

$$slope = \frac{\Delta P}{P} \Big/ \frac{\Delta Q}{Q} = \frac{1}{e} \tag{2}$$

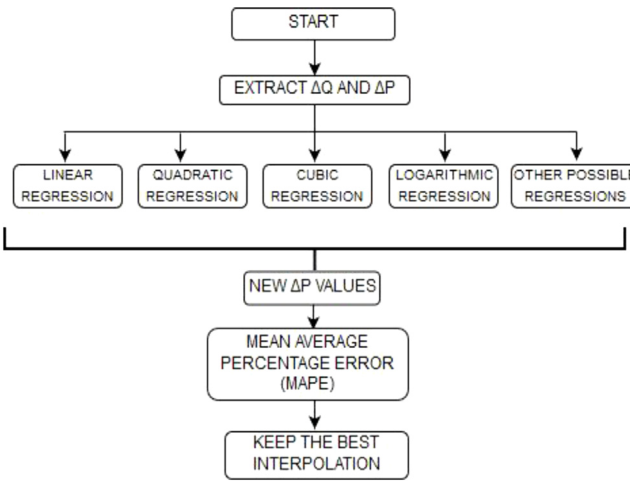

Fig. 1. Representing scheme of the adopted method.

The reliability of this formula is proved starting from the plot of Fig. 2. It must be said that since BTE and BTN-2 users' consumptions are the same, their respective lines are overlying. The slope of every line is shown as the angular coefficient in each equation: according to the previous consideration their reciprocals are the elasticity values. As can be seen, all elasticity values previously given (Table 1) match with high precision the computed ones. A note about the BTN-2 user type must be said since its value matches with less accuracy the given one: a possible cause is related to its power absorption values that are equal to BTE user's (that explains why they have the same elasticity values) despite they are two different user types.

It is important to remind that ΔP is given by the difference of final price Pfin (after DR) minus the initial one Pin (before DR): since price decreases, ΔP assumes negative sign. Negative sign of price elasticity indicates that consumption reduces with the increase in the prices and positive signs indicates reverse case [9]. In Table 3 absolute values of elasticities are reported.

3. Data and results

ΔP plots in function of ΔQ quantity have been made. Each plot has been interpolated with 3 different regression lines: interpolations are indeed necessary to make a prevision of future variations of consumptions and prices. In

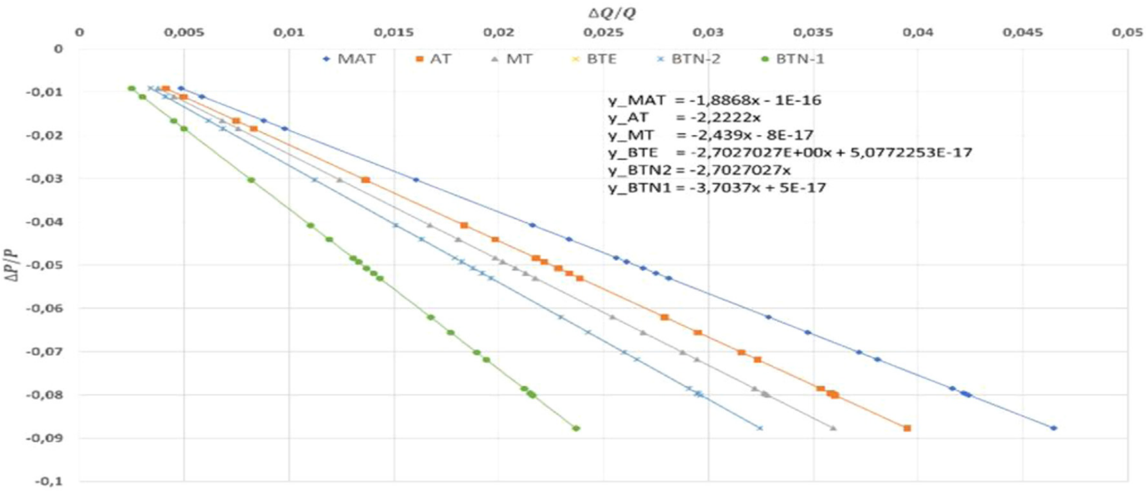

Fig. 2. Plot of ΔP/P over ΔQ/Q for every user with the relative equations.

Table 3. Slope of every line and its reciprocal value for each user type.

