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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

INDEX DECOMPOSITION ANALYSIS AND ENERGY CONSUMPTION OF TURKEY: 2000-2014

TÜRKİYE'NİN ENDEKS AYRIŞTIRMA ANALİZİ VE TÜRKİYE'NİN ENERJİ TÜKETİMİ: 2000-2014

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Abstract

Index decomposition analysis (IDA) has been one of the important tools in energy and environmental studies in identifying the level of contribution of the driving factors of a change in an aggregate of interest during a time period or across different units such as countries or regions. Aiming to be an informative source for further studies conducted with this methodology, this paper provides a general review covering its historical development and mathematical formula. To see the contribution of economic growth, sectoral composition and energy intensity to the energy consumption change in Turkey between 2000-2014, based on the energy and socio-economic accounts of the WIOD LMDI-I method is used as it is the most preferred IDA method due to its simplicity and ability to provide perfect decomposition.

Keywords: Decomposition Analysis, Divisia Index, LMDI, Energy Consumption, Turkey
JEL Classification: C43, Q43, Q48

Öz

Endeks ayrıştırma analizi (EAA), enerji ve çevre ile ilgili çalışmalarda, bir değişkenin belirli bir dönemdeki veya ülke, bölge gibi farklı birimlere ait gözlem değerleri arasındaki değişiminde, bu değişkenin bileşenlerinin hangi düzeyde katkı yaptıklarının tespit edilebilmesi amacıyla başvurulan önemli araçlardan bir olmuştur. Bu çalışma, analizin tarihsel gelişimi ve matematiksel formülü hakkına temel bir değerlendirme sunarak; ileride EAA'nın kullanılacağı diğer çalışmalar için de kaynak olmayı amaçlamaktadır. Ekonomik büyüme, sektörel yapı ve enerji yoğunluğundaki değişimlerin, Türkiye'de üretim faaliyetlerinden kaynaklanan enerji tüketiminin 2000-2014 yılları arasındaki değişimine etkisi ise DGÇV'nin enerji ve sosyo-ekonomik hesaplarından yararlanılarak incelenmiştir. Çalışmada basitliği ve tam ayrıştırma sağlaması nedeniyle en fazla tercih edilen EAA metodu olan LMDI-I yöntemi kullanılmıştır.

Anahtar Kelimeler: Ayrıştırma Analizi, Divisia Endeksi, LMDI, Enerji Tüketimi, Türkiye
JEL Sınıflandırması: C43, Q43, Q48

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1. Introduction

As ecological constraints, rapidly increasing production and consumption activities, as well as their changing structures make continuous access to energy supply more critical than ever, energy policies are gaining increased attention not just for climate-related issues but also for reasons related to energy security. For this reason, breaking down energy demand into its driving factors becomes essential in evaluating the impact of each and thus the effectiveness of economic and energy policies to meet the growing demand for energy.

It is especially after the world oil crisis in the 1970s that energy security has become an important issue, especially in countries with high energy dependency and factors affecting industrial energy consumption and intensity have taken attention, leading to the emergence of decomposition analysis as a new line of research in energy studies (Ang, 2004a; Ang & Goh, 2019a).

Decomposition analysis is a descriptive technique enabling to explain of an observed change of an aggregate indicator of interest by distributing this change into its driving forces (Wang et al., 2017b), and studies are mainly divided into two independently developed categories; *structural decomposition analysis (SDA)* in which the link between different driving forces, such as population, sectoral production, sectoral energy intensity etc., are explored from the demand perspective by taking into account the production and consumption linkages within the economy and *index decomposition analysis (IDA)* in which these driving forces are quantified from the production perspective. Although the underlying concept behind these analyses is the same, their methodological bases and results differ from each other. In that light, SDA offers an in-depth analysis based on input-output tables. However, it has high-level data requirements and is limited by the availability of input-output tables. In a comprehensive study aiming to summarise the fundamental differences and similarities between them, Hoekstra & van den Bergh (2003) also emphasises the advantage of SDA in including the spill-over effects of demand as input-output tables enable to see the indirect need for inputs from other sectors when there is an increase in the direct demand of an industry, whereas IDA can only assess the impact of immediate demand. On the other hand, IDA has a straightforward mathematical formula and requires lower-level data since time series can be used. It also provides more flexibility regarding application areas, periods, and methods (de Boer & Rodrigues, 2020; Hoekstra & van den Bergh, 2003; Su & Ang, 2012; Wang et al., 2017a, 2017b) Due to these reasons, IDA has found an increasing place in the literature of energy studies for distinguishing the contributing factors to energy consumption either at country or regional levels and monitoring the improvement in energy efficiency. IDA literature contains many application examples, but several studies are solely focused on methodological aspects. These studies include but are not limited to the development of new methods (Ang et al., 1998, 2003, 2004; Ang & Choi, 1997; Ang & Liu, 2001; Boyd D. et al., 1987; Boyd et al., 1988; Boyd & Roop, 2004; Chung & Rhee, 2001; F. L. Liu & Ang, 2003; Reitler et al., 1987; Sun, 1998) and their comparisons (Ang, 2004b, 2015; de Boer & Rodrigues, 2020; Shenning, 2020), establishing linkages between different methods (Ang et al., 2009; Choi & Ang, 2003) as well as the improvement of existing ones for more insightful analysis (Ang, 1995b; Ang & Goh, 2019b; Ang & Wang, 2015; Xu & Ang, 2014).

