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Long-Term Demand Forecasting in a Scenario of Energy Transition

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Received: 9 July 2019; Accepted: 7 August 2019; Published: 12 August 2019

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Abstract: The energy transition from fossil fuels to carbon-free sources will be a big challenge in the coming decades. In this context, the long-term prediction of energy demand plays a key role in planning energy infrastructures and in adopting economic and energy policies. In this article, we aimed to forecast energy demand for Spain, mainly employing econometrics techniques. From information obtained from institutional databases, energy demand was decomposed into many factors and economy-related activity sectors, obtaining a set of disaggregated sequences of time-dependent values. Using time-series techniques, a long-term prediction was then obtained for each component. Finally, every element was aggregated to obtain the final long-term energy demand forecast. For the year 2030, an energy demand equivalent to 82 million tons of oil was forecast. Due to improvements in energy efficiency in the post-crisis period, a decoupling of economy and energy demand was obtained, with a 30% decrease in energy intensity for the period 2005–2030. World future scenarios show a significant increase in energy demand due to human development of less developed economies. For Spain, our research concluded that energy demand will remain stable in the next decade, despite the foreseen 2% annual growth of the nation's economy. Despite the enormous energy concentration and density of fossil fuels, it will not be affordable to use them to supply energy demand in the future. The consolidation of renewable energies and increasing energy efficiency is the only way to satisfy the planet's energy needs.

Keywords: long-term energy demand; energy demand forecasting; energy transition; econometric model

1. Introduction

Modern societies face the challenge of transitioning to a new energy model that permits continuing fulfilment of increasing energy demand while meeting the requirements presented for climate change and sustainability, which can be summarized in the so-called energy trilemma [1] depicted in Figure 1. Industry and governments have to simultaneously pursue energy security (reliability of energy infrastructure, and ability of energy providers to meet current and future demand), energy equity (accessibility and affordability of energy supply across the population), and environmental sustainability (energy efficiency and the development of energy supplies from renewable and other low-carbon sources).

The commitments of the European Union, derived from the Paris Agreement, established a goal of reducing emissions between 80% and 95% by 2050, compared to 1990 levels [2]. This necessarily leads to the electrification of most of the energy demand, which would cause the demand for electricity to approximately double what it is currently before the year 2060 [3].

In this context, the prediction of energy demand plays a key role in planning energy infrastructures and in adopting economic and energy policies. Besides institutional and national studies, many academic works have addressed this problem, adopting global [4], regional [5], national [6,7], or even local [8] perspectives.

Energy forecasting has been addressed in the literature, mainly considering three different prediction horizons: short-term (an hour to a week) [9,10], mid-term (a month to 5 years) [11], and long-term (5 to 20 years) [12]. Prediction methods can be additionally categorized into two types: data-driven methods, where the relationship between the energy demand and its causal variables is automatically discovered using statistical procedures [13]; and model-driven, where this relationship has been previously established [14].

Data-driven methods can be classified as autoregressive (those using only historical data to make predictions) and causal (those which also consider external variables influencing energy demand, such as temperature, economy, etc.).

Once the variables used to make predictions (either only past values or past and external values) have been established, different data-driven forecasting techniques have also been suggested in the literature, such as artificial neural networks [10], fuzzy logic [15], time-series analysis [16], regression models [6], support vector machines [17], or genetic algorithms [18].

By contrast, model-driven predictions can be made using system dynamics [19], or, more often, econometric models [20,21]. For large horizons (long-term predictions), data-driven methods are more likely to fail, as the forecasting error usually increases with the length of the prediction horizon. Thus, econometric models are the most commonly employed technique [22]. Ghalehkhondabi et al. [23] have made an overview of general energy demand forecasting methods.

Econometric models have been employed to forecast energy demand for regions as diverse as, for instance, China [24], South Korea [25], Mexico [26], United Kingdom [27], South Africa [28], United States [29], or Europe [30].

Some other works have also addressed long-term energy demand prediction for Spain, as it is an active country in the renewable energy market [31]. Most of them have addressed partial aspects [32–37], although research from a more general perspective can be found in References [38,39]. However, these two general approaches focus only on electricity demand and not overall energy consumption, which is the key factor determining CO_2 emissions.

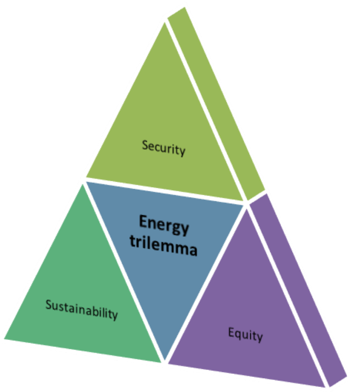


Figure 1. Energy trilemma.

In our research, the goal was to obtain a long-term forecast (year 2030) of the Spanish total energy demand. As was suggested by the literature review described in the previous paragraphs, the approach of this paper used econometrics techniques. From information obtained in institutional databases, energy demand was decomposed into many factors and economy-related activity sectors, obtaining a set of disaggregated sequences of time-dependent values. Using time-series techniques, a long-term prediction was then obtained for each component. Finally, every element was aggregated to obtain the final long-term energy demand forecast.

2. Materials and Methods

2.1. Data Sources

The data used in this paper can be found in the Eurostat (European Statistical Office) databases [40]. More specifically, for this research, population [41], economic [42], energy [43], and climate change [44] magnitudes were considered for Spain for the period 1990–2015.

The energy magnitudes have been disaggregated into $n = 30$ activity sectors (level 1), as it is detailed in Table 1.

Table 1. Sectors of activity considered for energy demand disaggregation.

<table>
<tr><th>Sector</th><th>Level 1</th><th>Level 2</th><th>Level 3</th></tr>
<tr><td>1</td><td>Agriculture and Forestry</td><td>A: Agriculture and Forestry</td><td>A: Agriculture and Forestry</td></tr>
<tr><td>2</td><td>Chemical and Petrochemical</td><td rowspan="13">I: Industry</td><td rowspan="13">I: Industry</td></tr>
<tr><td>3</td><td>Iron and Steel</td></tr>
<tr><td>4</td><td>Non-Metallic Minerals</td></tr>
<tr><td>5</td><td>Wood and Wood Products</td></tr>
<tr><td>6</td><td>Construction</td></tr>
<tr><td>7</td><td>Paper, Pulp and Print</td></tr>
<tr><td>8</td><td>Food and Tobacco</td></tr>
<tr><td>9</td><td>Textile and Leather</td></tr>
<tr><td>10</td><td>Machinery</td></tr>
<tr><td>11</td><td>Transport Equipment</td></tr>
<tr><td>12</td><td>Non-Specified (Industry)</td></tr>
<tr><td>13</td><td>Mining and Quarrying</td></tr>
<tr><td>14</td><td>Others (Industry)</td></tr>
<tr><td>15</td><td>Hotels, Restaurants</td><td rowspan="6">S: Services</td><td rowspan="6">S: Services</td></tr>
<tr><td>16</td><td>Health and Social Action Sector</td></tr>
<tr><td>17</td><td>Education, Research</td></tr>
<tr><td>18</td><td>Trade (Wholesale and Retail)</td></tr>
<tr><td>19</td><td>Public and Private Offices</td></tr>
<tr><td>20</td><td>Others (Services)</td></tr>
<tr><td>21</td><td>Cars</td><td rowspan="4">Tp: Passenger Transport</td><td rowspan="8">T: Transport</td></tr>
<tr><td>22</td><td>Buses</td></tr>
<tr><td>23</td><td>Rail Transport of Passengers</td></tr>
<tr><td>24</td><td>Others in Passenger Transport</td></tr>
<tr><td>25</td><td>Trucks and Light Vehicles</td><td rowspan="3">Tf: Freight Transport</td></tr>
<tr><td>26</td><td>Inland Waterways</td></tr>
<tr><td>27</td><td>Rail Transport of Goods</td></tr>
<tr><td>28</td><td>Others (Transport)</td><td>To: Others (Transport)</td></tr>
<tr><td>29</td><td>Occupied Dwellings</td><td>R: Residential</td><td>R: Residential</td></tr>
<tr><td>30</td><td>Others</td><td>O: Others</td><td>O: Others</td></tr>
</table>

Some medium (level 2) or coarse (level 3) partial disaggregation has also been employed in some representations through the article. The structure of energy demand disaggregation is depicted in Figure 2.

