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Macro modeling of electricity price towards SDG7

Florinda F. Martins[a,*], Carlos Felgueiras[b], Nídia S. Caetano[b,c]

[a] *School of Engineering (ISEP), Polytechnic of Porto (P. Porto), R. Dr. António Bernardino de Almeida, 4249-015 Porto, Portugal*
[b] *CIETI, School of Engineering (ISEP), Polytechnic of Porto (P. Porto), R. Dr. António Bernardino de Almeida, 4249-015 Porto, Portugal*
[c] *LEPABE-Laboratory for Process Engineering, Environment, Biotechnology and Energy, Faculty of Engineering of University of Porto (FEUP), R. Dr. Roberto Frias, 4200-465 Porto, Portugal*

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Abstract

Energy challenges are crucial issues to achieve Sustainable Development and its goals. Energy availability and affordability are pillars for ending poverty, giving access to commodities as well as water, etc. Modern lives rely on appliances and gadgets based on electric energy being its price a key issue making it worth to analyze and promote simple models able to predict electric energy prices to support in decision-making processes and in management. This work studied the correlation of electricity price with variables such as the electricity *mix*, GDP (gross domestic product), energy productivity, electricity consumption per capita, fossil fuel reserves, and diesel price, using Spearman correlation. To the significant correlations found it was then applied the Kruskal–Wallis test and the variables that presented statistically significant differences were then considered to model electricity price based on these macro variables. Our findings revealed that the best models were a logarithmic and a linear model of energy productivity to predict electricity price, which is fundamental to achieve Sustainable Development Goals (SDG), specifically SDG7. In the validation process, these models presented an average deviation of 10.3% and 11.7%, respectively, which is reasonable considering the simplicity of the models developed.

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Keywords: Electricity price; Energy; Regression models; Sustainable development goals

1. Introduction

The enormous World population growth, and the consumerism lifestyle are leading to extensive use of natural resources and goods per capita, causing huge generation of waste that is not bearable, as it exceeds Earth's carrying capacity. The Earth Over-shoot Day indicator clearly shows that humanity demand for resources and services in a given year exceeds Earth capacity of regeneration. In fact, in many European and other developed countries such as USA, Canada, etc., this day falls in the first semester of the year [1]. The Sustainable Development (SD) paradigm

* Corresponding author.
E-mail address: ffm@isep.ipp.pt (F.F. Martins).

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brought new insights to this challenge, that can be stated as living well within the limits of Earth, which is very difficult considering the asymmetries of countries' development, unevenness of resources and wealth distribution, combined with unsustainable consumption patterns of natural resources, energy, etc.

The Sustainable Development Goals (SDGs) adopted by the United Nations in 2015 are a measure to achieve several global aims within this context, namely to end poverty, protect Earth and give peace and prosperity to humanity [2]. SDGs have been addressed by several authors in different ways. Belmonte-Ureña et al. [3] considered circular economy, degrowth and green growth as pathways to SD, studying the exploration of each SDG and the quantity of research on each SDG. Lamichhane et al. [4] reported a comparison of SD performance considering the 17 SDGs for OECD (Organization for Economic Co-operation and Development) countries. Madurai Elavarasan et al. [5] analyzed the seventh SDG (SDG7) in the context of the recent pandemic. The SDG7 aims at having access to affordable and clean energy, as a fundamental right to have a good quality of life. In fact, energy is used from basic activities in households to industrial activities, transports, recreation, etc., and access to it provides an opportunity to end poverty and facilitates the access to other commodities, such as clean water.

The first target of SDG7 is "*to ensure access to affordable, reliable energy services by 2030*". However, the production of energy can be a highly pollutant and environment harmful activity depending on the source. Thermal power plants that use coal as raw material release not only greenhouse gases, that cause the global warming, but also other pollutants such as particles, that affect Human health. The growing concern about the depletion of Earth natural resources and environment pollution has motivated efforts to increase the share of renewables and many studies try to enhance that kind of energy production and overcome their limitations. Thus, the effect on solar photovoltaic performance was studied under desert climatic conditions [6] as well as other issues such as the integration of solar thermal and photovoltaic with wind and energy storage in batteries [7] or the decentralized electricity storage [8]. The intermittent and uncontrollable nature of solar and wind energy make it necessary to look for solutions to fully explore them. Thus, the optimization of wind energy systems reinforcing the role of wind energy to achieve sustainable development was studied by Sadorsky [9]. Battery energy storage solutions have been studied as well as the combination with other options such as the use of electric heat pumps with wind power (Rotella [10]. Biomass has also drawn much attention in Europe and around the World including G7 [11] and OECD countries [12], etc. To this respect, Moliner et al. [13] analyzed the status of energy production from solid biomass in a region of Italy.

