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The impact of virtual power plant technology composition on wholesale electricity prices: A comparative study of some European Union electricity markets.

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Abstract

Virtual Power Plant combines a wide variety of distributed generation resources and operates them as a unified resource on the energy markets. It gives an economic opportunity to renewable energy-based distributed generation, such as photovoltaic, small hydro or wind, as it can build a bridge to the integration of renewable resources in the wholesale electricity market. In this market, changes in the offers of portfolio electricity technologies affect wholesale electricity prices, since marginal generation costs are transmitted through to the wholesale market.
This paper investigates the impact of energy-based distributed generation technologies composition on wholesale electricity prices variations of different EU energy markets by using a Maximum Entropy Econometric estimation procedure. To know how much each unit of electricity produced by each technology can alter the electricity price could be very useful to develop optimal strategies in an electricity technologies portfolio decision.

Keywords: Distributed Generation, Renewable energy, Electricity market, Fuel prices

1. Introduction

European Union has shifted significantly toward a more decarbonized energy system with the introduction of emissions reduction policies which have meaningful impacts on electricity markets. For example, many EU countries have adopted support schemes to encourage electricity generated from renewable sources RES-E (see [1] for a review of support instruments). Under those supports, the number of renewable energy-based distributed generation (RDG) projects have become in the range of hundreds of thousands in a single country. Particularly, in Spain, the Spanish National Commission for Markets and Competition accounted of 60,000 photovoltaic plants (around 90% of them are connected to the electrical distribution grid) in 2014 in comparison with 10,000 plants that had been registered for 2006 [2]. In Italy, the electricity generation structure is

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currently characterized by having more than 700,000 distributed generation points as a consequence of the national RES-E support [3].

In this context, the rising of RDG plants increase the support cost, becoming an unsustainable long-term policy. For this reason, some of the EU regulators are reducing or stopping this support and other are linking the support to the return obtained by RDG in the electricity market. For example, the current Spanish Royal Decree 413/2014 [4] replaces the feed-in tariff and links the RDG supports to a collection of additional payments to what RDG producers receive in the electricity market at a reasonable return.

Thus, RDG is most exposed to electricity market and raises a number of challenges related to its integration in wholesale exchange market ([5] and [6] identify some of those challenges: (i) Under marginal cost pricing in competitive electricity markets the increasing offer of RES-E will reduce electricity price market-, turning renewable plants in less profitable[1], and (ii) as RES-E production is variable it increases RES-E owners´ imbalance costs due to the forecast error. In this context, RDG has to find new solution to increase its economic viability and reduce its risks of unavailability and imbalance generation.

One solution is to combine RDG plants with fueled-based technologies plants or to combine RDG plants ([9] show applications of portfolio optimisation to reduce the risk in the electricity sector). This combination can be done under the concept of Virtual Power Plant (VPP) that combines a wide variety of distributed generation resources (DG) and operates them as a unified resource on the energy markets (see [10] for a comprehensive review of VPP existing research and [11] for review of the value of aggregators in electricity systems). Commercial VPP has an objective to maximize an overall DGs portfolio profit function taking into account uncertainties as market price and RDG production, among others.

Regarding the market price, under VPP deterministic decision-making problems, the market price just appears the only uncertain parameter is most of the existing papers, but most of them consider VPP as price taker since wholesale prices are considered as exogenous inputs in their decision-making problem; for example [12] or [13] that assume that VPP “cannot resemble monopolistic behavior, i.e., have no considerable market power and thus they act as price-taker agents”.

However, by aggregating DG units into a single market unit they can large enough for trading at the wholesale price similar to large-scale producer as [14] pointed out,

[1] For example, [7] indicates that, under some forecasting scenarios about the RES-E penetration that wind and solar will generate 31% and 11% of electricity respectively 2050 ([8] presents a scenario of a Europe with a 100% renewable energy system for the 2050). [7] points out that, as result of lower prices when there is a lot RES-E, the market revenues of renewable will decline rapidly below the average market price. For wind and solar their market revenues will represent 50% and 90% of the average market price respectively.

following in changes in prices. In fact, few authors as [15] or [16] have studied the techno-economic impact of the VPPs considering that VPP is price-maker when it has sufficiently large number of distributed generating units able to alter the formation of the electricity prices.
This scenario is not very far from the real situation, as it is expected that in some countries RDGs units become very high, so its aggregation can have some degree of market power (for example, in Spain it is expected that DG will make up for more than half of the installed electric generation capacity in 2020, becoming the major part of this generation is renewable-energy based as [17] pointed out).
Under marginal cost pricing, changes in portfolio electricity technologies offers directly affect wholesale electricity prices, since marginal generation costs (including the primary energy cost and carbon emissions) are likely to be transmitted through to the wholesale electricity market (see [18] for a detailed discussion about the price formation in electricity markets).

Thus, this article analyses the impact of the variations of RDGs technologies on wholesale spot electricity market. To know how much each unit of electricity produced by each RDG unit can alter the electricity price could be very useful to develop optimal strategies in a commercial VPP portfolio decision.
Various papers focus on the analysis of the impact of renewable technologies and other influence variables on electricity prices at EU level. In that sense, [19] provide a comprehensive overview of some existing results for Germany, Spain, Denmark, Nordpool and Netherlands until 2012, although researches have continued intensively investigating about this topic: [20] estimate the effect of wind energy in the Irish and British wholesale prices; [21] assess the impact of wind generation on Irish electricity market prices and [19] estimate the effect of renewable production on electricity price in the German-Austrian market; [22] analyze the impact on photovoltaic and wind electricity generation on the day-ahead electricity price formation at EEX German; [23] quantify the effect of renewables on wholesale German prices; [24], [25] and [26] study the impact of wind and photovoltaic energies in Italian wholesale electricity prices; [27] and [28] investigate the effects of solar and wind power generation on electricity price in Germany and Netherlands respectively. The case of Portugal was studied by [29] and [30]. In Spain, [31] and [32] focus on the effect of renewables energies on the Spanish electricity prices. Recently, [33] show the effect of the renewable capacity on wholesale prices for Germany, Italy and Spain.

