Modelling demand-price curve: a clustering approach to derive dynamic elasticity for demand response programs

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Aim of the presentation

The **price elasticity of electricity demand** is crucial, as it affects profitability, tariffs and demand response programs.

In the majority of the literature of retailer profit maximization problems with demand response, the **value of elasticity is considered constant**.

However, this approach does not reflect always the actual behaviour of the consumers.

The **demand is more elastic** in various periods through the day and through the various seasons.

Flexible tariffs are linked to wholesale prices.
Aim of the presentation

In this paper, a novel and simplified method is proposed to extract dynamic elasticity curves, maximizing consumer’s benefit.

The clustering tool is utilized to extract the profiles of demand-price patterns through the day.

The profiles are used to determine the hourly elasticity of a complete year.

The proposed method estimates different elasticity value per hour, resulting in a more accurate modelling of the consumer’s responsiveness to the price signals.

The proposed method is applied to a high voltage industrial consumer located in Greece.
Hourly load data of industrial consumer
Hourly system marginal price data of the Greek wholesale market
Mathematical formulation

We assume a simplified short-term demand function, linked on the wholesale electricity price.

\[ d \ln (p(h)) = \alpha + b \ln (p(h)), \]

Demand in hour h \hspace{1cm} Price in hour h

It is a simplified representation of short-term price elasticity, we examined in a recent paper with the two-step Engler-Granger methodology, estimated an ECM model (however, with annual historical prices)
Mathematical formulation

The consumer’s benefit from the use of electricity corresponding to logarithmic demand function is given by:

\[
B^C (d^{log} (h)) = B_0^{log} (h) + p_0(h) d^{log} (h) E^{log} (h) \left\{ \frac{d^{log} (h) - d_0^{log} (h)}{E^{log} (h) d_0^{log} (h) - 1} \right\}
\]

- The initial and the final load (kW) per hour,
- Price in hour \( h \)
- Initial consumer’s benefit in hour \( h \)
- Price elasticity

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- Price in hour \( h \)
- Initial consumer’s benefit in hour \( h \)
- Price elasticity
The maximum consumer's benefit is estimated, by setting:

$$\frac{\partial B^C (d^{log} (h))}{\partial d^{log} (h)} = 0$$

we obtain the responsive load function:

$$d^{log} (h) = d_0^{log} (h) \left( 1 + E^{log} (h) \ln \left( \frac{p(h)}{p_0 (h)} \right) \right)$$
Mathematical formulation

**Price elasticity** of demand is given by:

\[ E(h) = \frac{p_0(h) \delta d(h)}{d_0(h) \delta p(h)} \]

we obtain **dynamic elasticities** of the model:

\[ E^{dyn}(h) = \frac{b^{dyn}}{a^{dyn} + b^{dyn} \ln(p_0(h))} \]

by estimating the coefficients a and b, we obtain **elasticity values** that change per hour.

We need pair of load/price data to estimate the a,b parameters, so the price elasticity.
Clustering algorithms

We cluster the data from 365 values (of each hour) to k clusters (for each hour).

Clustering is
• a robust un-supervised machine learning tool
• suitable in cases where no a priori knowledge of the data classes is available

The initial data set can represented with a reduced set of typical patterns or profiles

In the present paper, hourly System Marginal Price (SMP) and load pair values serve as inputs of the clustering

We select a specific profile (load/price pair) and employ it for the estimation of hourly elasticity.
Clustering algorithms

The algorithms can be divided in various categories, i.e. graphic-based, hierarchical, partitional and others.

For the purpose of the detailed evaluation of the proposed method, three different algorithms (from different categories) are compared, namely:

- the **K-means algorithm**, (partitional)
- **Wards algorithm** or Minimum Variance Criterion algorithm (hierarchical) and
- the **Self-Organized Map (SOM) algorithm** (neural network)

The algorithms differ in terms of efficiency, computational speed, input parameter requirements and complexity.
The core of the algorithm is the **minimization** of an objective function, which is the Sum of Squared Errors (SSE).
It not a cost optimization algorithm, but an **hierarchical** method that starts with each pattern being an own cluster, and merge them in fewer clusters, by considering the minimum distance between the patterns.
The SOM is an unsupervised learning **neural network** that consists of a layer of neurons that are arranged in a geometrical topology. Every neuron is connected via weights with the input layer. SOM is trained through competitive learning, until its optimum structure.
Data profiles (load/SMP)

5 clusters

hour#11 and hour#21 obtained by:
a/d) K-means, b/e) Ward`s algorithm, c/f) SOM algorithms respectively
Dynamic elasticity by K-means algorithm

a) k=5, b) k=10, c) k=15 and d) k=20 clusters
Dynamic elasticity by Ward’s algorithm

a) k=5, b) k=10, c) k=15 and d) k=20 clusters
Dynamic elasticity by SOM algorithm

a) $k=5$, b) $k=10$, c) $k=15$ and d) $k=20$ clusters
Mean daily elasticity

a) Linear demand function          b) logarithmic demand function
Conclusions

• Through a novel approach, we obtain **dynamic price elasticity of electricity demand**

• The level of the elasticity is comparable to **constant short-term price elasticity** through other approaches i.e. econometric with ECM

• **No strong correlation** between the shape of the dynamic elasticity and number of clusters.
  – mainly due to the consideration of low dimension patterns: load/SMP dimensions.

• The selection of the **demand function** affects the level and the volatility of the dynamic elasticity.
  – Linear function leads to lower values and volatile shapes while more smooth shapes are observed using the logarithmic demand function.
Conclusions

• The algorithm type (K-means, Ward’s, SOM) does not largely influence the results.
  – If complexity is significant factor, the Ward`s algorithm is proposed.

• The consumer is more elastic in periods with overall increased demand, i.e. interconnected system peaks.

• Therefore, the potential of DR to shave or shift the consumer`s peak is evident

• Could be incorporated/linked with robust methodologies for price and demand forecasting
Modelling journal papers


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