The second target of SDG7 reflects these concerns, since it aims to substantially increase the share of renewable energy by 2030. In spite of the limitations of renewable energy production due to its lower operational control and intermittency, it presents many advantages: the pollution caused is lower than from fossil fuel technologies; it allows the exploration of local resources such as the sun, wind or biomass; it can help decrease the external energy dependency, enhance economy, etc. Thus, tools to assess the life cycle of electricity have also been developed [14] and the effect of environmental policy instruments and technologies on energy generation was also studied [15]. Modeling energy communities is a crucial subject and was addressed considering collective photovoltaic self-consumption, enhancing synergies between a small city and a winery in Portugal [16].

The third and last target of SDG7 aims at doubling the rate of improvement in energy efficiency by 2030. This target is very important because it is also linked to products' design, that should use systematic approaches to reduce energy consumption and environmental impact of products during their life cycle. Thus, life cycle analysis and assessment can be useful tools to assist in decision making about renewable energy sources [17,18].

The link between energy and wellbeing of humanity is recognized and has been addressed by several authors, such as Ciplet [19] and Munro et al. [20] who studied energy justice. The link between renewable energy and standard of living has also been a topic of research in many regions of the World such as Europe [21] and India [22]. The link between energy and SDGs is also frequently considered and analyzed by researchers [23]. Given the climate change problem, other key aspect nowadays is the link among carbon dioxide emissions, electricity production and economic growth [24].

As noted, energy is essential to provide a good lifestyle and to achieve SDGs and that is why this link between energy and SD continues to be relevant for society and for all stakeholders in this area. It affects the three pillars (economic, environmental and social) of SD. It is a fundamental topic that can either support or hinder SD and the achievement of SDGs. For a European citizen it is unconceivable not having access to electricity, that can be easily produced from renewable sources and partially or totally replace fossil fuel production, which is important as it potentially complies with the target of SDG7, clean energy.

The other important target, electricity affordability, is the reason that motivated this work. The existence of models that can predict the market electricity price in each country based on macro indicators can be very important and useful to politicians and decision makers and has been the object of study of several authors [25,26]. Deng et al. [27] on the other hand studied short-term electricity price by using prediction based on long short-term memory for example. Rafiei et al. [28] developed a probabilistic model to predict the hourly electricity price. However, for a more efficient and sustainable use and provision, energy should be analyzed at a macro spatial level, that is, on a region level, and with a longer time frame. It is very important to study electricity prices and to be able to predict its price since it has major consequences at economic, environmental and social levels. Energy affordability, as an example, is very important because it affects people's health and quality of life. Of course, electricity price is also very important to the energy markets, definition of energy policy, and consequently to the economy. Thus, different from previous studies, the aim of this study was to model the relation between electricity price and some macro variables such as GDP, energy productivity, electricity consumption per capita, etc., at a macro scale, that is, not for a single country but for a set of 28 countries that have in common belonging to the European Community (EC). In this work statistical analysis and modeling are used to address relevant questions such as correlations between electricity price and other macro variables and study of models to predict electricity price, and consequently to enhance Sustainable Development. Correlation analysis was used to find significant correlations; Kruskal–Wallis test was used to assess the effect of variables on electricity price, and linear and nonlinear regression to study simple models that can be used to predict average electricity price. Data from a single year (2018) was used to develop the models, and then the best models were applied to predict the electricity prices in the 28 countries in another year (2019), comparing the predicted with the real values, showing the best models are robust. The results allowed an analysis of the electricity price contribution to achieve SDG7.

2. Methods

2.1. Scope, variables and data

In this study 28 countries of the EC and the year of 2018 were considered to perform calculations and statistical analysis. Then, the models produced were applied to the year 2019, and the estimations produced with the model were compared with the corresponding data.