In light of this vast literature, this study has two primary objectives. Firstly, it aims to provide an informative framework for IDA by bringing together the main conceptual and methodological information. Thus, the second part offers a historical insight into how IDA methods developed and were improved. It is followed by recommended criteria for method selection and other implementation issues in the third part. The next part focuses on the mathematical formulae of methods linked to the Divisia index.

In Turkey, IDA has recently become a widely used methodology for energy and emission studies, but relatively few studies have focused on energy consumption. And these studies are based on the energy balance tables, whose statistical approach is different from the national accounting framework. Thus, the second aim of this study is to contribute to this literature by providing an analysis based on a coherent dataset in terms of statistical approach and sectoral classification. Due to this, this study uses the energy and socio-economic accounts of the World Input-Output Database as its main data source. In that light, the fifth part of the study provides a brief overview of the literature of Turkey-related studies with a focus on energy consumption followed by the results of the analysis of Turkish energy consumption for the period 2000-2014 using the additive form of LMDI-I. The last two parts of the study are reserved for discussion and concluding remarks.

2. Historical Development of Index Decomposition Analysis

The term "index decomposition analysis" was used firstly by Ang & Zhang (2000) to distinguish what had formerly been known as "decomposition analysis" or "factorisation analysis" from the SDA. Ang (2004a) and Ang & Goh (2019a) summarise its application areas in six categories: (1*) energy supply and demand*, (2) energy-related *carbon/GHG emissions*, (3) *material use and other new areas,* (4) *national energy efficiency trend monitoring,* (5) *cross country comparison* and *(6) prospective studies.* Until the 1990s, the decomposition studies were mainly related to industrial energy demand and later expanded to cover economy-wide or sector-specific energy demand such as transportation and residential activities. It was after the 1990s that growing concerns about the environment and sustainability also led the scope of index decomposition to cover energy-related gas emissions, primarily carbon dioxide emissions. The number of these studies spurred considerable volume in the literature, especially after the 2000s. Decomposition studies of material use and resource consumption apply this methodology similar to those in energy or emission studies since the aggregate of interest is replaced by resource or material consumption such as water, oil etc. However, it is stated that IDA still needs to be well-established in other new areas like investment, agriculture, or natural capital because interpreting the drivers of the aggregate variables can be problematic. In national energy efficiency trend monitoring, a variety of index decomposition methods are used to separate out the impact of energy intensity and create more reliable energy efficiency indicators. In cross-country studies, the comparison is made between countries or regions based on the difference in the aggregate of interest, such as energy intensity or energy-related CO2 emissions. In these studies, data for two different years are substituted for the data for two countries, but factors contributing to the difference in the aggregate of interest stay similar to those affecting changes over time in one country. In addition to these areas, IDA has been used for prospective analyses as the most recent application area to make forecasts about aggregate indicators based on the decomposed effects in historical studies (Agnolucci et al., 2009; Lescaroux, 2013; O'Mahony, 2010; Saygin et al., 2013), to quantify the contributions of driving factors to changes in the aggregate of interest over a future period (Hasanbeigi et al., 2014; Köne & Büke, 2019) or to illuminate projection results across different scenarios (Förster et al., 2013; Smit et al., 2014). [1]

Ang (2004a) also categorises the methodological developments in index decomposition analysis within three periods; *introduction, consolidation, and further refinement*. Before 1985, in the "introduction phase", techniques applied to identify the impact of changes in sectoral production/ energy intensity on aggregate energy intensity are referred to as the "Laspeyres index-related decomposition approach". Initially, these techniques were developed independently from the index number theory but were later found similar to the Laspeyres index approach. In these studies, the contribution of changes in a specific factor to the aggregate energy variable is determined through the difference between a hypothetical and an observed value of the aggregate energy variable calculated by letting only one factor change and keeping other factors unchanged at their respective base year values during the analysed period. As an example of this approach, Bossanyi (1979) subdivides the change in the aggregate energy intensity into two contributors: the effect of changes in product mix (sectoral production share) and the impact of changes in the energy intensities. To separate these two effects, contributions of these two factors for a base year are calculated first. Then a hypothetical energy consumption level at a particular year is estimated if the product mix would have changed only, keeping the sectoral energy intensities unchanged. And the difference between actual aggregate energy consumption and this hypothetical aggregate energy consumption in the target year is attributed to the contribution of changes in energy intensity to the total change. The same approach can be seen in (Jenne & Cattell, 1983) analysing the changes in the energy intensity of industrial production in the UK from 1960 to 1980. Hankinson & Rhys (1983) utilises a similar approach to examine the UK industrial electricity consumption changes at 3-level disaggregation to see the impact of output growth and sectoral and intensity changes on electricity consumption.