Nevertheless, despite the ample literature studying the impact of renewable energies on electricity prices, (i) most of them restrict the analysis to wind, PV or all aggregated renewables and few of them attempted the analysis using the interaction of different types

of microgeneration plants and other renewable and non-renewable energy sources. Moreover, (ii) the most of existing papers only analyze one European electricity market or a limited number of countries belonging to the same wholesale market so (iii) their comparability is limited as these studies differ with respect to types of renewable sources, country analyzed, econometric approach, and, as well as frequency of the data used.
Our paper aims to extend this empirical literature related to the analysis of the effect of RDG on wholesale electricity markets (i) by taking into account more number of disaggregated renewable sources (we consider not only wind and/or photovoltaic technologies but also and micro and small hydro plants that are not taking into account in other studies), (ii) by extending the analysis to several spot electricity markets and countries: MIBEL (Spain) APX ENDEX (Netherlands), GME (Italy), EEX (Austria), EPEXSPOT-EPEX (Germany and France), and (iii) by allowing the comparability of the results as the same econometric approach, as well as frequency and sample of the data used is considered for each country.

It should be noticed that the most world base data are annual base-data, it gives a homogenous information for each country, but limiting the ample of data. In this situation traditional estimation procedures of economic models may provide biased parameter estimations, among others, or not provide solution. In order to overcome the problem, the Generalized Maximum Entropy Econometric approach ([34] and [35]) is proposed. This methodology has been suitably applied by [36] and [37] and [38] to model Spanish household and industrial electricity prices.

This paper is divided into four more sections. Section 2 presents the first existing literature review about the use of electricity prices on maximization profit of VPP. Section 3 describes the model specification and sample data to estimate the effect of several DERs on European wholesale electricity prices. Section 4 describes the used Maximum Entropy Econometric procedure to estimate the electricity price models. Section 5 presents the estimated models for the considered EU spot electricity markets. Finally, the conclusion section completes the paper.

2. Literature review

Our paper studies the impact of the variations of renewable energy-based distributed generation technologies (RDG) on some European wholesale spot electricity markets. To know how much each unit of electricity produced by each RDG unit can alter the electricity price could be very useful to develop optimal strategies in a commercial Virtual Power Plant portfolio decision. As it was showed in the introduction section, there is an ample literature studying the impact of renewable energies on electricity prices ([19-33]), some of them providing a comprehensive review about the impact of renewables energies on wholesale electricity prices at European level. For example [19] and more recently the paper published by [23] in *Renewable and Sustainable Energy Reviews* journal. Therefore, this section provides a comprehensive overview about the treatment of wholesale electricity price in distributed generation portfolio aggregator (VPP) decision problem.

As it was stated in the introduction section some studies consider electricity price as exogenous input in VPP decision-making problems (VPP is a price-taker) and others considers that price is an endogenous variable (VPPs act as a price-maker).

Regarding the first type of studies, [39] study the formation of a VPP that maximizes its expected profit based on weekly pool participation, among others. For handling market price uncertainties, decisions are made based on the most credible realizations of the prices. In that sense, [40] use a price confidence interval for the VPP decision-making tool for weekly pool participation but also for daily participation. Both studies consider that pool prices are exogenous inputs in the VPP decision-making process, so VPP acts as a price-taker agent. [13] study the reasons behind the profit of the aggregation of DGs under a VPP figure to participate in either wholesale markets or retail markets (under predetermined tariffs). They assume that such coalitions act as price-taker agents as have no considerable market power (they cannot resemble monopolistic behaviour). [41] focuses on the optimal operation of a VPP that aggregates small installed capacities in order to maximize its daily operation profits. As a consequence of the relatively small installed capacities of the VPP components, VPP operator cannot affect the market price so it is considered as a price-taker. [14] use a stochastic programming approach to decide about the participation of a VPP in the day-ahead market where VPP is a price-taker. [42] and [43] study the optimal strategy of a VPP offers by using a probabilistic price-based unit commitment approach. [42] obtain VPP earnings by selling its electricity generation at the market clearing price where VPP is price taker; Also by considering that VPP to act as price-taker, [44] study how the VPP maximizes its profit by deciding only its optimal self-schedule responding to the marginal prices that are considered known. In order to maximize the short-term expected profit of a VPP ([12] propose a two-stage stochastic daily offering model. The virtual power plant sells and purchases electricity where it is treated as a price-taker.
Moreover, [45] present a stochastic profit-based model for day-ahead operational planning of a combined wind farm-cascade hydro system that acts as a VPP. The size of VPP is small so it cannot impact the market price since it holds a small share of the whole electricity market. [46] address the VPP optimization that combines thermal, hydro and wind sources. It is assumed that the producer does not consider the behavior of the other competitors and is a price-taker.

Other authors as [47] and [48] consider the optimization procedure of a VPP that optimizes its benefit by coordinating output energy of DG units, energy storage system and the load demand to arbitrage in the intraday electricity market. Thus, VPP is price response to electricity prices. [49] propose a model to get an optimal dispatch strategy for the VPP under electricity price declared by a distribution company in advance. [50] has as an objective of the VPP to minimize the total operating cost in a circumstance where VPP is price taker and [51] focus on the optimal operation of a VPP by using stochastic programming that rely on the conditional value at risk. The VPP that they consider has no market power so the considered VPP has either no or very little influence on the clearing prices.

Those models can be further extended to consider that the VPP producer is able to influence market prices. For example, [16] describe a procedure to obtain the best offering strategy to maximize the benefit of the VPP from trading in the pool. The VPP optimization problem considers a price-maker power producer "that trades electric energy in a pool-based electricity market. This producer owns a sufficiently large number of generating units of diverse types to be able to alter the formation of the market clearing prices". Also considering that VPP acts as a price-maker [15] develop a model to obtain optimal strategies for commercial VPP. This work compares the VPP profit when it acts as price-maker or price-taker; finally, it should be noticed, that some authors treat VPP as an actor that can negotiate economic details about the price. For example, [52] use a probabilistic model for optimal day ahead scheduling of a VPP, where aggregator is already aware of his power production capability and can negotiate more economic details about the price of his possible power production profile. [53] consider that the VPP is able to influence market prices as the update of the prices needs the accumulated information from all DERs.