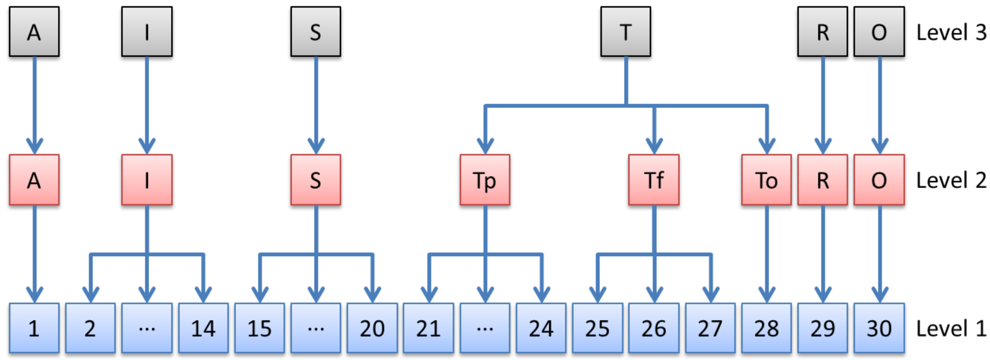


Figure 2. Structure of energy demand disaggregation.

2.2. The Kaya Identity

In energy transition scenarios, the emission of the greenhouse gas carbon dioxide is one of the most relevant variables to be considered. For that reason, in the last decade of the 20th century, the Kaya identity [45] was proposed as a method to decompose the influence of different elements on CO_2 emissions. This identity can be formulated as:

$$C = P \cdot G_p \cdot I_e \cdot F_e \tag{1}$$

where C is the global CO_2 emissions due to human activities; P is the world's total population; G_p is defined as G/P, that is, the world's gross domestic product (GDP: G) per person (P); I_e is the energy intensity, defined as E/G, with E being the global energy consumption; and F_e is the carbon footprint of energy, defined as F/E. Substituting these definitions into Equation (1), the Kaya identity can also be formulated as:

$$C = P \cdot \frac{G}{P} \cdot \frac{E}{G} \cdot \frac{F}{E} \tag{2}$$

The increase of the population (P) and the development of the economy (G_p) are the main elements that identify the energy needs of a society. Following the Kaya identity, future increase of population and economic growth can be compensated through an improvement in energy efficiency (lower values of I_e) and the decarbonization of the energy consumed (lower values of F_e). The reduction of greenhouse gas emissions justifies actions aimed at reducing these two factors. In the context of this paper, aimed at energy demand forecasting, only the first three factors of the Kaya identity were considered, while the fourth (F_e) should play a key role in energy production policies.

2.3. Laspeyres Decomposition

Most of the member countries of the OECD (Organisation for Economic Co-operation and Development) have established energy saving and efficiency objectives in their energy and environmental policies. However, there is a big challenge in measuring these values and their progress over the time. The problem becomes even more complex if there are economic changes and, jointly, improvements in energy efficiency. To tackle this issue, several decomposition methods have been proposed [46]. By far the most employed techniques in energy studies are the Laspeyres method [47–49] and the logarithmic mean Divisia index (LMDI) [50,51], due to their ease of understanding and their advantages over other competing indices (Fischer [52] or Paasche [53]).

To obtain the energy demand forecast, the following procedure (as depicted in Figure 3) was employed:

1. Using a decomposition method, the raw economic data (1990–2015) were disaggregated into several economic sectors and, for every sector, into three factors (activity, structure, and intensity), which will be defined below.

2. The time-series obtained for every sector and factor was used to forecast its values (2030). The forecasted values were then aggregated to obtain a prediction of the energy demand.

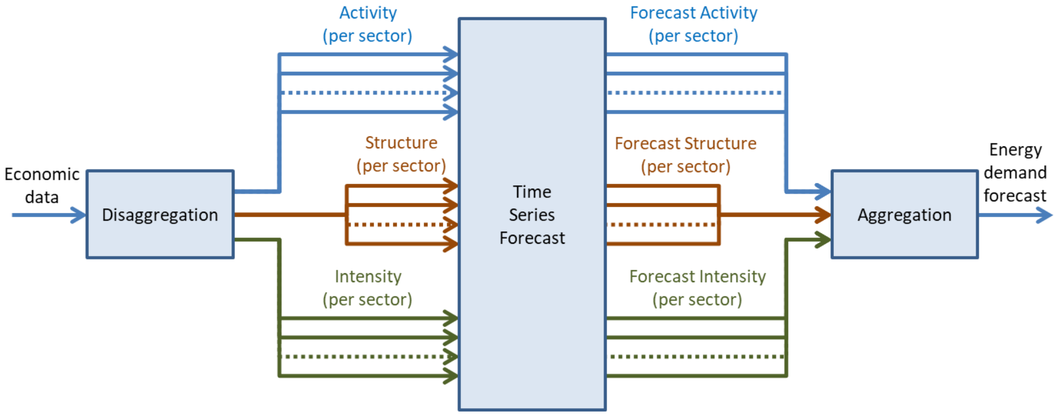


Figure 3. Procedure to obtain the energy demand forecast.

Let us call n the number of economic sectors of a certain economy. At a given time, t, we will use the following definitions:

- $A^{(i)}(t)$: level of activity of the i-th sector, which is measured by the gross value added for the industry and services sectors, by population for residential consumption, and by passenger-kilometers and ton-kilometers for the sectors of passenger and freight transport, respectively;
- $E^{(i)}(t)$: energy consumption of the i-th sector;
- $A(t)$: total level of activity, considering all the sectors;
- $S^{(i)}(t) = A^{(i)}(t)/A(t)$: weight of the i-th sector in the structure of the economy;
- $I^{(i)}(t) = E^{(i)}(t)/A^{(i)}(t)$: energy intensity of the i-th sector;

Based on these definitions, it can be written that:

$$E^{(i)}(t) = A(t) \cdot \frac{A^{(i)}(t)}{A(t)} \cdot \frac{E^{(i)}(t)}{A^{(i)}(t)} = A(t) \cdot S^{(i)}(t) \cdot I^{(i)}(t). \quad (3)$$

The change of energy consumption due to a change in the total level of activity for a period of time between t_0 and T can be expressed, as shown in Appendix A, as:

$$\Delta E_A^{(i)} = A(T) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) - E^{(i)}(\mathrm{t}_0) + \varepsilon_A^{(i)}. \quad (4)$$

Analogously, the other two components are defined as:

$$\Delta E_S^{(i)} = A(t_0) \cdot S^{(i)}(T) \cdot I^{(i)}(t_0) - E^{(i)}(\mathrm{t}_0) + \varepsilon_S^{(i)}; \Delta E_I^{(i)} = A(t_0) \cdot S^{(i)}(t_0) \cdot I^{(i)}(T) - E^{(i)}(\mathrm{t}_0) + \varepsilon_I^{(i)}. \quad (5)$$

Considering now the n sectors of the economy, we obtain:

$$\Delta E = \sum_{i=1}^{n} \Delta E^{(i)} = \sum_{i=1}^{n} \left(\Delta E_A^{(i)} + \Delta E_S^{(i)} + \Delta E_I^{(i)} \right) = \sum_{i=1}^{n} \Delta E_A^{(i)} + \sum_{i=1}^{n} \Delta E_S^{(i)} + \sum_{i=1}^{n} \Delta E_I^{(i)}. \quad (6)$$

For the activity component, it can be written, as shown in Appendix A, that:

$$\Delta E_A = \left[\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)} \right] - E_0 + \varepsilon_A. \quad (7)$$

Analogously, the other two components are:

$$\Delta E_S = \left[\mathrm{A}_0 \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)} \right] - E_0 + \varepsilon_S; \ \Delta E_I = \left[\mathrm{A}_0 \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)} \right] - E_0 + \varepsilon_I. \quad (8)$$

Finally, the increasing energy demand is decomposed as:

$$\Delta E = \Delta E_A + \Delta E_S + \Delta E_I. \quad (9)$$

This expression is called the additive decomposition. It is sometimes preferred to use the ratio of increasing energy demand, R_E, instead of the direct value of this increase (ΔE).

$$R_E \equiv \frac{E_T}{E_0}. \quad (10)$$

In the common case where $\Delta E_A, \Delta E_S, \Delta E_I \ll E_0$, the increase of energy demand is multiplicatively decomposed, as shown in Appendix A, as:

$$R_E \approx R_{EA} \cdot R_{ES} \cdot R_{EI} = \frac{\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)}}{E_0} \cdot \frac{\mathrm{A}_0 \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)}}{E_0} \cdot \frac{\mathrm{A}_0 \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)}}{E_0} + \varepsilon'. \quad (11)$$

2.4. LMDI Decomposition

In logarithmic mean Divisia index (LMDI) decomposition, the change of energy consumption due to a change in the total level of activity, for a period of time between t_0 and T, can be expressed, as detailed in Appendix B, as:

$$\Delta E_A^{(i)} \equiv E_A^{(i)}(T) - E_A^{(i)}(t_0) = E^{(i)}(t^*) \cdot \left\{ Ln\left[A^{(i)}(T)\right] - Ln\left[A^{(i)}(t_0)\right] \right\} + \varepsilon_A^{(i)} \quad (12)$$

where $E^{(i)}(t^*)$ is an approximate intermediate value of $E^{(i)}$ in the interval $[t_0, T]$. LMDI decomposition uses for the approximation the logarithmic mean, which is:

$$E^{(i)}(t^*) \ = L\left[E^{(i)}(T), E^{(i)}(t_0)\right] \equiv \frac{E^{(i)}(T) - E^{(i)}(t_0)}{Ln\left[E^{(i)}(T)\right] - Ln\left[E^{(i)}(t_0)\right]}. \quad (13)$$

Thus, as shown in Appendix B:

$$\Delta E_A = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{A_T^{(i)}}{A_0^{(i)}} \right) \right] + \varepsilon_A. \quad (14)$$

Analogously, the other two components are:

$$\Delta E_S = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{S_T^{(i)}}{S_0^{(i)}} \right) \right] + \varepsilon_S; \ \Delta E_I = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{I_T^{(i)}}{I_0^{(i)}} \right) \right] + \varepsilon_I. \quad (15)$$

LMDI decomposition can also be expressed in the multiplicative form as:

$$R_E \approx R_{EA} \cdot R_{ES} \cdot R_{EI}. \quad (16)$$

Laspeyres and LDMI factorial decomposition methods are summarized in Table 2.