In the "consolidation phase" over the years 1985-1995, attempts gained pace to establish a general framework for decomposition methods. Amongst those studies, Reitler et al.(1987) propose a new approach in the Marshall-Edgeworth index form as a refinement of the decomposition method of Hankinson & Rhys (1983). However, Park (1992) criticises the calculation of the structural effect in (Reitler et al., 1987) and formulates an approach based on the Laspeyres index used in previous

1 Further information on classification and review of studies in which index decomposition is used for prospective analysis can be found in (Ang, 2015; Ang & Goh, 2019b)

studies. Howarth et al. (1991) propose a similar approach and calculate the impact of changes in production structure or energy intensity on total energy use by keeping other variables constant at their initial levels. The first method based on the Divisa index was also proposed in this period by Boyd D. et al. (1987) and Boyd et al. 1988) and later referred to as the Average Mean Divisia Index (AMDI) as the arithmetic mean weight function is used in the decomposition of changes in the energy intensity into its components.

In this period, (X.Q.Liu et al., 1992) consolidated common methods, including those based on Laspeyres, Paasche or Marshal-Edgeworth indices, by proposing two general parametric Divisia methods and also offering a new technique called the Adaptive Weighting Divisia Method (AWDM) in which parameter values or weights of other variables vary through the time. Ang & Lee (1994) further develop five specific parametric Divisia methods as well as the multiplicative version of the AWDM and state that previous techniques proposed by different researchers such as Boyd et al. (1988), Park (1992), Reitler et al.(1987) and X.Q.Liu et al. (1992) were either identical or similar to these parametric methods. Ang (1994) extends their work by taking the energy intensity as an aggregate indicator instead of energy consumption and proposes a multiplicative decomposition framework based on two general parametric Divisia methods using time series data. Lastly, Ang (1995a) provides a methodological framework for previous decomposition studies covering three different approaches. In spite of the increasing number of new methods and efforts to improve the existing ones, decomposition studies conducted during this period left unexplained residuals.

After 1995, in the so-called "further refinement period", unexplained residual problems and the inability to handle zero values in big data sets led to the improvement of decomposition methods. The first technique, proposed by Ang & Choi(1997) was another Divisia index method using a logarithmic weight function in the decomposition of an aggregate index that was able to leave zero residual and deal with zero values in the data set. Ang et al. (1998) propose another Divisia index decomposition method using a different logarithmic weight function to extend this method by decomposing the differential change in the aggregate of interest in energy studies. These two methods were later referred to as Log-Mean Divisia Index II and I (LMDI-II and LMDI I), respectively (Ang et al., 2003; Ang & Liu, 2001).

Further improvements were also made in methods based on the Laspeyres index. Sun (1998) equally allocates residuals into contributing factors to resolve the residual problem. This method, named as "refined Laspeyres index method by Ang & Zhang (2000), was later found by Ang et al. (2003) to be identical to the Shapley decomposition technique that had long been used in cost-allocation problems and introduced to energy studies by Albrecht et al. (2002) and thus referred to as the Shapley/Sun method in (Ang, 2004b). Based on the geometric average of both Laspeyres and Paasche indices, the generalised Fisher Index technique was another perfect decomposition technique introduced to energy studies in this period by Ang et al. (2004). And, in decomposition with two factors, Shapley/Sun and generalised Fisher index methods became equivalent to the Marshall-Edgeworth and the conventional Fisher ideal index methods (Boyd & Roop, 2004;

F.L.Liu & Ang, 2003) respectively. Though the generalised Fisher ideal index and the Shapley/ Sun methods are able to overcome the residual problem, they have a common weakness: the number of factors necessary to distribute the residuals increases with the number of elements in the decomposition identity(Ang & Goh, 2019a).

During that period, another residual-free index, named the Mean Rate of Change Index (MRCI), was developed to be incorporated into the decomposition studies by Chung & Rhee (2001). By that time, this method had superiority over all Divisia index methods in dealing with negative values in the data set and thus specifically suited to analyses using input-output tables. Later on, the zero and negative value problems of LMDI were resolved by Ang & Liu (2007a) and Ang & Liu (2007b) providing a general guideline to deal with deviations in the large data sets by using analytical limits and small values. [2]

3. Method Selection for the Application of IDA

In energy-related studies, there are several index decomposition methods, which are divided into two groups by Ang (2004b). As shown in Figure 1 [3] methods derived from the Laspeyres index concept where the contribution of a factor is calculated while keeping other factors at their respective base years are categorised as "methods linked to Laspeyres index", while all other methods are categorised as "methods linked to Divisia index".