3. Model Specification and data: The Wholesale Electricity Market Model

Under the wholesale electricity market, the supply curve is constructed by using the merit order dispatch system that ranks the electricity generation companies offers on ascending order of their short-run marginal cost of production (as primary energy and EU emissions allowance costs). The demand curve is constructed by summing the demand of the consumers. The electricity price is determined by the meeting point between the supply and demand curves. Thus, changes in electricity technologies portfolio offers directly affect wholesale electricity prices as they have different marginal costs.

Following, we specify a model to explain the effect of changes in electricity generation portfolio composition and other explanatory variables on wholesale electricity price.

In order to estimate the effect of several variables (K) related to generation electricity on some EU electricity price (y) by using annual data (t=1,…,T) we specify an econometric model:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \qquad \text{Eq.1}$$

where $\mathbf{y} = (y_1, ..., y_T)'$ is a T-dimensional vector of observations, **X** is a known (TxK) matrix that contain the T observed data of each explanatory variable x_i (i=1,.., K), $\boldsymbol{\beta}$ is an unobservable K dimensional vector of unknowns parameters to be estimated that capture the response of each x_i (i=1,…, K) on **y**, and **u** is a T-dimensional vector of error $\mathbf{u} = (u_1, ..., u_T)'$. The u_t´s are independent random errors with conditional mean zero and positive conditional variance.

According to the merit order dispatch system, changes in short-run marginal cost of production (as coal, natural gas and EU emissions allowance costs) affect directly to electricity price, but also changes in electricity demand (mainly driven by economic activity) and electricity generation of each technology.
Thus, the following 11 (K) explanatory variables are proposed to explain the *wholesale electricity price* (y). :
- *Gross Domestic Product:* GDP. This variable is used as a proxy of Economic Activity.
-*Electricity generated by fuel technologies* (gas, coal and oil): EFU.
-*Electricity generated by nuclear:* ENU.
-*Electricity generated by pumped hydro*: EPH.
-*Electricity generated by small hydro* (hydro -1 MW): ESH.
-*Electricity generated by medium hydro* (hydro 1-10 MW)**:** EMH.
-*Electricity generated by win:* EWI.
-*Electricity generated by solar photovoltaic*: EPV.
-*Electricity generated by other* RES *technologies* (hydro 10+ MW, geothermal, tide, wave and ocean, biomass and waste): ORE.
-*Price of gas:* GAS.
-*Price of EU emission allowances prices:* EUA.

Therefore, the wholesale electricity price model could be specified as:

$$\begin{aligned} y_t = {} & \beta_0 + \beta_{GDP}{*}GDP_t + \beta_{EFU}{*}EFU_t + \beta_{ENU}{*}ENU_t + \beta_{EPH}{*}EPH_t + \\ & +\beta_{ESH}{*}ESH_t + \beta_{ESH}{*}EMH_t + \beta_{EWI}{*}EWI_t + \beta_{EPV}{*}EPV_t + +\beta_{ORE}{*}ORE_t + \qquad \text{Eq.2} \\ & \beta_{GAS}{*}GAS_t + \beta_{EUA}{*}EUA_t + u_t \end{aligned}$$

Our objective is to estimate the Eq.2. for each electricity market: MIBEL (Spain) APX ENDEX (Netherlands), GME (Italy), EEX (Austria), EPEXSPOT-EPEX (Germany and France). The specification for our countries of interest (Spain, Netherlands, Italy, Austria, Germany and France) is basically equal, but Italy and Austria do not have nuclear electricity generation and Netherlands does not have pumped hydro generation, as it is showed in Table 1.

Table 1. Installed Electricity Capacity and Gross Electricity Generation. 2014

	Spain	France	Germany	Italy	Netherland	Austria
Installed Electricity Capacity - MW	**106.470**	**127.791**	**197.501**	**121.747**	**31.762**	**24.048**
Combustible Fuels	49.786	24.387	97.203	71.272	27.286	7.859
Municipal wastes	234	837	1.888	826	649	524
Industrial waste	50	97	953	17	0	436
Solid biomass	677	354	1.589	620	325	959
Liquid biofuels	0	0	232	986	0	1
Biogases	223	290	5.437	1.336	237	192
Other combustible fuels	48.602	22.809	87.104	67.487	26.075	5.747
Nuclear	7.399	63.130	12.074	0	485	0
Hydro	19.223	25.315	11.234	22.098	37	13.293
Wind	22.975	9.068	38.614	8.683	2.865	2.110
Solar PV	4.787	5.669	37.898	18.594	1.048	785
Solar Thermal	2.300	0	2	0	0	0
Geothermal	0	2	24	768	0	1
Tide, Wave and Ocean	0	220	0	0	0	0
Other Sources	0	0	452	332	41	0
Gross Electricity Generation, by Fuel - TWh	**278,7**	**564,2**	**627,8**	**279,8**	**103,4**	**65,4**
Solid Fuels	43,8	9,5	274,4	43,5	29,5	3,0
Petroleum and Products*	14,1	2,1	5,7	14,2	1,9	0,6
Gases	48,8	15,7	72,8	96,7	54,5	7,4
Nuclear	57,3	436,5	97,1	0,0	4,1	0,0
Renewables	114,1	97,6	168,4	122,4	11,7	53,8
Hydro	43,0	68,6	25,4	60,3	0,1	44,8
of which Small Hydro <1MW	0,7	1,3	2,0	3,1	0,0	1,9
of which Medium Hydro 1-10 MW	4,9	4,9	2,6	10,6	0,0	3,9
of which pumped hydro	3,8	5,8	5,9	1,7	0,0	3,8
Wind	52,0	17,2	57,4	15,2	5,8	3,8
Biomass and Renewable Wastes	5,4	5,3	49,4	18,7	5,0	4,3
Solar	13,7	5,9	36,1	22,3	0,8	0,8
Geothermal	0,0	0,0	0,1	5,9	0,0	0,0
Tide, Wave and Ocean	0,0	0,5	0,0	0,0	0,0	0,0
Wastes non-RES	0,7	2,1	7,4	2,5	1,6	0,7
Other	0,0	0,7	2,0	0,7	0,1	0,0

Note*: include crude oil, NGL and other petroleum products
Source: [54]

Our EU base data is annual base-data, it gives a homogenous information for each country, but limiting the ample of data. Moreover, the EU trading system started in 2005 [55], so no information about carbon prices exists before.