The variables that can potentially affect electricity price, *EP* (€/kWh), and that were considered are as follows: percentage of electricity produced from fossil fuels, *FF* (%); percentage of electricity produced from renewable sources, *R* (%); percentage of electricity produced from nuclear, *N* (%); gross domestic product, *GDP* (10^3 Million €); energy productivity, *EnP* (€/kgoe); consumption of electricity per capita, *CEC* (GJ/capita); fossil fuel reserves, *FFR* (TJ); diesel price, *DP* (€/L). *EnP* reflects the decoupling of energy use from growth in *GDP*. *CEC* was obtained dividing electricity consumption by the corresponding population for a given year. *DP* represents the price of fossil fuels and was calculated as an average value.

All primary data was collected from Eurostat [29] except diesel price that is from European Commission [30]. *EP* is an average value of the two semesters, Band DC consumption between 2500 and 5000 kWh with all taxes and levies included.

2.2. Correlation analysis, Kruskal–Wallis and linear and nonlinear regression

To assess the relationship between two variables, different methods can be used. The Pearson *r* correlation is more suitable when the distribution is normal and the results are more reliable. On the other hand, Spearman's correlation does not require a normal distribution since it is a non-parametric method. To assess normality the Shapiro–Wilk test was used in all data sets. All variables were considered in this stage to determine the significant correlations between *EP* and all other variables. Significant correlation between variables exists if the *p* value is lower than 0.05. If variables are positively correlated the higher one is the higher the other one is; if negatively correlated the higher one is the lower the other one is. The Kruskal–Wallis non-parametric test was applied to compare two or more independent groups. It was used as a confirmation process after correlation analysis to determine if there were statistical differences between groups of a categorical independent variable on a continuous dependent variable. Only the variables that present either positive or negative significant correlation with *EP* were considered. Then, the considered variables were divided in three groups, obtained by dividing the maximum value by three for each variable and considering afterwards three intervals leading to the three groups to perform this test except for *DP* for which was the difference between maximum and minimum. This test was applied to assess the effect of the variables in *EP*.

It was applied linear and nonlinear regression to study possible models to predict *EP* considering the variables that statistically affect it [31]. The Software used was SPSS Statistics 26 [32].

3. Results

3.1. Variable's analysis and tests

The first variable analyzed was the energy mix, that is related with the sources used to produce electricity. As shown in Fig. 1(a), the situation is quite different among European countries, with some having >50% energy from renewable sources (namely Denmark, Croatia, Lithuania, Luxembourg, Austria, Portugal and Sweden) and with Lithuania and Luxembourg with almost 100%. France, Hungary and Slovakia are more dependent on nuclear sources to produce electricity, with France relying on over 70% of electricity from this source. This state of affairs is caused by the availability of technology for nuclear energy production in these countries, while for the former ones there was a high investment on renewable energy resources (such as hydro, and wind, or biomass/biofuels) [33].

GDP is an accepted country economic development indicator, however, the *EnP* that relates *GDP* and energy consumption is even more important from a sustainable point of view. Fig. 1(b) shows *GDP* and *EnP* of the 28 countries under study. I is possible to conclude that there are countries that present high *EnP* and low *GDP* such as Denmark, Ireland and Luxembourg, while others, such as Germany and France have a much higher GDP with lower *EnP*. This is an important variable because it reflects the degree of wealth created with the energy consumed.

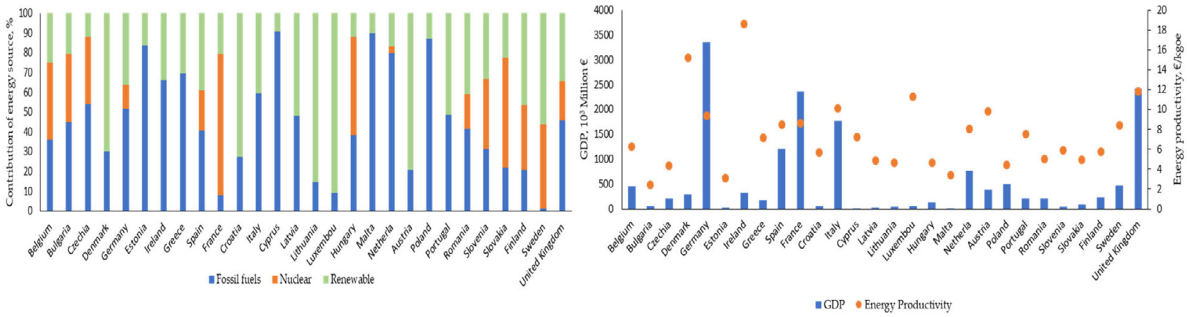

Fig. 1. (a) Sources of electricity production; (b) *GDP* and Energy Productivity (*EnP*) for 28 European Countries.