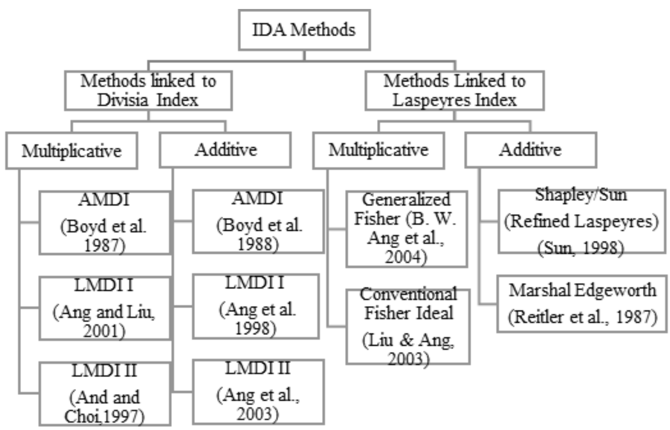

Figure 1: Classification of Index Decomposition Methods

Source: Prepared by the author according to (Ang, 2004b, 2015)

2 While Ang et al.(1998) and Ang & Choi (1997), proposed replacing zero values in the data set with positive values to resolve the zero value problem of LMDI Method, Ang & Liu (2007a) provides a general framework for all possible cases involving zero values.

3 Following (Ang, 2004b), methods linked to conventional Laspeyres index are not included into this classification because of large residual problems, and AWDM and MRCI methods are also left outside because of their complicated formulae.

Since the relative contributions of the factors to the energy-related aggregate of interest are measured in each method differently, Ang (2004b) recommends four criteria to be taken into account in assessing the desirability of a decomposition method: (a) theoretical foundation (b) adaptability (c) ease of use and (d) ease of result interpretation.

As methods in IDA have a strong affinity with index numbers, their theoretical foundation is highly related to index number theory. In that light, Ang & Zhang (2000) consider two desirable properties of index numbers and zero-robustness to identify an appropriate method for decomposition. The most crucial desirable property in the index number theory is factor reversal; that is, the multiplication of all decomposed components can give the aggregate's observed ratio. The equivalent of this property in index decomposition analysis is to leave no residual terms, i.e., being perfect in decomposition. Time reversal is another desirable property of index numbers, which requires that an index number calculated from one period to another is the reciprocal of an index number calculated backwards. In index decomposition analysis, this property means that the results of the analysis should be consistent independently from its application prospectively or retrospectively. Except for AMDI, all methods linked to the Laspeyres and Divisia Indices in Figure 1 possess these two desirable properties, whereas AMDI passes only the time reversal test (Ang, 2004b; Ang et al., 2004; Ang & Zhang, 2000).

The adaptability of methods refers to being easily applicable for a variety of cases as well as suitable for different decomposition techniques. In that sense, decomposition methods that can be used for various analyses such as time-series and cross-country comparisons are accepted to have this property. On the other hand, methods that cannot meet the criterion of factor reversal, e.g., AMDI, are also recommended not to be applied when there are significant variations in the data sets; such as in cross-country comparisons or period-wise analyses where the size of the change in the data can be large (Ang, 2004b). In addition to the type of analysis, decompositions can be carried out in two ways: additively or multiplicatively. Additive decomposition is performed for analysing a difference change of aggregate indicators, such as energy consumption or carbon emission, whereas, in multiplicative analysis, a ratio change of an aggregate indicator is decomposed, such as energy or carbon intensity. Within that context, convertibility between these different decomposition techniques can also be accepted as a positive indicator of the adaptability of the method of interest. In that regard, LMDI methods have superiority over other methods since the results of different techniques can be directly converted to each other by a simple formula. In contrast, in methods based on the Laspeyres index, there is not such a direct relationship (Ang et al., 2009).

Another parameter accepted as a positive indicator for the adaptability of the decomposition method is the ability to deal with differences in the data set, such as zero/negative values. Zero value problems frequently occur, particularly in emission studies, as fuel types are considered amongst the contributing factors to emission change, and the amount of specific kind of fuels can be equal to zero at some time point or place, whereas negative values are relatively rare, especially in energy studies (Ang & Liu, 2007b). Both methods linked to the Laspeyres index and

Divisia index, except AMDI, are zero-and negative-value robust (Ang, 2004b; Ang & Goh, 2019a; Ang & Zhang, 2000). However, if zero or negative values prevail in the data set, Laspeyres-based methods can still be recommended over Divisa-based methods (Ang & Goh, 2019a).