The considered *wholesale electricity price* (y) is the baseload Spot Price (€/MWh) collected by DataStream. The *Gross Domestic Product* considered is the *GDP per capita* at constant price (Millions of €, chain-linked volumes, reference year 2005, at 2005 exchange rates) obtained from Eurostat. The *Electricity generated by each technology* is its gross electricity production measured as (GWh) and obtained from Eurostat. As a *Price of gas* the Natural Gas-Henry Hub is taken as a reference (€/million Btu) and it is obtained from the BP Statistical Review of World Energy. The *Price of EU emission allowances prices* (€/tonne of CO_2) is obtained from DataStream. Table 2 and 3 show the main descriptive statistics of the variables used in the analysis.

Table 2. Descriptive values for GDP and electricity generations. 2005-2014

Variables	y	GDP	EFU	ENU	EPU	ESH	EMH	EWI	EPV	ORE
Units	€/MWh	Mill. €	GWh	GWh	GWh	GWh	GWh	GWh	GWh	GWh
Spain										
Mean	46,5	1064952,4	155366,8	57971,1	3437,5	761,0	4076,9	38742,4	4778,7	35048,6
Min	37,0	1021031,0	106689,0	52761,0	2315,0	448,0	1365,0	21176,0	41,0	21675,0
Max	64,1	1120820,0	188773,0	61990,0	4632,0	1451,0	7953,0	55646,0	8327,0	53213,0
St.Devt	8,5	34361,3	30729,4	2821,7	715,6	305,5	2014,6	12160,8	3569,2	10338,8
France										
Mean	47,0	2009332,1	49951,4	434710,2	5134,3	1449,8	4864,2	9008,5	1761,9	62689,7
Min	34,6	1923243,0	26558,0	409736,0	4714,0	1018,0	3749,0	962,0	11,0	51052,0
Max	69,2	2068624,0	61699,0	451529,0	5797,0	1764,0	5611,0	17249,0	5913,0	75201,0
St.Devt	9,0	46566,9	9671,7	12919,8	374,0	219,1	555,8	5754,3	2290,2	6814,3
Germany										
Mean	44,8	2603357,9	374496,3	129669,1	6210,6	2186,9	2861,6	42328,4	14235,4	54347,1
Min	32,8	2426546,4	352439,0	97129,0	5651,0	1890,0	2315,0	27229,0	1282,0	36135,0
Max	65,8	2743893,8	397892,0	167269,0	6915,0	2388,0	4769,0	57357,0	36056,0	70136,0
St.Devt	9,4	103727,5	14574,0	27157,4	466,9	160,4	721,9	9622,9	13045,6	11703,7
Italy										
Mean	68,2	1609768,9	219013,1	0,0	3967,8	2049,6	7817,6	8321,7	7643,2	54040,6
Min	52,1	1541171,9	154324,0	0,0	1711,0	1416,0	5684,0	2344,0	31,0	42209,0
Max	86,7	1687143,2	257790,0	0,0	6860,0	3148,0	10993,0	15178,0	22306,0	70765,0
St.Devt.	9,8	52389,1	35338,8	0,0	2055,8	542,8	1622,8	4910,2	9752,0	9015,7
Netherlands										
Mean	50,0	629853,4	90709,3	3909,0	0,0	0,0	0,0	4258,1	185,0	5893,9
Min	39,1	592792,9	84841,0	2891,0	0,0	0,0	0,0	2067,0	35,0	4108,0
Max	70,0	647158,8	102386,0	4248,0	0,0	0,0	0,0	5797,0	785,0	7307,0
St.Devt	9,2	16323,8	6091,6	421,0	0,0	0,0	0,0	1222,1	254,6	1058,9
Austria										
Mean	45,2	296298,3	18474,1	0,0	3021,1	1660,6	3433,4	2254,7	211,3	40879,7
Min	32,9	276290,2	10922,0	0,0	2145,0	1376,0	2954,0	1331,0	21,0	37183,0
Max	66,2	307508,9	23155,0	0,0	3891,0	2012,0	4214,0	3846,0	785,0	46544,0
St.Devt.	9,5	10120,9	3850,3	0,0	698,8	231,0	399,1	732,0	271,8	3287,5

Table 3. Descriptive values of EUA and Gas prices. 2005-2014

	Mean	Min	Max	St.Devt.
EUA (€/tonne of CO2)	9,8	0,0	22,1	7,3
GAS (€/MM Btu)	7,3	3,5	13,0	3,1

Thus, our annual sample data is limited from 2005 to 2014, so traditional estimation procedures of economic models may provide biased parameter estimations, among others, or not provide solution. The Generalized Maximum Entropy Econometric approach is proposed for modelling estimation.

4. Method: General Maximum Entropy Econometric procedure

We are interested in the estimation of $\boldsymbol{\beta} = (\beta_1,...,\beta_K)'$ of Eq. 1, where each β_i captures the effect of x_i on y (i=1,…, K). We know **X** and observe **y**, but we have K+T unknowns related to each unknown parameter β_i and each residual u_t respectively.

Usually, the estimation of $\boldsymbol{\beta}$ is solved via least square or maximum likelihood methods if the number of observations is larger than the number of unknown parameters (T>K) However, when the number of unknown parameters is higher than the number of observations (T<K) it is not possible to estimate the $\boldsymbol{\beta}$ parameter vector by traditional estimation methods as the problem is ill-posed.