CEC varies along the countries and, as expected, countries with severe weather conditions in the winter, such as Finland, Sweden and Luxembourg, present a higher *CEC*. In what concerns *DP* Finland, Belgium, France, the United Kingdom, Italy and Sweden present the highest values as shown in Fig. 2(a). The *DP* reflects not only its production cost, but especially the taxes that are applied by governments, not only fiscal but especially environmental taxes. Most European countries do not have fossil fuel reserves. Only Bulgaria, Czechia, Denmark, Germany, Greece, Spain, Italy, Hungary, Netherlands, Poland, Romania and UK have reserves and in some cases they are quite insignificant [34]. The *EP* for the European countries was also considered. As shown in Fig. 2(b), the *EP* varies between 0.1 and 0.31 €/kWh in Bulgaria and Denmark, closely followed by Germany and Belgium (0.30 and 0.29 €/kWh).

Shapiro–Wilk normality test was applied to all variables and the results are presented in Table 1 as well as some descriptive such as mean, minimum and maximum. Analyzing the p value it is possible to conclude that all hypotheses of normal distribution were rejected, except for *FF*, *DP* and *EP*, because in these cases $p > 0.05$ using Shapiro–Wilk. Skewness and kurtosis are closer to zero when the sample is normally distributed and that happens for the set of these variables. According to the Kolmogorov–Smirnov test the conclusions are similar with the difference that *R* and *EnP* also follow a normal distribution. However, Skewness and Kurtosis values are high for *EnP*. Kolmogorov–Smirnov test is less powerful and rejects null normality hypothesis less frequently, what is in accordance with the results obtained. The size of sample is reasonable to apply these tests. *FFR* is not a relevant issue since many European countries do not own these kind of reserves and even the ones that have them, have only small amount, especially if compared to the demand [34].

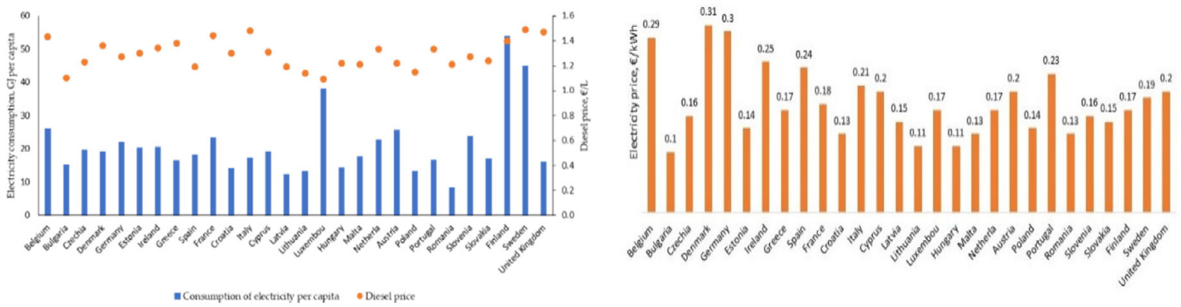

Fig. 2. (a) Consumption of electricity per capita and diesel price; (b) Electricity price in the 28 European Countries.

Table 1. Results of the Shapiro–Wilk normality test.

	Mean	Minimum	Maximum	Kolmogorov–Smirnov [a]			Shapiro–Wilk		
				Statistic	df	Sig.	Statistic	df	Sig.
Fossil Fuels	45.07	1.30	90.60	0.092	28	0.200*	0.959	28	0.328
Renewable	38.24	9.40	90.80	0.133	28	0.200*	0.915	28	0.026
Nuclear	16.69	0.00	71.30	0.285	28	0.000	0.791	28	0.000
GDP	5.69×10^5	1.26×10^4	3.36×10^6	0.319	28	0.000	0.661	28	0.000
Energy Productivity	7.40	2.41	18.58	0.121	28	0.200*	0.901	28	0.012
Consumption of Electricity per Capita	21.13	8.41	53.94	0.216	28	0.002	0.779	28	0.000
Fossil Reserves	1.24×10^3	0.00	1.61×10^4	0.423	28	0.000	0.376	28	0.000
Diesel Price	1.28	1.09	1.49	0.083	28	0.200*	0.970	28	0.584
Electricity Price	0.18	0.10	0.31	0.144	28	0.140	0.931	28	0.066

a Lilliefors Significance Correction * This is a lower bound of the true significance.