Table 2. Laspeyres and logarithmic mean Divisia index (LMDI) factorial decomposition.

Component	Symbol	Laspeyres	LMDI
Activity	ΔE_A	$\left[A_T \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)}\right] - E_0 + \varepsilon_A$	$\left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{A_T^{(i)}}{A_0^{(i)}}\right)\right] + \varepsilon_A$
Structure	ΔE_S	$\left[A_0 \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)}\right] - E_0 + \varepsilon_S$	$\left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{S_T^{(i)}}{S_0^{(i)}}\right)\right] + \varepsilon_S$
Intensity	ΔE_I	$\left[A_0 \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)}\right] - E_0 + \varepsilon_I$	$\left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{I_T^{(i)}}{I_0^{(i)}}\right)\right] + \varepsilon_I$

2.5. Time-Series Forecasting

To predict future values of a time-dependent magnitude (activity, structure, or intensity for a certain sector), time-series forecasting models were employed. Some authors [54] have classified these models according to the estimation period: short-, medium-, or long-term.

In shorter terms, prediction of seasonal behaviors, such as climate or labor market variations, has to be considered. However, for long-term forecasting, only time-series trends are really relevant. For this reason, linear regression (or linear trend) [55] is one of the most employed forecasting techniques.

Let us denote x_i the i-th value of a certain variable (or magnitude) x. This value has been obtained at time t_i, so N pairs (t_i, x_i) are available. The linear regression method obtains a straight line in the (t, x) plane, defined as $x = m\,t + b$, where m is the slope of the line and b is the interception point with the vertical line. The values of $\hat{m}$ and $\hat{b}$ are estimated to minimize the root mean squared error (*RMSE*), defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}\left[x_i - \left(\hat{m}\,t_i + \hat{b}\right)\right]^2}. \tag{17}$$

The resulting line parameters are:

$$\hat{m} = \frac{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)(x_i - \bar{x})}{\sum_{i=1}^{N}\left(t_i - \bar{t}\right)^2};\ \hat{b} = \bar{x} - \hat{m}\,\bar{t}. \tag{18}$$

A more advanced prediction technique is exponential smoothing [56], where, to forecast new values, the more recent data have greater weight than the older ones. In this method, the prediction $\hat{x}_t$ at a certain time t is obtained as:

$$\hat{x}_t = \alpha \cdot x_{t-1} + (1 - \alpha)\hat{x}_{t-1}, \tag{19}$$

where $0 \le \alpha \le 1$.

If the time series has a trend, a double exponential smoothing (Holt–Winters model) is usually preferred [57], which is formulated as:

$$\hat{x}_t = \alpha \cdot x_{t-1} + (1 - \alpha)(\hat{x}_{t-1} + \hat{m}_{t-1});\ \hat{m}_t = \beta \cdot (\hat{x}_t - \hat{x}_{t-1}) + (1 - \beta)\hat{m}_{t-1}, \tag{20}$$

where α is the data smoothing constant, $0 \le \alpha \le 1$, and β is the trend smoothing constant, $0 \le \beta \le 1$. These parameters are also estimated, minimizing the *RMSE*, defined now as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}. \tag{21}$$

As this paper was focused on long-term prediction, there was no need for seasonal or short-term details. Moreover, as complex models tend to overfit available data, more sophisticated predictors were avoided.

3. Results

3.1. Evolution of Main Carbon-Related Magnitudes

Human and economic activity is related to energy consumption and carbon dioxide emissions. In Figure 4, we see the evolution of four key parameters for the period 1990–2015: population, gross domestic product (GDP), primary energy demand, and CO_2 emissions. When energy comes from different sources (not just electricity) it is usually expressed in tons of oil equivalent (toe; 1 toe = 11.63 MWh).

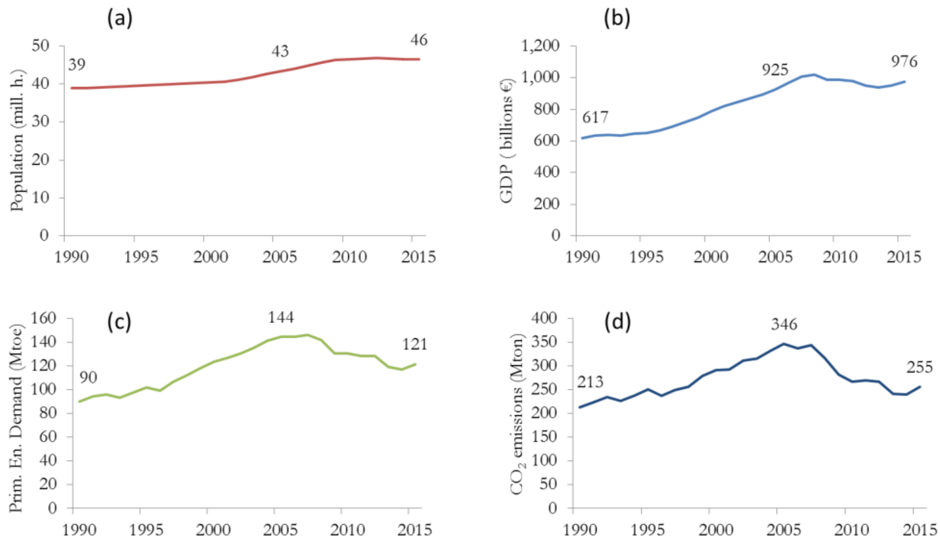
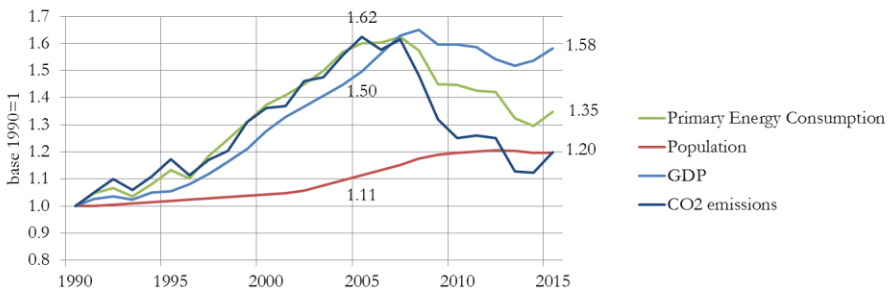


Figure 4. Magnitudes (absolute values) of the Kaya identity for Spain (1990–2015): (**a**) population; (**b**) gross domestic product; (**c**) primary energy demand; (**d**) CO_2 emissions.

Taking values in 1990 as the baseline, the evolution of the four previous magnitudes can be compared in Figure 5 Between 1990 and 2005, a high rate of economic growth (GDP) can be seen: 2.7% in Spain vs. 3.1% in the European Union (EU). By contrast, in the period 2005–2015, the years of crisis and subsequent recovery can clearly be observed, with a GDP increase of 0.5% in Spain vs. 1% in EU). The impact on primary energy consumption was 3.2% and −1.7% in each period. All these percentage values correspond to the compound annual growth rate (CAGR).



% cagr 1990/2005	% cagr 2005/2015	% cagr 1990/2015	% Δ 1990/2015
3.2%	-1.7%	1.2%	34.8%
0.7%	0.7%	0.7%	19.6%
2.7%	0.5%	1.8%	58.1%
3.3%	-3.0%	0.7%	19.8%

Figure 5. Magnitudes (base 1990 = 1) of the Kaya identity for Spain (1990–2015).

During these 25 years, the population in Europe grew at 0.3% (CAGR), whereas Spain presented a strong growth of 0.7%. While the population of Europe grew 7% in this period in accumulated terms, Spain reached an almost 20% increase, a value consistent with other not fully-developed countries and, therefore, with greater energy requirements.