In that situation of small sample data, General Maximum Entropy Econometric approach gives us a solution to estimate $\boldsymbol{\beta}$ (see [34] and [35] for a detailed description of the methodology).

This approach is building based on the entropy-information measure [56] and the classical maximum entropy principle ([57] and [58]) as it is explained in following sub-sections.

4.1. The Maximum Entropy principle

A measure of entropy H(**P**) quantifies the uncertainty associated to a random event. Suppose X to be a random variable with n possible outcome values x_i (i=1, …, n) with an associated probability distribution $\mathbf{P} = (p_1,...,p_n)$ restricted to be strictly positive for each i and sum 1 ($p_i \geq 0$ and $\sum_{i=1}^{n} p_i = 1$), Shannon defined as a measure of entropy [56]:

$$H_S(\mathbf{P}) = H_S(p_1,...,p_n) = -\sum_{i=1}^{n} p_i \ln p_i \qquad \text{Eq.3}$$

The value of the entropy reaches a maximum when **P** is a uniform distribution, in other words, all the values x_i have the same probability. According to indifference principle of Laplace, the uniform distribution adequately represents the case when there is a complete ignorance about the random variable. Nevertheless, sometimes there is some partial information on the distribution of X in terms of aggregates or moments as a_r (r=1..., s) associated with functions $g_r(X)$ of the values of X: $a_r = g_r(X)$. In such case, by using a Maximum Entropy principle ([57] and [58]) is possible to estimate the probability distribution that satisfies the available information.

The problem consists of estimating a **P** distribution by maximizing the value of the entropy measure H(**P**) subject to the available information (a_r, r=1..., s) and non-negative and normalization constraints ($p_i \geq 0$ i=1, ..., n and $\sum_{i=1}^{n} p_i = 1$ respectively). The estimated probability distribution $\hat{\mathbf{P}}$ is obtained by solving the maximization problem.

4.2. The General Maximum Entropy Estimator

In order to estimate the Eq.1 by using entropy tools, we need that all K+T unknown quantities (related to each β_i and u_t) are specified in terms if probability distributions that will allow us to define their entropies H. In other words, to get the General Maximum Entropy estimator (GME), it is first necessary to reparametrize the model of Eq. 1 by recasting each β_i parameter and each u_t disturbance in terms of probability distributions. The entropy estimation approach views β_i and u_t as expected values of some well-defined discrete random variables.

Regarding the unknown parameters, it is assumed that each β_i is a random variable with M possible discrete values (M≥2) defined in the vector $\mathbf{z_i} = (z_{i1}, \ldots, z_{iM})'$ with corresponding probabilities $\mathbf{p_i} = (p_{i1}, \ldots, p_{iM})'$. Then, β_i is considered as the expected value of the variable $\mathbf{z_i}$: $\beta_i = E_{\mathbf{pi}}[\mathbf{z_i}]$.

Thus:

$$\boldsymbol{\beta}\mathbf{=ZP} = \begin{bmatrix} \mathbf{z}_1' & 0 & \cdot & 0 \\ 0 & \mathbf{z}_2' & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \mathbf{z}_K' \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \cdot \\ \mathbf{p}_K \end{bmatrix} \qquad \text{Eq.4}$$

Where **Z** is a (KxKM) matrix, **P** is a KM-dimensional vector of weights restricted to be strictly positive and sum 1 for each i.

On the same way, for each u_t (t=1, ..., T) it is assumed that each one is a random variable with J possible discrete values (J≥2) defined in the vector $\mathbf{v_t} = (v_{t1}, \ldots, v_{tJ})$ and with the corresponding vector of probabilities $\mathbf{w_t} = (w_{t1}, \ldots, w_{tJ})'$. Then, u_{it} is considered as the expected value of the random variable $\mathbf{v_t}$: $u_t = E_{\mathbf{w_t}}[\mathbf{v_t}]$.

Thus:

$$\mathbf{u=VW} = \begin{bmatrix} \mathbf{v}_1' & 0 & \cdot & 0 \\ 0 & \mathbf{v}_2' & \cdot & 0 \\ \cdot & \cdot & \cdot & \cdot \\ 0 & 0 & \cdot & \mathbf{v}_T' \end{bmatrix} \begin{bmatrix} \mathbf{w}_1 \\ \mathbf{w}_2 \\ \cdot \\ \mathbf{w}_T \end{bmatrix} \qquad \text{Eq.5}$$

Where **V** is a (TxTJ) matrix and **W** is a TJ-dimensional vector of weights restricted to be strictly positive and sum 1 for each t.

Therefore the model of Eq. 1 becomes:

$$\mathbf{y} = \mathbf{X\beta} + \mathbf{u} = \mathbf{XZP} + \mathbf{VW} \qquad \text{Eq.6}$$

The objective of interest is the estimation of probability distributions **P** and **W**. The estimated probabilities ($\hat{\mathbf{P}}$ and $\hat{\mathbf{W}}$) allow to estimate each β_i and u_t, as $\hat{\beta}_i = E_{\hat{p}_i}\left[z_i\right]$ and $\hat{u}_t = E_{\hat{w}_t}\left[v_t\right]$ respectively.

The following question is how to estimate **P** and **W** by using the limited information we have. Those distributions are estimated by maximizing the joint Shannon Entropy Measure[2] subjected the information about the model (Eq.1) called consistency constraint, and the positive and normalization constraints about each $\mathbf{p_i}$ and $\mathbf{w_t}$:

$$\begin{cases} \text{Max} \quad H(\mathbf{P},\mathbf{W}) = -\mathbf{P}'\ln(\mathbf{P}) - \mathbf{W}'\ln(\mathbf{W}) \\ \text{st.} \quad \mathbf{y} = \mathbf{X} + \mathbf{u} = \mathbf{XZP} + \mathbf{VW} \\ \quad \sum_{m=1}^{M} p_{im} = 1 \quad p_{im} \geq 0 \quad i = 1,\dots,K \\ \quad \sum_{j=1}^{J} w_{tj} = 1 \quad w_{tj} \geq 0 \quad t = 1,\dots,T \end{cases} \qquad \text{Eq.7}$$

The solution of the optimization problem allows to obtain the estimated probability distributions $\hat{\mathbf{P}}$ and $\hat{\mathbf{W}}$ and therefore to recover $\hat{\boldsymbol{\beta}} = \mathbf{Z}\hat{\mathbf{P}}$ and $\hat{\mathbf{u}} = \mathbf{V}\hat{\mathbf{W}}$ respectively.