Ease of use relates to the ability of a specific method to be applied to different problems and the simplicity of its formula. In that sense, one of the common disadvantages of processes linked to the Laspeyres index is that the formulae used in these methods get complex if the number of factors exceeds three, whereas LMDI methods carry the same form irrespective of the number of factors taken into account (Ang, 2004b; Ang & Goh, 2019a).

Ease of result interpretation is directly linked with the decomposition performance of the method. In other words, results of an index decomposition analysis that meet the criterion of the factor reversal test are easier to understand as there is no factor left unexplained, and these decomposition methods can cover all of the changes in the related aggregate. In addition, the technique of the decomposition analysis, whether it is additive or multiplicative, also affects the understandability of the results. Additive analysis may be preferred to multiplicative analysis as the explanation of differential changes in physical units can be perceived more easily than ratio changes (Ang & Zhang, 2000).

Regarding the four criteria mentioned above, both methods have some strengths and weaknesses. Especially for analyses based on two factors and with no zero/negative value in the data set, all methods passing factor reversal can be applicable. However, the decomposition results will be different because of the difference in their mathematical formula. On the other hand, for environmental and emission studies in which there are generally more than three factors contributing to the changes in the related aggregate, the LMDI method is recommended as the most appropriate choice (Ang, 2004b). It is also preferable when the conversion between additive and multiplicative decompositions is needed and to ensure the comparableness if there is a possibility to extend the analyses with added factors in the future depending on the data availability [4].

There are also subtle differences between these two different LMDI methods (-I and – II), which become essential when decomposition is conducted with sophisticated data sets. The first difference is being perfect in decomposition at the sub-category level. For example, if an analysis focuses on changes in total energy consumption that is divided by industrial sectors; this property means that decomposition is consistent, leaving no residual at each sector (sub-category) level, and only the LMDI-I method ensures this property (Ang et al., 2009; Ang & Wang, 2015). Another feature is being consistent in aggregation, meaning that aggregation of decomposition results at each sub-category to higher levels of aggregations can be realised consistently; in other words, decomposition results obtained at the higher aggregate level, i.e., at the country level, are equal to the aggregation of decomposition results at the sub-category levels, e.g., at industry or

4 For a recent and more comprehensive overview of index decomposition methods, please also see (Ang & Goh, 2019a; de Boer & Rodrigues, 2019; Shenning, 2020)

regional levels. Still, only LMDI-I possess this feature (Ang & Liu, 2001), making this method specifically useful for multidimensional and multilevel analyses (Ang & Wang, 2015) [5]. In the LMDI-II formula, on the other hand, weights in the decomposition formula can be summed into unity, meeting a different desirable property in the index construction (Ang & Choi, 1997). [6] Based on this property, (Choi & Ang, 2012) proposes an extended LMD-II method to measure sub-sectors' contribution to total percentage changes in real energy intensity – and structural change-related components of aggregate energy intensity. However, in this paper, the LMDI-I method has been preferred for the illustration of index decomposition analysis for its extensive usage and simple formula compared to other methods and its availability for multilevel analysis for future studies.

In addition to method selection, there are additional issues related to applying index decomposition analysis in energy studies. As explained before, the aggregate indicator of interest can either be a quantity (i.e., energy consumption and emissions) or a ratio (i.e., energy intensity or CO2 emissions per unit GDP). Although a quantity indicator is easy to decompose and it always has one additional factor (that is, industrial/national output showing the production effect; and takes place as the denominator in a ratio indicator-e.g., energy intensity.), it has the disadvantage of having a disproportionately large impact of this additional factor in the analysis, leading to surpass the effects of other factors (Ang & Zhang, 2000). On the other hand, when research focuses on absolute changes and/or the additive decomposition approach is to be used, a quantity indicator is recommended for decomposition analysis as it is easier to understand (Ang, 2015).

Another issue concerning the application of IDA is the time period. In a chaining analysis, time series data are analysed every two years and decomposition results are computed cumulatively, while a non-chaining analysis covers the difference between specific dates. In a chaining basis analysis, decomposition results change relatively less than in a non-chaining basis analysis because decomposition is path dependent. However, non-chaining analysis can be recommended if there is a lack of data, especially if a large number of subcategories are included (Ang, 2004a).

4. Mathematical Formulae of Index Decomposition Analysis

As Ang & Zhang (2000) states that there is a strong affinity between index numbers and index decomposition analysis as the impact of production structure and energy intensity on aggregate energy intensity is quite similar to the effects of the commodity quantity and price on the aggregate commodity consumption. For that reason, the mathematical formula of index decomposition analyses is explained by using the index number concept in many studies [7]. Following Ang et al. (2009) and Choi & Ang (2003);

5 Detailed explanations for multilevel IDA applications and further details regarding the necessary transformation of formulae are given in (Xu & Ang, 2014) and its Appendix A-B, respectively.