These values can be expressed in terms of the Kaya identity factors (Equation (1)), as seen in Table 3.

Table 3. Factors of the Kaya identity for Spain (baseline: 1990).

Factor	Symbol	1990	1995	2000	2005	2010	2015
Population	P	1.00	1.02	1.04	1.11	1.20	1.20
GDP per person	G_p	1.00	1.03	1.23	1.34	1.33	1.32
Energy Intensity	I_e	1.00	1.08	1.07	1.07	0.91	0.85
Carbon footprint of energy	F_e	1.00	1.00	0.99	1.01	0.87	0.89
CO_2 emissions	C	1.00	1.17	1.36	1.62	1.25	1.20

The emissions produced between 1990 and 2015 grew by 20%, mainly due to the growth of the population by the same proportion, 20%, in addition to an increase of the GDP per person of 32%, which was compensated with improvements in the energy intensity by 15% and in the carbon intensity by 11%.

The process of tertiarization describes the phenomenon of evolving from an economy centered on agriculture, livestock, and fisheries to an economy in which the services sector has the greatest role. Every society begins first with a process of urbanization and industrialization, which is followed by the development of tourism and public services, as well as the incorporation of women into the labor market. This presence of the service sector in the economy translates into jobs, reaching 76% of the active population in Spain.

The relative weight of this sector in GDP, measured through gross value added (GVA) at basic prices, also reached a similar proportion, as depicted in Figure 6. By 2015, at 2015's prices, the industrial sector represented 33.2% of the GVA, compared to 64.6% for the services sector and 2.2% for agriculture.

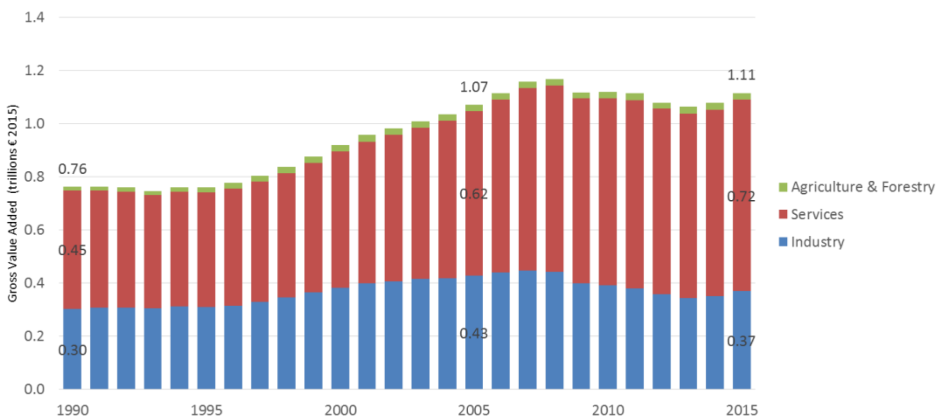


Figure 6. Gross value added for Spain (1990–2015). Units: billions of euros at 2015 prices.

The energy consumed by sector is depicted in Figure 7. In this graph, only the energy demand directly related to the economy has been included, that is, the activity sectors 1 to 20, as they are identified in Table 1.

Relating the energy consumed by sector, shown in Figure 7, to its economic contribution, shown in Figure 6, shows that the tertiary sector is less intensive in energy consumption (measured in Mtoe per billion of euro in 2015): 13.9 for services vs. 51.1 for the industry sector and 92.0 for the agricultural and forestry sector.

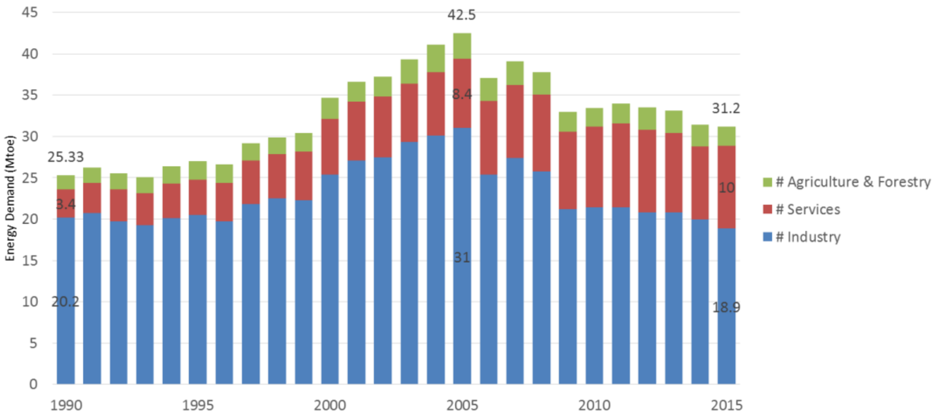


Figure 7. Energy demand (Mtoes) for Spain (1990–2015): Industry, Services, and Agriculture and Forestry.

3.2. Energy Demand Decomposition

We next applied the Laspeyres and LDMI factorial decomposition methods (summarized in Table 2) to the data depicted in Figure 5 (energy) and Figure 6 (activity). The results are shown in Figure 8.

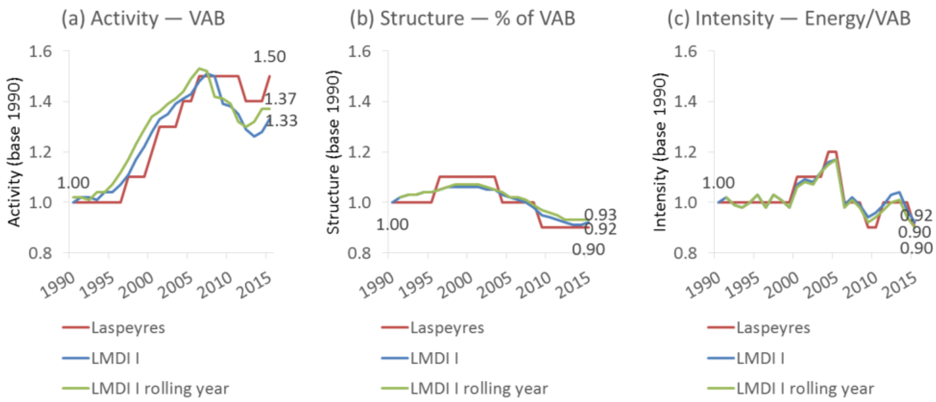


Figure 8. Energy demand multiplicative decomposition: (**a**) activity; (**b**) structure; (**c**) energy intensity.

It can be seen that both methods offered quite similar results. As the Laspeyres decomposition is easier to understand, it has been used in the rest of the paper. A more detailed analysis of the results obtained employing the Laspeyres method is depicted in Figure 9.

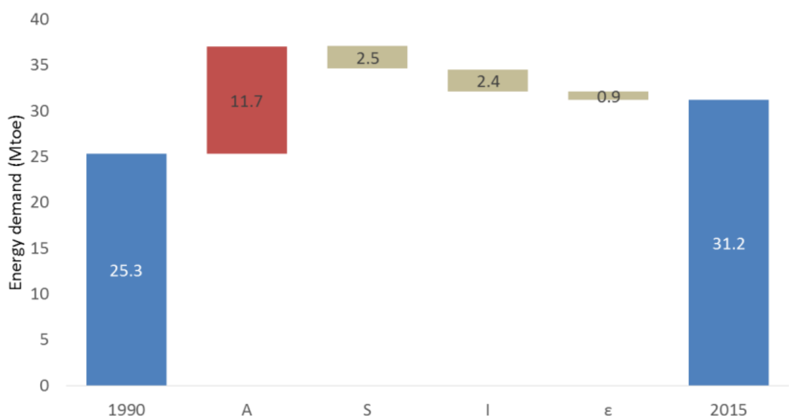


Figure 9. Energy demand Laspeyres decomposition (toes) for Spain (1990–2015).

A decomposition of the energy demand showed the drivers behind the initial variation observed. The variation in energy demand (from 25.3 Mtoes in 1990 to 31.2 in 2015) was explained by an increase (11.7 Mtoes) in the economic activity (A), partially compensated (−2.5 Mtoes) by the structural change from industrial to tertiary economy (S), and a decreasing (−2.4 Mtoes) in intensity or energy efficiency (I).

Following techno-economic factors, it was possible to make an analysis of the past variation in Spain. Following the Annex XIV, part 1 of the Energy Efficiency Directive [58]: "In sectors where energy consumption remains stable or is growing, Member States shall analyze the reasons for it and attach their appraisal to the estimates".

The activity effect is the measure of value added variation, very much linked to the economic setting. Since 1990, it has been the main effect that explains the variation, shown in Figure 9, of final energy growth. The economic activity trend was linked to the energy demand with a positive elasticity until the appearance of the recession period. Structural changes represent internal evolution with different energy intensities; the evolution of individual branches represents different global energy needs, and they did not grow at the same rate. The energy efficiency depended on technological improvements, fuel substitution, and highest output per unit.