If sample information gives us some information about the effect of x_i on y, entropy econometric procedures allows estimating $\mathbf{p_i}$ probability distribution for each β_i far from the situation of complete uncertainty or ignorance (uniform distribution).

It is highlighted that there are more methods to estimate the unknown parameters of a model where they are related to an unknown distribution as the Empirical Likelihood, the Generalized Method of Moments or the Bayesian Method of Moments, among others. However the Generalized Maximum Entropy Econometric approach i) produces efficient estimations when small data set is available, (ii) uses minimal assumptions on the data generating process, iii) does not require restrictive distributional error assumptions as

[2] Although the number of entropy measures is very ample, [35] (page 363) indicates the suitability of Shannon´s entropy measure [56] in the optimization procedures.

Least Square procedure and (iii) can incorporate economic prior information regarding the behaviour of each β_i in its support spaces $\mathbf{z_i}$.

5. Estimated model: Results and discussion

Once the model has been specified (Eq. 2) and the econometric tool for its estimation has been defined (section 4), in this section we present the estimated model for each electricity market: MIBEL (Spain) APX ENDEX (Netherlands), GME (Italy), EEX (Austria), EPEXSPOT-EPEX (Germany and France).

In order to arrive to the GME estimations, it is first necessary to determine the possible values that can take each β_i and each u_t which are and collected in $\mathbf{z_i}$ and $\mathbf{v}_t$ respectively

The parameter space $\mathbf{z}_i$ should be used to reflect the previous knowledge about the unknown parameters β_i. When there is no a compelling economic theory o prior empirical studies giving us some idea about the possible values of β_i, the upper or lower bounds of $\mathbf{z}_i$ can be specified wide enough. However, when a priori information or economic theory about the direction of the impact of one variable (x_i) on other (y), these bounds can be specified to restrict the coefficient to be either non-positive or non-negative as each β_i captures the effect of x_i on y (i=1,…, K). If β_i is restricted to be non-negative, then $z_{i1}=0$ with $z_{im}>0$ for all m>1. Similarly, if β_i is restricted to be non-positive, then $z_{i1}=0$ and $z_{im}<0$ for all m<M.

Regarding the effect of electricity generation technologies on wholesale electricity market, there is a quite generalized idea supported by economic theory and empirical studies that electricity generated by renewables causes a decrease in marginal electricity prices ([19-33]). In all the markets using a merit order dispatch system, electricity generation technologies with lower marginal cost, such as renewable generators, shifts the supply curve of the wholesale electricity market to the right with the result of lower marginal prices. Thus, the coefficients related to small and medium hydro, wind, solar photovoltaic and other electricity generated by RES are restricted to be negative (β_{ESH}, β_{ESH}, β_{EWI}, β_{EPV} and β_{ORE} respectively).

In the other hand, the coefficients related to fuel, nuclear and pumped hydro electricity generation (β_{EFU}, β_{ENU} and β_{EPH} respectively) are restricted to be non-negative as they involve positive generation costs. Moreover, as increases in the price of primary energy sources can directly increase electricity price β_{EUA} and β_{GAS} are restricted to be non-negative. Finally, as increases in the economic activity directly increase electricity demand and thus electricity price, the coefficient β_{GDP} is constrained to be non-negative. Moreover, the amplitude of the range of values which $\mathbf{z_i}$ may assume is arbitrary, but [34] suggest that $\mathbf{z_i}$ can be specified with equally spaced distance discrete points.

Moreover, the a priori range for the possible values that u_t is also arbitrary but it may be used to assume certain characteristics of the error distribution (kurtosis and symmetry). Usually, the vector support $\mathbf{v_t}$ is symmetrically chosen around zero. Regarding the amplitude of the range of values which $\mathbf{v_t}$ may assume [34] suggest to use the *three standard deviation rule* [59] as estimation for v_{tJ} (v_{tJ}=3s, where s is the sample variance of y). $\mathbf{v_t}$ is also specified with equally spaced distance discrete points.
In all cases, the vector supports take three values (M=3 and J=3) because [34] Golan et al (1996) showed a substantial decrease in the error of the estimates when the number of support points increases from 2 to 3.

5.1. Results

Table 4 shows our estimated weights $\hat{\beta}_i$ of Eq. 2 for each EU wholesale electricity price model considered. In order to avoid stationary regression problems, the differenced logarithms of the variables are used. Thus, each estimated $\hat{\beta}_i$ is interpreted as the percentage of the variation in the rate of growth of the electricity prices due by a one unit of percentage variation in each explanatory variable.

We also define a measure to evaluate the contribution of each variable x_i to explain the wholesale electricity price (y) as the *normalized entropy* ([60] and [61]):

$$S\left(\hat{\beta}_i\right) = \frac{-\sum_{m=1}^{M} \hat{p}_{im} \ln\left(\hat{p}_{im}\right)}{\ln(M)} \qquad \text{Eq.8}$$

where $S\left(\hat{\beta}_i\right) \in [0,1]$, zero reflects no uncertainty while one reflects total uncertainty. In other words, $S\left(\hat{\beta}_i\right) \cong 1$ implies $\beta_i \cong 0$ being interpreted that variable x_i is not relevant to explain wholesale electricity price (y).

In order to have a measure of the goodness of fit of the overall estimated model, we use the *information index* entropy measure ([60] and [61]) defined as:

$$R=1\text{-}S\left(\hat{\beta}\right)=1-\frac{-\sum_{i=}^{K}\sum_{m=1}^{M}\hat{p}_{im}\ln\left(\hat{p}_{im}\right)}{K\ln(M)} \qquad \text{Eq.9}$$

being $S\left(\hat{\beta}\right)$ the model´s normalized entropy measure. $R\in\left[0,1\right]$ and it measures the reduction in the initial uncertainty. When higher is the value of R better is the goodness of fit of the overall estimated model.