6 (Ang, 2015) provides a detailed guidance for the method selection between 8 different LMDI formulae.

7 Other examples for these studies include (Ang, 2004b, 2005; Ang et al., 2009; Ang & Zhang, 2000; de Boer & Rodrigues, 2019).

V represents an aggregate of interest with n components:

$$V_i = X_{1,i}X_{2,i}X_{3,i} \ldots . X_{n,i} \text{ and } V = \sum_i^m V_i = \sum_i^m X_{1,i}X_{2,i} \ldots X_{n,i} \tag{1}$$

Aggregate indicators are generally energy consumption or energy intensity in energy studies, and *n* refers to the different components of the total change in these aggregate indicators, such as changes in economic activity, the sectoral composition of the economy or sectoral energy intensity. On the other hand, subscript *i* denotes sub-categories of the related aggregate, such as different sectors or regions in economy-wide studies or countries in cross-country studies, and *m* represents the number of these sub-categories. And the values of the aggregate in time periods 0 and T are shown below:

$$V^0 = \sum_i^m X_{1,i}^0, X_{2,i}^0 \ldots \ldots \ldots X_{n,i}^0 \tag{2}$$

$$V^T = \sum_i^m X_{n,i}^T, X_{2,i}^T \ldots \ldots \ldots X_{n,i}^T \tag{3}$$

As stated in the third part, the decomposition of a change in the aggregate of interest in the time period (0-T) can be carried out multiplicatively and additively:

Multiplicative Decomposition:

$$D_{tot} = \frac{V^T}{V^0} = D_{X1}D_{X2} \ldots . D_{Xn}D_{rsd} \tag{4}$$

Additive Decomposition:

$$\Delta V_{tot} = V^T - V^0 = \Delta V_{X1} + \Delta V_{X2} + \cdots + \Delta V_{Xn} + \Delta V_{rsd} \tag{5}$$

D_{rsd} and ΔV_{rsd} represent the residual terms and are equal to zero when there is perfect decomposition. In this study, total energy consumption will be used as an aggregate indicator, and thus analysis will be conducted in additive form because of its simplicity and ease of interpretation.

To explore how this energy-related aggregate is affected by the changes in its components by using the Divisia index, firstly, the differentiation of Eq. (1) is taken with respect to time:

$$\frac{dV}{dt} = \sum_i^m \frac{dV_i}{d_t} = \sum_i^m \frac{dX_{1,i}}{d_t} X_{2,i} \ldots X_{n,i} + \sum_i^m X_{1,i} \frac{dX_{2,i}}{d_t} \ldots X_{n,i} + \cdots + \sum_i^m X_{1,i}X_{2,i} \ldots \frac{dX_{n,i}}{d_t} \tag{6}$$

With some manipulation, the right side of the equation gives logarithmic growth rates of each of the variable:

$$\frac{dV}{dt} = \sum_i^m \frac{dV_i}{d_t} = \sum_i^m \boldsymbol{X_{1,i}} \frac{\boldsymbol{dX_{i,1}}}{\boldsymbol{d_t}} \frac{\boldsymbol{1}}{\boldsymbol{X_{1,i}}} X_{2,i} \ldots X_{n,i} + \sum_i^m X_{1,i}\boldsymbol{X_{2,i}} \frac{\boldsymbol{dX_{i,2}}}{\boldsymbol{d_t}} \frac{\boldsymbol{1}}{\boldsymbol{X_{2,i}}} \ldots X_{n,i} + \cdots + \sum_i^m X_{1,i}X_{2,i} \ldots \boldsymbol{X_{n,i}} \frac{\boldsymbol{dX_{i,n}}}{\boldsymbol{d_t}} \frac{\boldsymbol{1}}{\boldsymbol{X_{n,i}}} \tag{7}$$

$$\frac{dV}{dt} = \sum_i^m \frac{dV_i}{d_t} = \sum_i^m X_{1,i}X_{2,i} \dots X_{n,i} \frac{dlnX_{1,i}}{d_t} + \sum_i^m X_{1,i}X_{2,i} \dots X_{n,i} \frac{dlnX_{2,i}}{d_t} + \dots + \sum_i^m X_{1,i}X_{2,i} \dots X_{n,i} \dots \frac{dlnX_{n,i}}{d_t} \quad (8)$$

$$\frac{dV}{dt} = \sum_i^m \frac{dV_i}{d_t} = \sum_i^m X_{1,i}X_{2,i} \dots X_{n,i} \left[\frac{dlnX_{1,i}}{d_t} + \frac{dlnX_{2,i}}{d_t} + \dots + \frac{dlnX_{n,i}}{d_t}\right] \quad (9)$$

$$dV = \sum_i^m dV_i = \sum_i^m V_i \left[dlnX_{1,i} + dlnX_{2,i} + \dots + dlnX_{n,i}\right] \quad (10)$$