Let us now consider the Laspeyres multiplicative decomposition of energy demand, as depicted in Figure 8. A demand growth of 23% over 1990 was justified by a 50% growth in gross value added (GVA), a −10% reduction due to a structural change in economy (variations of weights between industry, services, and agriculture), and a −10% improvement in energy efficiency or energy use per economic unit.

Around the year 2005, with the economic crisis, an inflection point was seen that invited a more detailed analysis considering two periods: pre-crisis (1990–2005) and post-crisis (2005–2015). Figure 10 shows the results of that analysis, where a pre-crisis growth of energy demand can be seen, mainly based on the positive economic evolution of the country, followed by a post-crisis energy demand decrease, based primarily on a higher energy efficiency (intensity), and secondarily on the tertiarization of the economy (change of economy structure).

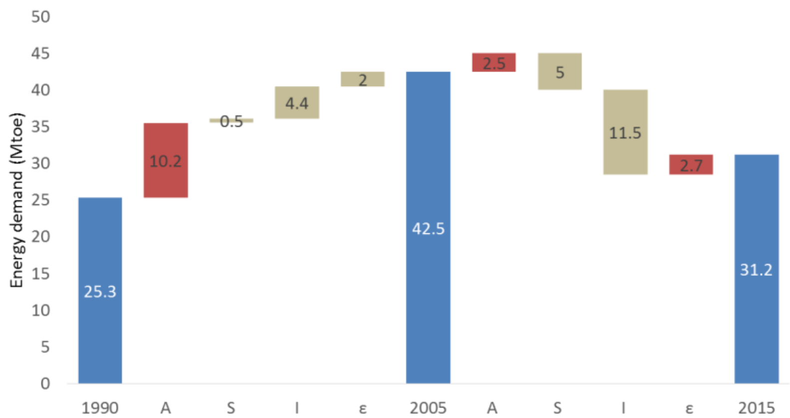


Figure 10. Energy demand Laspeyres decomposition for Spain during the pre-crisis (1990–2005) and the post-crisis (2005–2015) periods.

Figure 10 shows a different decomposition in both periods. In the second one, due to the crisis, there was a lower demand for energy in all branches of activity, but the contribution of the construction sector was particularly negative. After the crisis, Spain significantly reduced its energy requirements with an improvement of energy efficiency, reinforced by variation in structure branches with different energy intensity compositions, also reducing energy needs.

3.3. Population and Aggregated GDP Forecasting

Projections of the United Nations [59,60] estimate for Spain in the year 2030 a low scenario of 44.80 million inhabitants (−0.24%) against a high scenario of 47.37 million inhabitants (+0.18%), as depicted in Figure 11, similar predictions to those of the Spanish National Institute of Statistics [61], which forecast 45.89 million inhabitants, and which could be taken as a central and flat value used to compute the evolution of future energy demand.

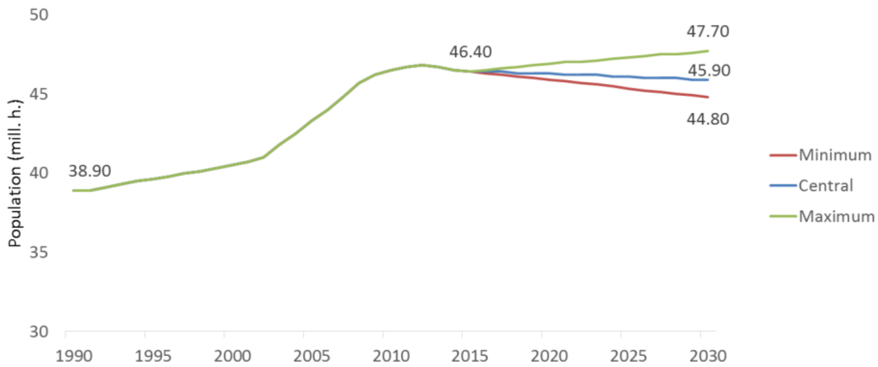


Figure 11. Evolution and forecast of population for Spain [60].

Along with population forecasts, to make a projection of long-term energy demand, it is also essential to analyze the growth of the economy. As shown in Table 3, these two magnitudes (population and economy) have been the determining factors in the growth of CO_2 emissions in Spain, having to be compensated with the improvement of energy and carbon intensity.

Regarding GDP growth, projections by the European Commission to 2030 [62] and the OECD [63] forecast the GDP growth of Spain at a 1.9% compound annual growth rate (CAGR). On the other hand, similar results (depicted in Figure 12) were obtained using the previously described time-series models.

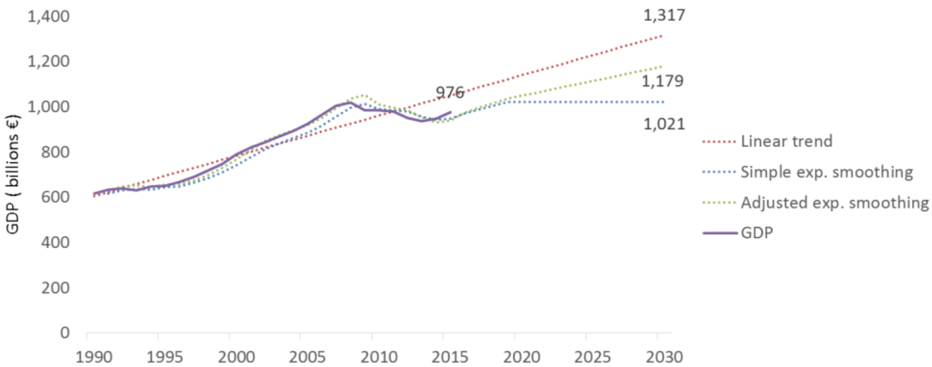


Figure 12. Evolution of GDP and its forecast for Spain.

Table 4 summarizes the total growth (% ∆) and the CAGR predicted using three time-series forecasting methods. The 2% GDP growth (CAGR) obtained using a linear regression time-series predictor was the same as the forecast published in a recent report driven by the Spanish Government [1]. This value is also very similar to the 1.9% EU and OECD predictions. For these reasons, linear regression was employed to make time-series predictions in the following sections of the paper.

Table 4. Growth of GDP for Spain as predicted for several time-series methods.

Time Series Predictor	% CAGR 1990/2005	% CAGR 2005/2015	% CAGR 1990/2015	% CAGR 2015/2030	% Δ 1990/2015	% Δ 2015/2030
Linear regression	2.7%	0.5%	1.8%	2.0%	58.1%	34.9%
Exponential smoothing	2.7%	0.5%	1.8%	0.2%	58.1%	2.9%
Holt-Winters	2.7%	0.5%	1.8%	1.1%	58.1%	17.9%

3.4. Energy Demand Forecasting

To forecast the energy demand, the procedure described in Figure 3 was followed. The final energy demand was disaggregated into the $n = 30$ level-1 components described in Figure 2 and Table 1. Later, for the sake of representation, sectors 1 to 20 have been grouped into level-2 components (agriculture and forestry, industry and services).

The results are shown in Figure 13, where it can be seen that the energy demand of the activities related to transport represented the largest share of 2015 (42%), while the energy supplied to Industry, Services, and Agriculture represented 39%, and residential activities accounted for 18%.

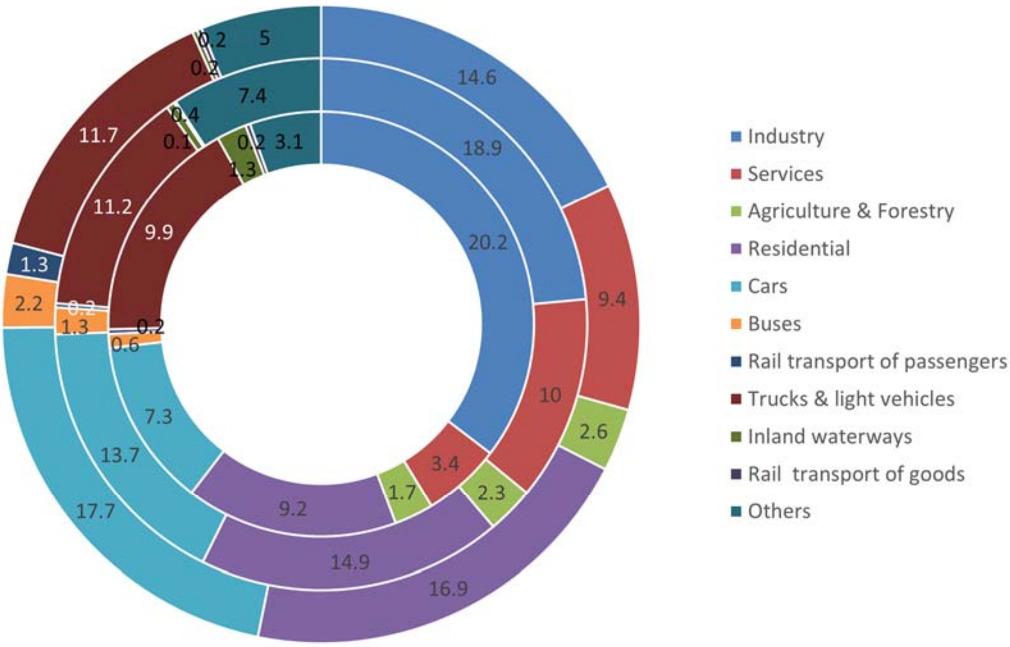


Figure 13. Disaggregation of final energy (Mtoe) for Spain. Inner: 1990; middle: 2015; outer: 2030 (forecast).