3.2. Spearman Correlation

After the application of Shapiro–Wilk test it was possible to conclude that it was more adequate to use the non-parametric Spearman test to find significant correlations between the selected variables and *EP* since many of the variables are not normally distributed. The Spearman's correlation does not require a normal distribution. Table 2 presents the results obtained by applying Spearman method.

There are four significant correlations in what concerns *EP* namely with *GDP*, *EnP*, *CEC* and *DP*, all of them positive, so the higher the value of the variables the higher the price of electricity. There is also a negative correlation of *FF* and *R* and *N* which makes sense, the higher one of them the lower the other. Correlation between renewables and nuclear is not significant.

3.3. Kruskal—Wallis test

For the variables that presented significant correlations with electricity price it was applied the Kruskal–Wallis test. For each variable 3 groups were considered and then the test was applied. Table 3 presents the results obtained. With this methodology it was found that only *EnP*, *CEC* and *DP* present significant results since the p value is less than 0.05, which means that there is evidence that there is a significant difference between the *EP* across the three groups of each variable. These three variables will be considered in the next phase of this study, namely electricity price modeling that will be performed using linear and nonlinear regression. Concerning *GDP* most countries were placed in group 1 and groups 2 and 3 that correspond to high *GDP* have only five countries, Germany, France, United Kingdom, Spain and Italy. This contributed to the result obtained and there was no evidence that there is a significant difference between the electricity price across the three groups of *GDP*.

3.4. Macro modeling of electricity price

In this step several models were considered to find out the best mathematical function to predict *EP*.

Table 2. Results of the Spearman test.

		FF	*R*	*N*	*GDP*	*EnP*	*CEC*	*FFR*	*DP*	*EP*
FF(%)	Correlation Coefficient	1.000	−0.628**	−0.437*	−0.112	−0.218	−0.294	0.373	−0.037	0.016
	Sig. (2-tailed)		0.000	0.020	0.570	0.265	0.128	0.051	0.851	0.936
R(%)	Correlation Coefficient	−0.628**	1.000	−0.281	0.102	0.454*	0.056	−0.322	0.000	0.214
	Sig. (2-tailed)	0.000		0.148	0.604	0.015	0.776	0.095	0.999	0.274
N(%)	Correlation Coefficient	−0.437*	−0.281	1.000	0.288	−0.130	0.257	0.131	0.167	−0.073
	Sig. (2-tailed)	0.020	0.148		0.138	0.511	0.187	0.505	0.394	0.712
GDP(10^9 €)	Correlation Coefficient	−0.112	0.102	0.288	1.000	0.609**	0.271	0.423*	0.452*	**0.618****
	Sig. (2-tailed)	0.570	0.604	0.138		0.001	0.162	0.025	0.016	**0.000**
EnP(€/kgoe)	Correlation Coefficient	−0.218	0.454*	−0.130	0.609**	1.000	0.425*	−0.078	0.493**	**0.831****
	Sig. (2-tailed)	0.265	0.015	0.511	0.001		0.024	0.692	0.008	**0.000**
CEC(GJ/capita)	Correlation Coefficient	−0.294	0.056	0.257	0.271	0.425*	1.000	−0.350	0.400*	**0.504****
	Sig. (2-tailed)	0.128	0.776	0.187	0.162	0.024		0.068	0.035	**0.006**
FFR(TJ)	Correlation Coefficient	0.373	−0.322	0.131	0.423*	−0.078	−0.350	1.000	−0.172	−0.025
	Sig. (2-tailed)	0.051	0.095	0.505	0.025	0.692	0.068		0.382	0.901
DP(€/L)	Correlation Coefficient	−0.037	0.000	0.167	0.452*	0.493**	0.400*	−0.172	1.000	**0.549****
	Sig. (2-tailed)	0.851	0.999	0.394	0.016	0.008	0.035	0.382		**0.003**
EP(€/kWh)	Correlation Coefficient	0.016	0.214	−0.073	0.618**	0.831**	0.504**	−0.025	0.549**	1.000
	Sig. (2-tailed)	0.936	0.274	0.712	0.000	0.000	0.006	0.901	0.003	

** Correlation is significant at the 0.01 level (2-tailed).

Table 3. Results of the Kruskal–Wallis test.