As Eq. (10) shows the instantaneous change, it is integrated over a discrete time period, from 0 to T in Eq. (11) and then approximated in Eq. (12), where appropriate functions replace the asterisked variables:

$$\Delta V = \sum_i^m \left(\int_0^T V_i dlnX_{1,i} + \int_0^T V_i dlnX_{2,i} + .. + \int_0^T V_i dlnX_{n,i}\right) \quad (11)$$

$$\Delta V \cong \sum_i^m V_i^* \ln\left(\frac{X_{1,i}^T}{X_{1,i}^0}\right) + \sum_i^m V_i^* \ln\left(\frac{X_{2,i}^T}{X_{2,i}^0}\right) + .. + \sum_i^m V_i^* \ln\left(\frac{X_{k,i}^T}{X_{k,i}^0}\right) + .. + \sum_i^m V_i^* \ln\left(\frac{X_{n,i}^T}{X_{n,i}^0}\right) \quad (12)$$

There are different functional forms proposed for asterisked variables and these functional forms differentiate Divisia index-linked decomposition methods from each other as well as determining their ability to leave zero residual. For example, the first method linked to the Divisia index, AMDI, proposed by (Boyd, D. et al., 1987), uses the arithmetic mean of the energy-related aggregate between different years in the additive form of the analysis. However, as this method provided imperfect decomposition, various functional forms based on logarithmic weight functions were developed later, as explained in the second part.

w_i^* being a weight function showing the share of the component in the total energy-related aggregate, Eq. (13) shows that the total change of energy-related aggregate equals the energy weighted average of the growth rates of each of the component:

$$\Delta V \cong \sum_i^m w_i^* \ln\left(\frac{X_{1,i}^T}{X_{1,i}^0}\right) + \sum_i^m w_i^* \ln\left(\frac{X_{2,i}^T}{X_{2,i}^0}\right) + .. + \sum_i^m w_i^* \ln\left(\frac{X_{k,i}^T}{X_{k,i}^0}\right) + .. + \sum_i^m w_i^* \ln\left(\frac{X_{n,i}^T}{X_{n,i}^0}\right) \quad (13)$$

And the magnitude of a specific component, *k*, is shown as

$$\Delta V_{X_k} = \sum_{i=1}^m w_i^* \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right) \quad (14)$$

Table 1 shows different types of the Divisa-linked decomposition methods and their weight function, w_i. In the additive form of the LMDI-I, the weight function equals the logarithmic average of the aggregate of interest in two periods [8]:

$$\bar{w_i} = L(V_i^T, V_i^0) \quad (15)$$

8 In a recent study(Chen et al., 2020) this weight function is changed to capture the effects of changes that occur during a research period.

Table 1: Decomposition Formulas in Methods Linked to Divisa Index

IDA	*MD*	*WF(MD)*	*AD*	*WF (AD)*
AMDI	$Dx_k = exp\left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = \frac{V_i^T/V^T + V_i^0/V^0}{2}$	$\Delta V x_k = \left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = \frac{V_i^T + V_i^0}{2}$
LMDI-I	$Dx_k = exp\left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)}$	$\Delta V x_k = \left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = L(V_i^T, V_i^0)$
LMDI-II	$Dx_k = exp\left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = \frac{L(V_i^T/V^T, V_i^0/V^0)}{\sum_i(L(\frac{V_i^T}{V^T}, V_i^0/V^0))}$	$\Delta V x_k = \left(\sum_i w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right)\right)$	$w_i = \frac{L\left(\frac{V_i^T}{V^T}, \frac{V_i^0}{V^0}\right)}{\sum_i(L(\frac{V_i^T}{V^T}, V_i^0/V^0))} L(V^T, V^0)$

Source: Prepared by the author based on (Ang, 2004b; Ang et al., 2003, 2009)
MD-AD: Multiplicative-Additive Decomposition; WF: Weight Function

As the logarithmic average of two positive numbers is calculated as;

$$L(x, y) = \frac{x-y}{\ln x - \ln y} \;; for\ x \neq y; L(x, y) = x, if\ x = y.$$

the general formula used to decompose the underlying effects of energy consumption in the additive form of the Divisia index takes the form below:

LMDI-I (Additive) [9]

$$\Delta V_{X_k} = \sum_{i=1}^m w_i \ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right) = \sum_{i=1}^m L(V_i^T, V_i^0)\, ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right) = \sum_{i=1}^m \frac{V_i^T - V_i^0}{lnV_i^T - \ln V_i^0}\ ln\left(\frac{X_{i,k}^T}{X_{i,k}^0}\right) \quad (16)$$

5. Index Decomposition Analysis of Energy Consumption in Turkey

Turkey's dependence on fossil fuels and lack of self-sufficiency has not changed over the past 30 years, which has made energy supply security an important pillar of national energy policy (IEA, 2021). As of 2020, fossil fuels accounted for 83.3% of the total energy supply, up from 81.7% in 1990. Hard coal, oil and gas import rates [10] rose to 97.8%, 91.4% and 98.6% in 2020 from 69.6%, 87.6% and 95.3% in 1990 (MENR, 2022). Accordingly, continuous, sustainable and secure provision of energy supply with high quality and low cost is set as the main aim for the energy sector by the 11th Development Plan (2019-2023) (PSB, 2019).