For factor decomposition, the Laspeyres method (Equations (9) and (11)) was employed because, as was shown earlier, it offered very similar results to LMDI and it is easier to understand. Thus, each of the $n = 30$ activity sectors was decomposed into $f = 3$ factors, obtaining a total of $m = n{\cdot}f = 30{\cdot}3 = 90$ time-series.

To obtain the 2030 horizon forecast for any of the $m = 90$ disaggregated time series, a linear regression method was then employed, because, as shown previously, it offered the most accurate predictions in population and GDP forecasts.

The results for the five most energy-demanding level-2 components (as described in Figure 2) are summarized in Figure 14.

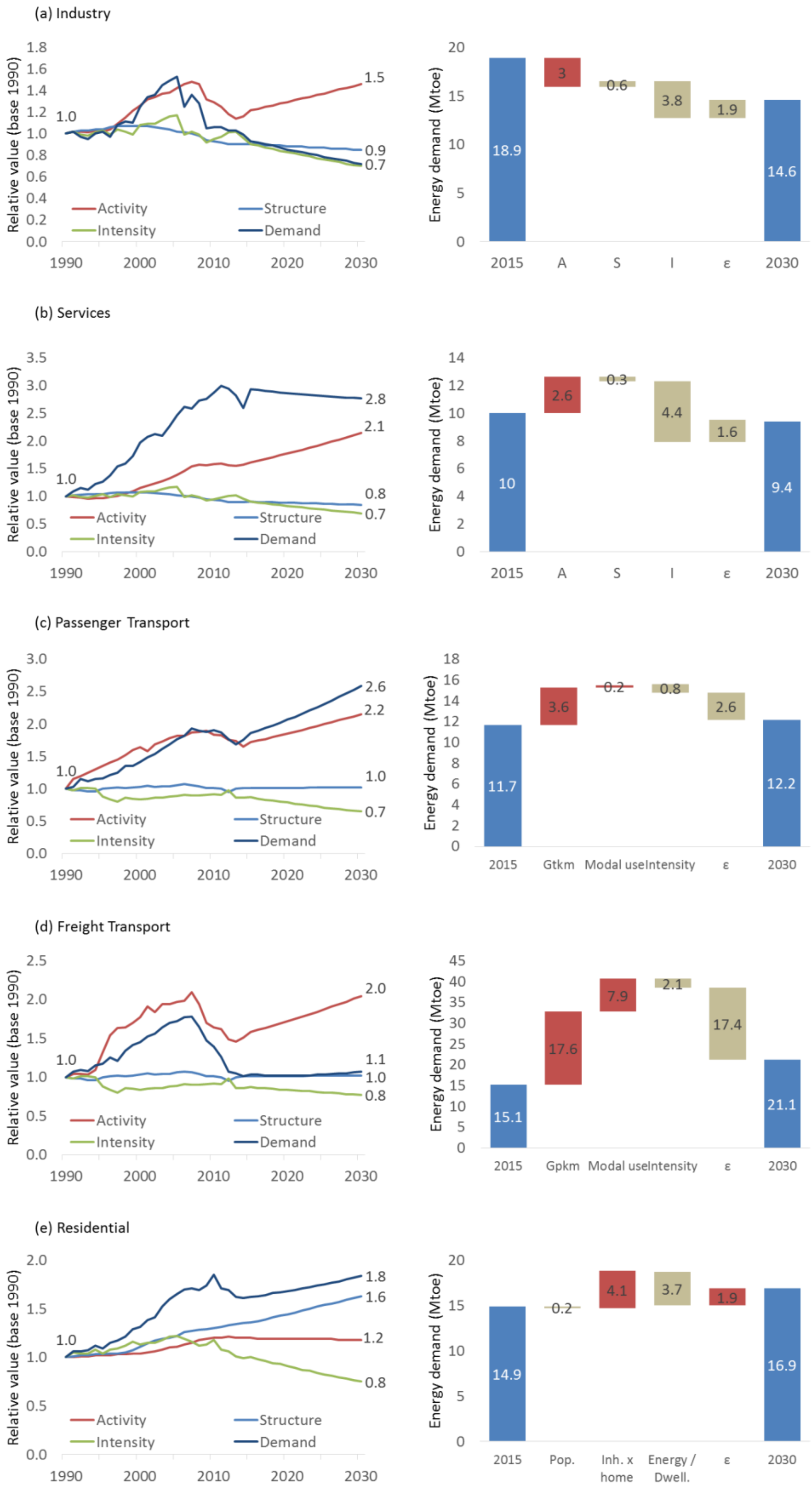


Figure 14. Projection of indices (left) and decomposition of energy demand (right) for 2015–2030: (**a**) industry; (**b**) services; (**c**) passenger transport; (**d**) freight transport; (**e**) residential.

Finally, in the third and last step of the proposed methodology (Figure 3), the $m = 90$ forecasted values were aggregated to obtain a prediction of the final energy demand. The results are depicted in Figure 15, where the level-2 components are also shown.

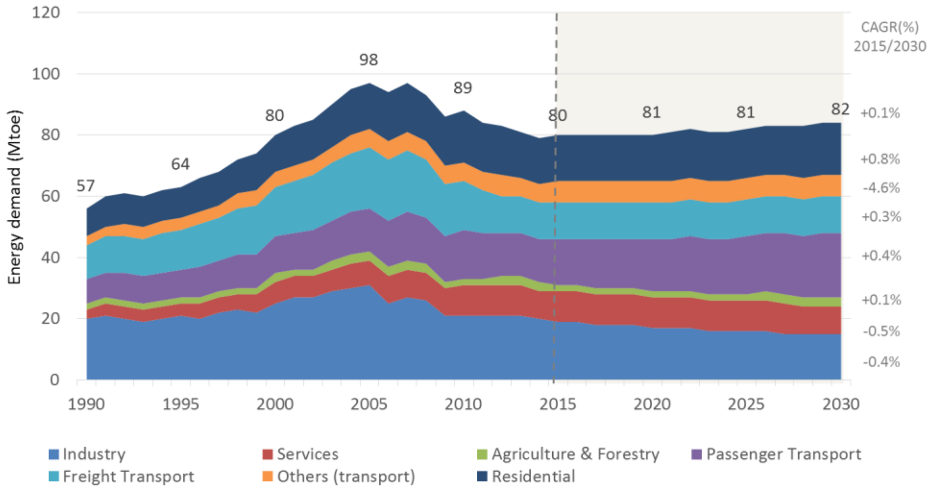


Figure 15. Final energy demand forecast (Mtoe) for Spain.

4. Discussion

In Figure 16, the final energy demand (red line) and GDP (blue line) are compared. They show a coupled evolution in the pre-crisis period (1990–2005). However, in the post-crisis scenario (2005–2030), they behave in an uncoupled way due to increasing energy efficiency, depicted in the graph by decreasing energy intensity (green line).

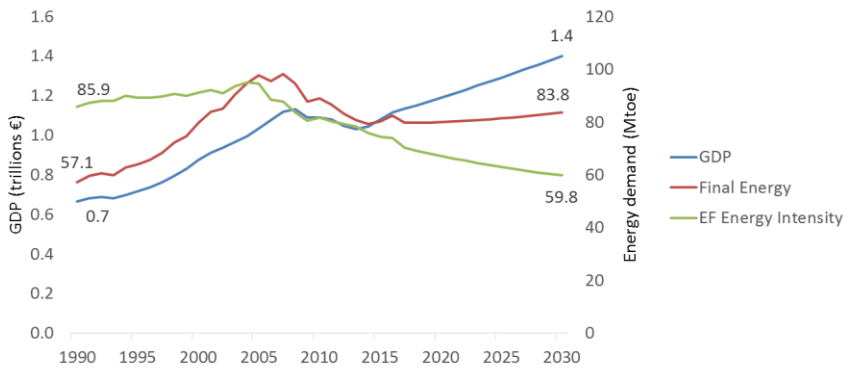


Figure 16. Final energy demand (Mtoe), GDP (T€: trillions of €), and energy intensity (toe/M€).