	Slope	$\|e\|$	*Original e value*
MAT	−1.8868	0.52999831	0.53
AT	−2.2222	0.45000450	0.45
MT	−2.4392	0.41000410	0.41
BTE	−2.7027	0.37000000	0.37
BTN-2	−2.7027	0.37000000	0.33
BTN-1	−3.7037	0.27000027	0.27

order to judge the reliability of a prediction, MAPE has been calculated for each case. Values under 10 can be considered of highly accurate forecasting [10].

3.1. Consumer profiles

Interpolation graphs for AT and MT consumers are presented in Figs. 3 and 4.

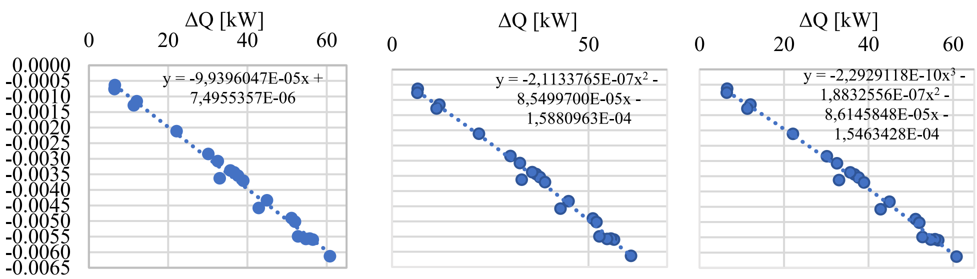

Fig. 3. Linear, quadratic and cubic interpolations of AT user type with their respective equations.

3.2. MAPEs values and BTN-1 logarithmic interpolation

Table 4 shows MAPEs values for all users calculated for each interpolation. All values are under 10, meaning that each interpolation can be considered accurate. For higher voltage levels quadratic interpolations are slightly more accurate: that is the proof that higher interpolation grade (that brings higher computational costs) does not

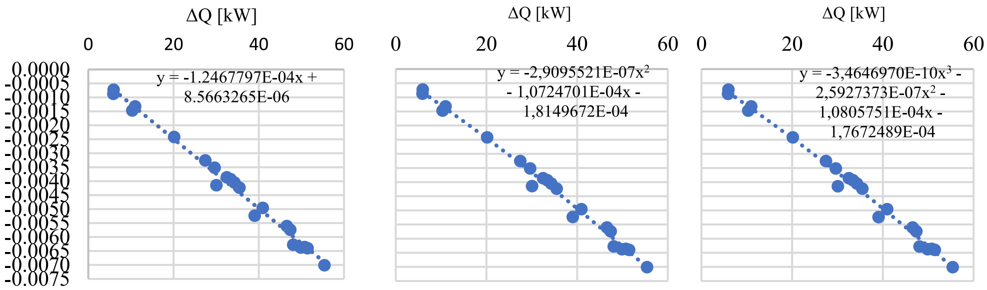

Fig. 4. Linear, quadratic and cubic interpolations of MT user type with their respective equations.

Table 4. Mapes values for all user types for each interpolation.

Mapes	Linear	Quadratic	Cubic
MAT	4.8894412	4.3930200	4.3969621
AT	4.8841733	4.3930200	4.3969610
MT	4.8841733	4.3930201	4.3969610
BTE	4.8841733	4.3930213	4.3969600
BTN-2	4.8841733	4.5605391	4.2337620
BTN-1	4.8841733	4.3930196	4.3969610

bring necessarily to smaller errors. For the BTN-1 user only, a logarithmic interpolation has been studied too. This kind of fit is not as good as the others. For that reason, the plot has been reported only for this consumer type. In this case MAPE = 21.1365. Instead, linear, quadratic and cubic regressions represent a good solution to fit this kind of data.

3.3. Data evaluation method

It was showed how consumption-price values can be interpolated in different ways. Those interpolations bring errors that may result in wrong estimations of the power available for the DNO (Distribution Network Operator) or different price remunerations expected by end-users. Since a model able to represent and predict data is needed, a useful operation is to valuate which regression brings the smallest error and how much it influences DR programs both in terms of power and remuneration. As previously said, logarithmic interpolation is not used due to its high MAPE. For that reason, a comparison only between the first, second and third grade interpolation has been made: for each case it was assumed that the DNO wanted to remunerate the end-user with a specific ΔP value; a comparison between implemented powers in each case was done. Fig. 5 shows the adopted method. Starting from the equations of ΔQ in terms of ΔP, a value of ΔP taken from the original data was used as input for the equations. Each interpolation brought to a different value of ΔQ (Table 5). Those values represent the actual power that the DNO receives from DR users.