Table 4 also shows $S\left(\hat{\beta}\right)$ of each variable and the R associated to each estimated model.

Table 4. Estimates of Wholesale Electricity Prices equation by GME estimators

	Spain		France		Germany		Italy		Netherlands		Austria	
i	$\hat{\beta}_i$	$S(\hat{\beta}_i)$	$\hat{\beta}_i$	$S(\hat{\beta}_i)$	$\hat{\beta}_i$	$S(\hat{\beta}_i)$	$\hat{\beta}_i$	$S(\hat{\beta}_i)$	$\hat{\beta}_i$	$S(\hat{\beta}_i)$	$\hat{\beta}_i$	$S(\hat{\beta}_i)$
Const	0,490	0,007	1,060	0,031	0,546	0,008	0,975	0,026	0,330	0,003	0,461	0,006
GDP	2,615	0,001	2,243	0,007	2,562	0,000	2,012	0,026	2,403	0,001	2,475	0,000
EFU	2,128	0,015	2,833	0,012	2,879	0,016	2,860	0,014	1,228	0,186	0,673	0,413
ENU	1,973	0,031	2,164	0,012	1,411	0,135	-	-	0,322	0,637	-	-
EPU	1,228	0,186	0,676	0,412	1,805	0,053	1,850	0,047	-	-	2,463	0,000
ESH	-0,194	0,747	-0,202	0,739	-1,996	0,028	-1,148	0,212	-	-	-0,700	0,399
EMH	-0,217	0,725	-0,882	0,314	-0,302	0,652	-0,746	0,376	-	-	-1,224	0,188
EWI	-1,105	0,227	-0,818	0,342	-1,807	0,053	-1,226	0,187	-1,386	0,141	-0,817	0,342
EPV	-0,005	0,986	-0,669	0,415	-0,592	0,457	0,000	1,000	-0,509	0,507	-0,842	0,331
ORE	-1,017	0,259	-1,220	0,189	-1,931	0,036	-0,951	0,285	-0,544	0,486	-0,805	0,348
EUA	0,203	0,738	0,033	0,935	0,001	0,996	0,175	0,765	0,037	0,929	0,001	0,996
GAS	1,780	0,057	0,634	0,434	0,408	0,574	0,976	0,275	0,791	0,355	0,526	0,497
R	0,332		0,32		0,251		0,351		0,52		0,377	

Note: We have considered several support vectors for z_{iM}. The results presented in this table correspond to the vector support giving the highest goodness of fit of the models, $|z_{iM}|=5$ for all.

5.2. Result analysis

The obtained results show that an increase in GDP has greater impact on electricity prices than fossil fuel related coefficients. On the other hand, and more interesting for the purpose of our assessment, the results show that those coefficients related to renewable energies with negative impact on electricity prices might affect final prices in a percentage as high as 2% per technology.

Among renewable coefficients, wind brings the most widespread market impacts across countries. This impact is reflected on the percentage reduction of electricity prices that each additional unit of percentage variation dispatched from wind power plants carries out. As per country, the highest impact obtained corresponds to Germany (1,807%), followed by Netherlands (1,386%), Italy (1,226%) and Spain (1,105%). Wind impact in most of the countries may be partially explained by the lower price level that traditional fossil fuels receive during night hours, when wind resources increase their capacity and thus spur wind based electricity supply.

On the other hand the model yields significant differences between the coefficients for wind and photovoltaic production in the selected countries (except Austria). The most relevant differences between these technologies correspond to Spain (1,105% wind and 0,005% photovoltaic) and Italy (1,226% wind and 0% photovoltaic).
Other outstanding energy renewables coefficients are related to hydro. For instance, small hydro accounts greater impact on electricity prices in Germany (1,996%) than wind. In the case of Italy, this technology has the second largest impact (1,148%) right after wind. Also, medium size hydro power plants impact particularly the Austrian market displaying its largest reduction on electricity prices (1,224%) followed by solar (0,842%).

Lastly, other renewable energies assessed in the model yield important price impacts in the German (1,931%) market, followed by the French (1,220%) and Spanish (1,017%) markets. Nevertheless, given the portfolio mix on this category, identifying each technology's contribution on the aggregate impact might be difficult.

When assessing comprehensive impact per country, Germany yields by far the most price sensitive market to renewable participation. In the German market, small hydro, wind and other renewable energies are the top three technologies impacting electricity prices. Germany and Spain are the countries where wind power penetration has been more intensive. As a result, the price formation shows to be more complex. The generation uncertainty associated to wind generation makes dispatchable technologies necessary to provide frequency support and load-following capabilities. Particularly, this is shown in our model by the significant values of pumping hydro (1.208 and 1.805 in Spain and Germany, respectively) and of fuel-based plants. The effect of pumping hydro is associated to conventional hydro, but with different signs. Pumping provokes an increase of the price, which is later countered by hydro. The complexity of the price formation is increased by the use of fuel-based generation, which due has tended to increase the price, more notably when fast IGCC (integrated gasification combined cycle) must be used.

Other markets with similar overall impact from RES are EEX (Austria) and GME (Italy). Both markets have important price variations to hydro power generation, although small hydro has a greater impact in Italy and medium hydro in Austria. Wind and other RES are also among the most relevant technologies impacting the electricity prices in both markets.

The variations on comprehensive RES impact across countries reveal other valuable information. When comparing the influence of renewable energy production on electricity prices, market size arises as a possible reason to better explain comprehensive impacts. Furthermore, countries showing substantial RES impact reduction of electricity prices like Germany, Italy and Austria correspond to those countries expanding their RES markets by decreasing fossil fuel and nuclear generation.