The energy intensity had a value of 85.9 toe/M€ in 1990, it was slightly flat till 2005, and decreased to a value of 74.4 in 2015. In Spain, energy efficiency is driven by the European Directive on Energy Efficiency [58] and its transposition into the Spanish legal system. Energy intensity was reduced in Spain by 18.4% between 2000 and 2015, mainly in the post-crisis period, reaching recent reductions of −0.6% in 2016 and −5.0% in 2017. Projecting this trend, the energy intensity will reach a value of 59.8 toe/M€ in 2030.

Some other works have also addressed long-term energy demand prediction for Spain. The results of the present paper were compatible with the findings in Reference [38], which used a similar methodological approach. However, our approach had three main improvements: (a) it employed data spans to 2015 (instead of 2012), gaining a more precise overlook of the post-crisis period; (b) predictions involved the whole energy demand (and not only electricity), obtaining a more comprehensive view;

and (c) through the Kaya identity, it was easier to obtain CO_2 emissions, as they depend on the total energy demand.

The results presented in Reference [39], using an econometric model similar to our approach, were also compatible with our findings, confirming the post-crisis decoupling of economy and energy demand due to improvements in energy efficiency. However, our research presented three advantages: (a) it used a more detailed and precise disaggregation; (b) predictions involved the whole energy demand (and not only electricity); and (c) CO_2 emissions were more easily derived.

Energy is essential for the normal functioning of modern societies, although excessive energy consumption becomes a major problem. The energy resources of the planet have to be consumed in a rational way. Energy industry planners and policy makers need accurate tools for prediction.

The world needs energy to keep developing, with more people accessing better life conditions. Energy demand is closely related to the prosperity of people and the competitiveness of economies, which can be measured by the Human Development Index (HDI) [64]. Their relationship is plotted in Figure 17.

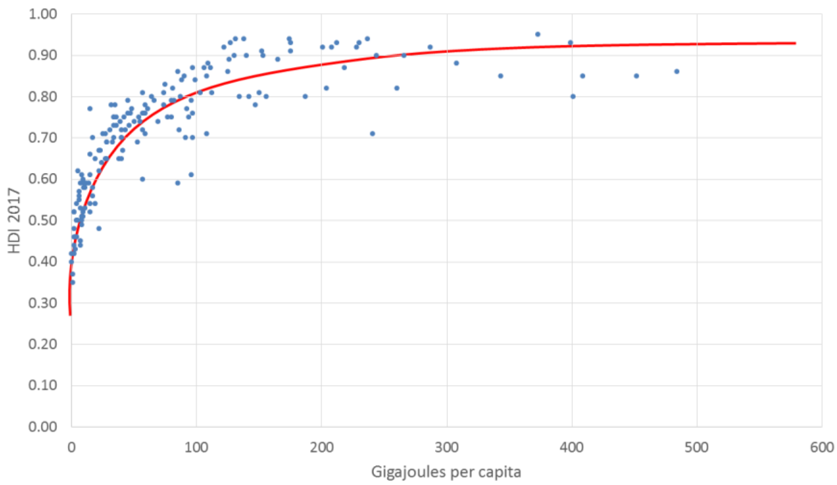


Figure 17. Human Development Index vs. energy consumption (GJ) per capita.

5. Conclusions

The forecasting of energy demand is a key issue for making decisions on future investment needs, and also for monitoring energy policy objectives, both for the reduction of CO_2 emissions and the improvement of energy efficiency. Knowledge of the evolution of demand is also the appropriate way to establish alternative plans to correct our course towards our goals and to carry out permanent monitoring.

Our methodological contribution offers a complement to both traditional and data-driven prediction techniques. The possibility of making an individualized projection for each explanatory key parameter separately improves the observability of each effect and trend in a method of "energy forecast by factorial decomposition." To the extent that each effect maintains its own trends of activity, efficiency, and structural changes separately, different forecasting techniques have been applied and more accurate predictions have been obtained.

The results found in this paper forecast an energy demand in Spain of 82 millions of tons of oil equivalent for the year 2030. Due to improvements in energy efficiency in the post-crisis period, a decoupling of economy and energy demand has been obtained, with a 30% decrease in energy intensity for the period 2005–2030.

In the coming years, energy demand will continue to grow due to the increasing population and economic development. World future scenarios show a significant increase in energy demand due to the human development of less developed economies. For Spain, our research concluded that energy demand will remain stable in the next decade, despite the foreseen 2% annual growth of its economy. The factorial decomposition methodology used through the paper showed that it is possible to decouple economic growth and energy demand via improved energy efficiency.

Finally, from the energy offer perspective, in the future it will not be affordable to supply energy demand using fossil fuels. Despite their enormous energy concentration and density, they represent the waste of a stored energy reservoir to supply the needs of a few moments in humankind history. The consolidation of renewable energies and increasing energy efficiency will reduce future need of fossil fuels.

Author Contributions: Conceptualization, R.S.-D.; Investigation, R.S.-D., J.L. and J.B.; Writing—original draft, R.S.-D., J.L. and J.B.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

The equations defining Laspeyres decomposition can be obtained from (3). Taking derivatives,

$$dE^{(i)}(t) = S^{(i)}(t) \cdot I^{(i)}(t) \cdot d[A(t)] + A(t) \cdot d\left[S^{(i)}(t)\right] \cdot I^{(i)}(t) + A(t) \cdot S^{(i)}(t) \cdot d\left[I^{(i)}(t)\right]. \tag{A1}$$

That is, the change of energy consumption is due to three components: change in the total level of activity; change in the structure of the economy; and change in the energy intensity. This result can be written as:

$$dE^{(i)}(t) = dE_A^{(i)}(t) + dE_S^{(i)}(t) + dE_I^{(i)}(t). \tag{A2}$$

Let us now consider any of these components, for instance the activity component. In this case:

$$dE_A^{(i)}(t) \equiv S^{(i)}(t) \cdot I^{(i)}(t) \cdot d[A(t)]. \tag{A3}$$

The change of energy consumption due to a change in the total level of activity, for a period of time between t_0 and T, can be expressed as:

$$\Delta E_A^{(i)} \equiv E_A^{(i)}(T) - E_A^{(i)}(t_0) \approx S^{(i)}(t^*) \cdot I^{(i)}(t^*) \cdot [A(T) - A(t_0)]. \tag{A4}$$

$$\Delta E_A^{(i)} = S^{(i)}(t^*) \cdot I^{(i)}(t^*) \cdot [A(T) - A(t_0)] + \varepsilon_A^{(i)}. \tag{A5}$$

$$\Delta E_A^{(i)} = S^{(i)}(t^*) \cdot I^{(i)}(t^*) \cdot \Delta A + \varepsilon_A^{(i)}, \tag{A6}$$

where $\varepsilon_A^{(i)}$ summarizes the approximation errors for the total level of activity of the *i*-th sector; and t^* is an approximate intermediate time in the interval $[t_0, T]$. Laspeyres Decomposition uses the approximation $t^* = t_0$, so

$$\Delta E_A^{(i)} = S^{(i)}(t_0) \cdot I^{(i)}(t_0) \cdot \Delta A + \varepsilon_A^{(i)} = S^{(i)}(t_0) \cdot I^{(i)}(t_0) \cdot [A(T) - A(t_0)] + \varepsilon_A^{(i)}. \tag{A7}$$

$$\Delta E_A^{(i)} = A(T) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) - A(\mathrm{t}_0) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) + \varepsilon_A^{(i)}. \tag{A8}$$

$$\Delta E_A^{(i)} = A(T) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) - E^{(i)}(\mathrm{t}_0) + \varepsilon_A^{(i)}. \tag{A9}$$

Analogously, the other two components are defined as:

$$\begin{aligned} \Delta E_S^{(i)} &= A(t_0) \cdot S^{(i)}(T) \cdot I^{(i)}(t_0) - E^{(i)}(\mathrm{t}_0) + \varepsilon_S^{(i)}; \\ \Delta E_I^{(i)} &= A(t_0) \cdot S^{(i)}(t_0) \cdot I^{(i)}(T) - E^{(i)}(\mathrm{t}_0) + \varepsilon_I^{(i)}. \end{aligned} \tag{A10}$$

For the activity component in (6) it can be written that

$$\Delta E_A \equiv \sum_{i=1}^{n} \Delta E_A^{(i)} = \sum_{i=1}^{n} \left[A(T) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) - E^{(i)}(\mathrm{t}_0) + \varepsilon_A^{(i)} \right]. \tag{A11}$$

$$\Delta E_A = \sum_{i=1}^{n} A(T) \cdot S^{(i)}(t_0) \cdot I^{(i)}(t_0) - \sum_{i=1}^{n} E^{(i)}(\mathrm{t}_0) + \sum_{i=1}^{n} \varepsilon_A^{(i)}. \tag{A12}$$