		N	Mean Rank		EP
GDP Groups	1.00	23	12.91	Kruskal–Wallis H	4.865
	2.00	2	23.00	df	2
	3.00	3	21.00	Asymp. Sig.	0.088
EnP Groups	1.00	13	7.00	Kruskal–Wallis H	21.204
	2.00	13	20.15	df	2
	3.00	2	26.50	Asymp. Sig.	0.000
CEC Groups	1.00	13	9.69	Kruskal–Wallis H	8.905
	2.00	12	19.5	df	2
	3.00	3	15.33	Asymp. Sig.	0.012
DP Groups	1.00	10	9.30	Kruskal–Wallis H	7.280
	2.00	10	15.60	df	2
	3.00	8	19.63	Asymp. Sig.	0.026

According to the previous steps there are now three variables that should be used to develop and test the models: *EnP*, *CEC* and *DP*. Table 4 summarizes the models considered in this study and the results of regression. The two parameters chosen to select the best model are the sum of squares of residuals and R square. The sum of squares must be low and R square high. Looking at the results there are three interesting cases, namely models 15, 4 and 1, since they present the lowest sum of squares and the highest R square. Models 4 and 7 are similar because $b = 0$ in model 7. Models 5 and 1 are similar because $b = 0$ in model 5. For models 15, 4 and 1 it was calculated the deviation as the difference between real value for *EP* and the *EP* estimated by the model divided by real value of *EP* for each country. For models 4 and 1 calculations were done using the coefficients obtained with model 7 and 5, respectively, since they conduct to better results. It was also determined the average deviation for each model. Fig. 3 shows the deviations for the three models.

Model 1 and model 15 perform better than model 4 and the average deviation is 15.2%, 39.7% and 13.6% for models 15, 4 and 1, respectively. Linear model 1 can be further improved because looking at the scatter plot (figure not included) there are 3 points that can be considered outliers, Belgium and Germany and Ireland. If these countries are not considered there is an improvement and the sum of squares residual is 0.016, the R square is 0.70, the average deviation is 11.7%. Considering model 15 there are also three outliers corresponding to Belgium,

Table 4. Results of the modeling analysis.

Model		Sum of Squares Residual	R Square	Coefficients
Linear				
1	*EP*=const+a· *EnP*	0.045	0.477	const=0.103a=0.011
2	*EP*=const+a· *DP*	0.068	0.212	const=-0.113a=0.229
3	*EP*=const+a· *CEC*	0.083	0.035	a=0.159b=0.001
4	*EP*=const+a· *EnP*+b· *DP*	0.041	0.519	const=-0.030a=0.009; b=0.110
5	*EP*=const+a· *EnP*+b· *CEC*	0.044	0.481	const=-0.096a=0.010; b=0
6	*EP*=const+a· *CEC*+b· *DP*	0.067	0.214	const=-0.109a=0; b=0.222
7	*EP*=const+a· *EnP*+b· *CEC*+c· *DP*	0.041	0.519	const=-0.029a=0.009; b=0; c=0.110
Nonlinear				
8	*EP*=a· exp(b· *EnP*)	0.049	0.431	a=0.127b=0.047
9	*EP*=a· exp(b· *DP*)	0.069	0.201	a=0.040b=1.176
10	*EP*=a· exp(b· *CEC*)	No convergency		
11	*EP*=a· exp(b· *EnP*)+ c· exp(d· *DP*)	0.045	0.472	a=0.089; b=0.054c=0.002; d=2.303
12	*EP*=a· exp(b· *EnP*)+ c· exp(d· *CEC*)	No convergency		
13	*EP*=a· exp(b· *DP*)+ c· exp(d· *CEC*)	No convergency		
14	*EP*=a· exp(b· *EnP*)+c· exp(d· *CEC*)+e· exp(f· *DP*)	No convergency		
15	*EP*=a· ln(b· *EnP*)	0.040	0.528	a=0.087b=1.223
16	*EP*=a· ln(b· *DP*)	0.067	0.219	a=0.299b=1.432
17	*EP*=a· ln(b· *CEC*)	0.078	0.091	a=0.044b=3.172
18	*EP*=a· ln (b· *EnP*)+ c· ln(d· *DP*)	No convergency		
19	*EP*=a· ln (b· *EnP*)+ c· ln(d· *CEC*)	No convergency		
20	*EP*=a· ln (b· *CEC*)+ c· ln(d· *DP*)	No convergency		
21	*EP*=a· ln (b· *EnP*)+ c· ln(d· *DP*)+e· ln(f· *CEC*)	No convergency		