Table 5. ΔQ values for each regression type and their deviation from real ΔQ.

$\Delta P = -0{,}0039$ [€/kWh]	ΔQ [MW]	Deviation from original ΔQ [MW]
Linear interpolation	26,94652527	−1,6940980211
Quadratic interpolation	27,16229970	−1,9098724593
Cubic interpolation	27,08780488	−1,8353776303
$\Delta P = -0{,}0040$ [€/kWh]	ΔQ [MW]	Deviation from original ΔQ [MW]
Linear interpolation	27,63050168	−2,3780744329
Quadratic interpolation	27,80148071	−2,5490534669
Cubic interpolation	27,72538433	−2,4729570872

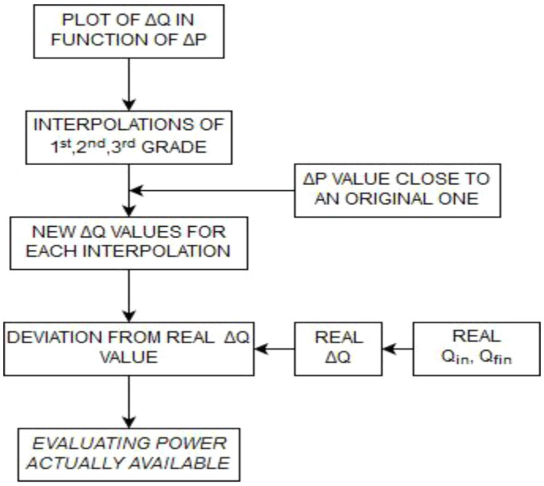

Fig. 5. Representation of the method adopted to evaluate money loss.

4. Conclusions

This paper introduced elasticity explaining why its definition may assume importance in the future: a good estimation indeed allows to deal with environmental, technical and social issues relative to production and consumption of electric energy. There is not a sensible difference between MAPE values, especially between close voltage levels users. At the end, effects caused by wrong elasticity estimations were presented, analyzing differences between the obtained $\Delta Q/\Delta P$ values and the real ones.

Funding

The present work was done and funded in the scope of the following projects: European Union's Horizon 2020 project DOMINOES (grant agreement No 771066), COLORS Project PTDC/EEI-EEE/28967/2017 and UID/EEA/00760/2019 funded by FEDER Funds through COMPETE program, Portugal and by National Funds through FCT, Portugal.

References

[1] Siano P. Demand response and smart grids - a survey. Renew Sustain Energy Rev 2014;30:461–78.
[2] Silva C, Faria P, Vale Z. Assessment of distributed generation units remuneration using different clustering methods for aggregation, In: 2018 IEEE Int. Conf. Commun. Control. Comput. Technol. Smart Grids, SmartGridComm. 2018.
[3] Faria P, Vale Z. Demand response in electrical energy supply: An optimal real time pricing approach. Energy 2011;36(8):5374–84.
[4] Allcott H. Rethinking real-time electricity pricing. Resour Energy Econ 2011;33(4):820–42.
[5] Faria P, Spínola J, Vale Z. Methods for aggregation and remuneration of distributed energy resources. Appl Sci 2018;8(8):1283.
[6] Asadinejad A, Rahimpour A, Tomsovic K, Qi H, fei Chen C. Evaluation of residential customer elasticity for incentive-based demand response programs. Electr Power Syst Res 2018;158:26–36.
[7] Feuerriegel S, Neumann D. Measuring the financial impact of demand response for electricity retailers. Energy Policy 2014;65:359–68.
[8] Faria P, Spínola J, Vale Z. Aggregation and remuneration of electricity consumers and producers for the definition of demand-response programs. IEEE Trans Ind Inform 2016;12(3):952–61.
[9] Joshi SK. Estimation of Price Elasticity of Electricity to Evolve a Methodology for Implementing Load Management Programs At Discom Level, in India. No. January. 2014, p. 115–20.
[10] Montaño Moreno JJ, Palmer Pol A, Sesé Abad A, Cajal Blasco B. Using R-MAPE index as a resistant measure of forecast accuracy. Psicothema 2013;25(4):500–6.