Austria has a high penetration of hydro energy (see [62] the evolution for small hydropower in Europe) and related storage. The flexibility of hydro combined with storage to follow the load makes it marginal, rather than in other countries where fuel-based generation must be used as regulation technologies. The reliance on one particular generation is also captured by the model in the case of Austria. With a 55 % of its power capability corresponding to hydro energy, the results of the model observing energy generation show that the price formation is due to the three related technologies: pumping, large and mini hydro. It is remarkable the extent to which this dependence is captured by the model, when for instance the pumping-hydro coefficient is the largest across all countries.

Netherlands is a different case, in that the fuel-based generation is visibly prevalent. This country relying heavily on gas and coal generation (81%) has one of the lowest overall RES impact (except wind) among the selected countries. As a result, primary and secondary services are provided by these plants in a situation in which the perturbing effect of renewables is reduced. Differently, in other countries, in which wind generation is associated to a highly uncertain negative load that must be subtracted from the load forecast to provide an estimate of the residual load, more expensive fuel-based technologies must be called upon as a consequence of wind power shortage, becoming marginal units, and resulting in a price increase.

Similarly, France with an important share of its total electricity production coming from nuclear power generation (78%), exhibits relatively low price impacts from most RES (except other RES). The case of France is particularly instructive. The coefficient for fuel-based generation is large. However, the share of fuel-based generation capacity is the lowest across all the analyzed countries, with just 18% of its generation based on fuels (see Table 1). This may well be due to the large share of nuclear-based generation, visibly higher than in any other country (48 %). If we work out an approximation of the capacity factor of this generation using the data in Table 1, with France producing 436 TWh of nuclear power, the result is 79%. This is a remarkably high value, which is in line with the use of nuclear power as base-load power plants, due to techno-economic restrictions at the time of start-up. In Spain, for instance, the same calculation shows a capacity factor equal to 88%. As a consequence, load following must be done by other more flexible thermal units (mainly coal-based, or the more expensive but also more flexible IGCC). It is noticeable that these two generation technologies, having the only significant coefficients, are responsible for the formation of the price over the last years.

Results on Netherlands show an extreme case. Visibly most of the generation capability in this country comes from fuel-based plants. As a consequence, the regression coefficient related to this technology is the only one showing significance.
Other results indicate that the price of the gas is an important variable to explain wholesale electricity prices in most of the countries (according to the values of the normalized entropy). The deployment of IGCC units in European Union increases the gas demand following in higher prices for gas and in higher prices for electricity, as [63] have shown in the EU. The use of the predictor gas may well serve as an indication of the reliance on IGCC units to follow the load. The case of Spain shows by far the largest coefficient. It is a reflection of the generation model developed in that country over the last two decades [64]. Based on an early strong support of renewable energy, it has been necessary to provide high load-following capabilities to guarantee the reliability of the power system. Unlike the conventional coal plants, IGCC plants are fast units that can absorb the fast changes in load. In Spain, a fast growth of renewables has over-estimated the need for this type of units, however. As a result, their capacity factor is around 16%, which mean they must be remarkably expensive units. This is reflected in the high sensitivity of the electricity price to the gas price.

6. Conclusions

The rising of renewable energy-based distributed generation (RDG) plants have increased the support cost in the EU so some members are reducing, stopping this support or linking it to the return obtained in the electricity market. In this context, RDG is most exposed to electricity market and raises a number of challenges related to its integration ([65] and [66] identify some of those challenges). RDG has to find new solutions to increase its economic viability and reduce its risks of unavailability and imbalance generation (a review of energy system flexibility measures to enable high levels of renewable electricity is showed in [67]).

One solution is to combine RDG plants with others RDG or with dispatchable power plants in a hybrid model [68] under the concept of Virtual Power Plant. Since distributed RDG can participate in the electricity market through smart grid, the aggregator tries to optimize its portfolio in order to obtain the maximum benefit. Although the most common uncertainties modelled for the planner problem are fuel prices or investment costs, among others, for private agents uncertainty produced by electricity spot prices is commonly the most important variable in their portfolio optimization problem [9]. The decision should be mainly driven by market price signals. Therefore, to quantify the impact of each different electricity generation technologies portfolio on wholesale electricity prices it is important for aggregator agent.

This paper presents a new empirical exercise about the impact of the renewable energy-based distributed generation, such as photovoltaic, small hydro or wind, on some EU wholesale electricity prices by using a Maximum Entropy Econometric approach. The considered spot electricity markets and chosen country for the analysis are: MIBEL (Spain) APX ENDEX (Netherlands), GME (Italy), EEX (Austria), EPEXSPOT-EPEX (Germany and France).
The obtained results indicate that among renewable coefficients, wind brings the most widespread market impacts across countries. This impact is reflected on the percentage reduction of electricity prices that each additional unit of percentage variation dispatched from wind power plants carries out. As per country, the highest impact obtained corresponds to Germany, followed by Netherlands, Italy and Spain. For instance, small hydro accounts greater impact on electricity prices in Germany than wind. In the case of Italy, this technology has the second largest impact right after wind. Also, medium size hydro power plants impact particularly the Austrian market displaying its largest reduction on electricity prices followed by solar.

The proposed model was estimated by using annual data and it allows forecasting wholesale electricity price according to several input scenarios such as economic growth, price of fuels, EU RES targets or electricity generated by each RDG technology, as the future trends of these variables are usually published by international and national agencies. For example, the International Energy Agency shows in its last publication [69] forecasts for renewable for 2022. Moreover some countries give more detailed information about annual investment of different renewable technologies or electricity generated by each technology, among others. For example the *Spanish Action Plan for Renewable Energy 2011-2020* [70] gives a detailed pathway of renewable investment for 2020, but also forecasts for fuel prices and CO_2 prices until 2020. The elaboration of price scenarios can be used as a risk-management tool for VPPs.

Moreover, within a medium long-term market horizon, the obtained results provide useful information to commercial virtual power plant to form an optimal coalition of RDGs.

In light of our assessment, we would like to highlight, that the results on the electricity price effects of renewables should be interpreted carefully. Factors, like the market structure of the power sector and sensibility analysis (per hour or day), were not considered in this assessment and may be potentially relevant.

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