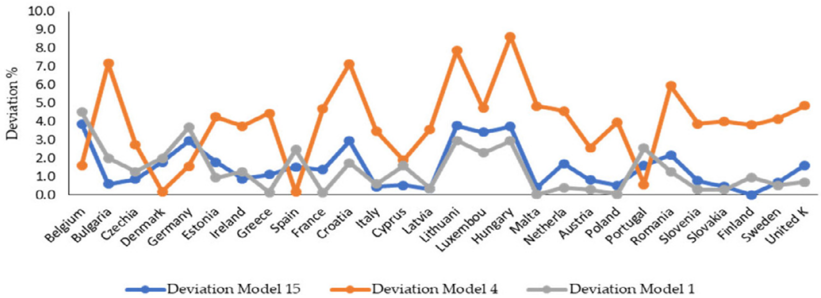

Fig. 3. Consumption of electricity per capita and diesel price for European Countries.

Germany and Denmark (very similar to previous model). Taking this into consideration there is also an improvement in this model and the sum of squares is 0.013, the R square is 0.67 and the average deviation 10.3%. Finally the models that considered all countries, since this may be the most unfavorable situation, were applied to the year 2019 and an average deviation of 13.9% was obtained for logarithmic model and 13.9% for linear model. There are some countries that present high deviation in both models namely Belgium, Germany and Hungary. Both models are based on *EnP* and that may lead to a challenge. *EnP* is positively correlated with *EP* as shown by the Spearman correlation and by the positive values of coefficients, which means the higher the *EnP* the higher the *EP*. *EnP* is an eco-efficiency indicator, so the higher the better, and it brings potentially global economic and environmental advantages. However, this correlation with *EP* may be a drawback in at least some regions of the World, since its improvement can lead to an increase in *EP* that people may not afford. *EnP* is being studied by several authors that analyzed *EnP* and its influence on other areas. At last, but not the least important, it is electricity price that varies significantly across European countries.

Atalla and Bean [35] analyzed the determinants of *EnP*, Alataş et al. [36] studied the potential of material productivity when *EnP* was adopted and Parker and Liddle [37] addressed the *EnP* dynamics in the manufacturing sector. This reveals the importance of *EnP* that should be high because it means that more wealth is generated per unit of energy consumed. Climate change challenges may also affect *EnP* and also other variables including *EP*, since renewable energy sources will be a preferred alternative.

4. Conclusions

This work used a novel approach concerning macro-variables and macro-modeling of *EP*, allowing knowledge sharing between all practitioners to enhance the SD, since it does not need any dedicated software, and it can be used both at a region level and at a local level. Therefore, it was identified the variables that can affect *EP* and a correlation analysis was performed. *GDP*, *EnP*, *CEC* and *DP* presented significant positive correlations with *EP*, which means the higher *the variables* the higher the *EP*. The Kruskal–Wallis test applied to these four variables allowed to verify that *EnP*, *CEC* and *DP* present significant differences and *GDP* does not. These three variables were then applied in 21 linear and nonlinear regression models, of which only, two linear and one logarithmic model (models 1, 4 and 15) presented interesting results. The deviation was calculated using the real *EP* and the value predicted with the models. The simpler linear model $EP=0.103+0.011 \cdot EnP$ (1), and the logarithmic model $EP=0.087 \cdot \ln(1.223 \cdot EnP)$ (15) led to the best values of average deviation, respectively 13.6% and 15.2%, which are reasonable values. It was possible to improve both models by excluding outliers, achieving lower average deviation of 11.7% for the linear and 10.3% for the logarithmic model. *EnP* outstands from the other variables, showing the importance of *EnP* that should be high. However, the positive correlation of *EnP* with *EP* can lead to a rise of *EP* and that can be a challenge in low income regions. *EP* affects millions of people in Europe and in the rest of the World, affecting daily comfort and quality of life. Therefore, it is relevant to analyze important correlations between relevant variables such as *EnP*, *GDP*, etc. and *EP* and to have good models to predict the values to help in the decision-making process and in management. Electricity affordability is crucial to achieve SDG7 and the positive correlation found between *EnP* and *EP* is at least troubling.

CRediT authorship contribution statement

Florinda F. Martins: Conceptualization, Methodology, Data collection, Calculations, Statistical analysis, Writing. **Carlos Felgueiras:** Validation, Review & editing. **Nídia S. Caetano:** Validation, Review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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