Calling

$$\varepsilon_A = \sum_{i=1}^{n} \varepsilon_A^{(i)}, \tag{A13}$$

it can be written that

$$\Delta E_A = \left[A(T) \sum_{i=1}^{n} S^{(i)}(t_0) \cdot I^{(i)}(t_0) \right] - E(\mathrm{t}_0) + \varepsilon_A, \tag{A14}$$

or more compactly,

$$\Delta E_A = \left[\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)} \right] - E_0 + \varepsilon_A. \tag{A15}$$

Analogously, the other two components are

$$\Delta E_S = \left[\mathrm{A}_0 \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)} \right] - E_0 + \varepsilon_S;\ \Delta E_I = \left[\mathrm{A}_0 \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)} \right] - E_0 + \varepsilon_I. \tag{A16}$$

Finally, the increasing of energy demand is decomposed as

$$\Delta E = \Delta E_A + \Delta E_S + \Delta E_I \tag{A17}$$

Let us now consider the ratio of energy increasing demand R_E as it is expressed in (1010). For a change in the activity component it can be written that

$$R_{EA} = \frac{E_A(T)}{E(t_0)} = \frac{E(t_0) + \Delta E_A}{E(t_0)} = \frac{E_0 + \Delta E_A}{E_0}. \tag{A18}$$

Analogously, the other two components are

$$R_{ES} \equiv \frac{E_S(T)}{E(t_0)} = \frac{E_0 + \Delta E_S}{E_0};\ R_{EI} \equiv \frac{E_I(T)}{E(t_0)} = \frac{E_0 + \Delta E_I}{E_0}. \tag{A19}$$

The product of the three decomposed factors is

$$R_{EA} \cdot R_{ES} \cdot R_{EI} = \frac{E_0 + \Delta E_A}{E_0} \cdot \frac{E_0 + \Delta E_S}{E_0} \cdot \frac{E_0 + \Delta E_I}{E_0} = \left(1 + \frac{\Delta E_A}{E_0}\right)\left(1 + \frac{\Delta E_S}{E_0}\right)\left(1 + \frac{\Delta E_I}{E_0}\right). \tag{A20}$$

$$R_{EA} \cdot R_{ES} \cdot R_{EI} = 1 + \frac{\Delta E_A}{E_0} + \frac{\Delta E_S}{E_0} + \frac{\Delta E_A}{E_0}\frac{\Delta E_S}{E_0} + \frac{\Delta E_I}{E_0} + \frac{\Delta E_A}{E_0}\frac{\Delta E_I}{E_0} + \frac{\Delta E_S}{E_0}\frac{\Delta E_I}{E_0} + \frac{\Delta E_A}{E_0}\frac{\Delta E_S}{E_0}\frac{\Delta E_I}{E_0}. \tag{A21}$$

In the common case where $\Delta E_A, \Delta E_S, \Delta E_I \ll E_0$

$$R_{EA} \cdot R_{ES} \cdot R_{EI} \approx 1 + \frac{\Delta E_A}{E_0} + \frac{\Delta E_S}{E_0} + \frac{\Delta E_I}{E_0} = \frac{E_0 + \Delta E_A + \Delta E_S + \Delta E_I}{E_0}. \tag{A22}$$

Recalling Equation (9) it can be written that

$$R_{EA} \cdot R_{ES} \cdot R_{EI} \approx \frac{E_0 + \Delta E}{E_0} = \frac{E_T}{E_0} = R_E. \tag{A23}$$

For the activity component, let us substitute Equation (7) in Equation (A18)

$$RE_A = \frac{E_0 + \left[\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)} \right] - E_0 + \varepsilon_A}{E_0} = \frac{\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)}}{E_0} + \varepsilon'_A. \tag{A24}$$

Analogously, the other two components are

$$RE_S = \frac{\mathrm{A_0} \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)}}{E_0} + \varepsilon'_S;\ RE_I = \frac{\mathrm{A_0} \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)}}{E_0} + \varepsilon'_I. \tag{A25}$$

Finally, the increasing of energy demand is multiplicatively decomposed as

$$R_E \approx \frac{\mathrm{A_T} \sum_{i=1}^{n} S_0^{(i)} \cdot I_0^{(i)}}{E_0} \cdot \frac{\mathrm{A_0} \sum_{i=1}^{n} S_T^{(i)} \cdot I_0^{(i)}}{E_0} \cdot \frac{\mathrm{A_0} \sum_{i=1}^{n} S_0^{(i)} \cdot I_T^{(i)}}{E_0} + \varepsilon'. \tag{A26}$$

Appendix B

To derive the Logarithmic Mean Divisia Index (LMDI) decomposition, let us first consider the energy consumption of the *i*-th sector, which can be written as

$$E^{(i)}(t) = e^{Ln[E^{(i)}(t)]} = e^{Ln[A^{(i)}(t) \cdot S^{(i)}(t) \cdot I^{(i)}(t)]}. \tag{A27}$$

$$E^{(i)}(t) = e^{\{Ln[A^{(i)}(t)] + Ln[S^{(i)}(t)] + Ln[I^{(i)}(t)]\}}. \tag{A28}$$

$$E^{(i)}(t) = e^{Ln[A^{(i)}(t)]} e^{Ln[S^{(i)}(t)]} e^{Ln[I^{(i)}(t)]}. \tag{A29}$$

Taking derivatives and considering changes only in the activity component, it can be written that

$$dE_A^{(i)}(t) = e^{Ln[S^{(i)}(t)]} e^{Ln[I^{(i)}(t)]} d\left\{ e^{Ln[A^{(i)}(t)]} \right\}. \tag{A30}$$

$$dE_A^{(i)}(t) = e^{Ln[S^{(i)}(t)]} e^{Ln[I^{(i)}(t)]} e^{Ln[A^{(i)}(t)]} d\left\{ Ln\left[A^{(i)}(t) \right] \right\}. \tag{A31}$$

Recalling Equation (A29)

$$dE_A^{(i)}(t) = E^{(i)}(t) d\left\{ Ln\left[A^{(i)}(t) \right] \right\}. \tag{A32}$$

The change of energy consumption due to a change in the total level of activity, for a period of time between t_0 and T, can be expressed as

$$\Delta E_A^{(i)} \equiv E_A^{(i)}(T) - E_A^{(i)}(t_0) = E^{(i)}(t^*) \cdot \left\{ Ln\left[A^{(i)}(T) \right] - Ln\left[A^{(i)}(t_0) \right] \right\} + \varepsilon_A^{(i)} \tag{A33}$$

where $E^{(i)}(t^*)$ is an approximate intermediate value of $E^{(i)}$ in the interval $[t_0, T]$. LMDI decomposition uses for the approximation the logarithmic mean, that is,

$$E^{(i)}(t^*) \ = L\left[E^{(i)}(T), E^{(i)}(t_0) \right] \equiv \frac{E^{(i)}(T) - E^{(i)}(t_0)}{Ln\left[E^{(i)}(T) \right] - Ln\left[E^{(i)}(t_0) \right]}. \tag{A34}$$

So,

$$\Delta E_A^{(i)} = L\left[E^{(i)}(T), E^{(i)}(t_0) \right] \cdot Ln\left[\frac{A^{(i)}(T)}{A^{(i)}(t_0)} \right] + \varepsilon_A^{(i)}. \tag{A35}$$

It can be shown that the value of the logarithmic mean is between the arithmetic and geometric means, that is,

$$\sqrt{a \cdot b} \leq L(a,b) \leq \frac{a+b}{2},\ \forall a,b > 0. \tag{A36}$$

Considering now the activity component of the n sectors of the economy, we obtain

$$\Delta E_A \equiv \sum_{i=1}^{n} \Delta E_A^{(i)} = \sum_{i=1}^{n} \left\{ L\left[E^{(i)}(T), E^{(i)}(t_0)\right] \cdot Ln\left[\frac{A^{(i)}(T)}{A^{(i)}(t_0)}\right] + \varepsilon_A^{(i)} \right\}. \tag{A37}$$

$$\Delta E_A = \sum_{i=1}^{n} L\left[E^{(i)}(T), E^{(i)}(t_0)\right] \cdot Ln\left[\frac{A^{(i)}(T)}{A^{(i)}(t_0)}\right] + \sum_{i=1}^{n} \varepsilon_A^{(i)}, \tag{A38}$$

or more compactly,

$$\Delta E_A = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{A_T^{(i)}}{A_0^{(i)}}\right)\right] + \varepsilon_A. \tag{A39}$$

Analogously, the other two components are

$$\Delta E_S = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{S_T^{(i)}}{S_0^{(i)}}\right)\right] + \varepsilon_S;\ \Delta E_I = \left[\sum_{i=1}^{n} L\left(E_T^{(i)}, E_0^{(i)}\right) \cdot Ln\left(\frac{I_T^{(i)}}{I_0^{(i)}}\right)\right] + \varepsilon_I. \tag{A40}$$

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