9 The transformation of additive decomposition to multiplicative decomposition can be realized through this formula(Ang, 2004b): $\frac{\Delta V_{Xk}}{\ln D_{Xk}} = L(V^T, V^0) = \frac{V^T - V^0}{\ln(V^T/V^0)} = \frac{\Delta V_{tot}}{\Delta D_{tot}}$

10 Exports and bunker fuels are included in the calculation of import rates.

In that light, the expansion of upstream oil and gas activities and domestic sources have been the main strategies for achieving this objective. Even so, the slight increase in domestic energy sources' share in total energy supply, from 33.3% in 2000 to 36% in 2020 (MENR, 2022), along with limited upstream energy resources and climate-related concerns, indicates that measures in increasing energy efficiency and changes in the composition of production activities are equally needed to meet the energy demand expected to increase with economic growth and population. And for this reason, decomposing changes in energy consumption into its driving forces both at aggregate and sub-sectoral level provides valuable inputs for energy policies.

The analysis will be preceded by a review of Turkish literature on decomposing changes in energy – or emission-related aggregates in Turkey.

Table 2: Brief Summary of Turkey Related Studies in the Literature

Author	Scope	Period	Aggregate	Method
1.(Alkan& Binatlı, 2021)	Economy wide	1990-2015	Emissions	SDA-A
2.(Bektaş, 2021a)	Economy wide with 4 sub-sectors	1998-2017	Emissions	LMDI-I – A
3.(Bektaş, 2021b)	Economy wide with a focus iron and steel industry	1999-2017	Emissions	LMDI-I – A
4.(Isik et al., 2021)	Electricity	1990-2018	Emissions	Multilevel LMDI-I-A
5.(Rüstemoğlu, 2021)	Economy wide&Electricty-Heat	1990-2017	Emissions	R.Laspeyres-A
6.(Türköz, 2021)	Economy wide with 4 sub-sectors	1970-2018	EC	LMDI-I – A
7.(Akyürek, 2020)	Manufacturing with 10 sub-sectors	2005-2014	EC	LMDI-I-M
8(Isik et al., 2020)	Transportation Sector	2000-2017	Emissions	LMDI-I – A
9.(Karakaya et al., 2019)	Economy wide	1990-2016	Emissions	LMDI-I-A +Decoupling
10.(Köne & Büke, 2019)	Economy wide	1971-2014& 2015-2060	Emissions	LMDI-I-A
11.(Özşahin, 2019)	Economy wide and industrial sector with 12 sub-sectors	2003-2017	EI	Extended LMDI-II – M
12.(Akbostancı et al., 2018)	Economy wide Manufacturing &Construction	1990-2013	Emissions	LMDI-I – A
13.(Selçuk, 2018)	Industry with 12 sub-sectors	2003-2011	EI	Extended LMDI-II – M
14.(Özçağ et al., 2017)	Industry and agriculture	1990-2014	Emissions	LMDI-I-A
15.(Köne & Büke, 2016)	Economy wide	1971-2010	Emission Intensity	R.Laspeyres-A
16.(Rüstemoğlu, 2016)	Economy wide (Turkey and Iran)	1990-2011	Emissions	LMDI-I-A +Decoupling
17.(Yılmaz et al., 2016)	Industry with 13 sub-sectors	1981-2011	EC	LMDI-I – A

18.((Kumbaroğlu, 2011)	Electricity,Manufacturing,Transportation, Household,Agriculture	1990-2007	Emissions	R.Laspeyres-A
19.(Akbostancı et al., 2011)	Manufacturing with 51 sub-sectors	1995-2001	Emissions	LMDI-I – A
20.(Yilmaz & Atak, 2010)	Economy wide in 4 sub-sectors	1980-2005	EC	C.Laspeyres-A
21.Çermikli & Öztürkler (2009)	Industry with 7 sub-sectors	1981-2000	EC	R.Laspeyres-A
22.(Tunç et al., 2009)	Economy wide with 3 sub-sectors	1970-2006	Emissions	LMDI-I – A
23.(Ediger & Huvaz, 2006)	Economy wide with 3 sub-sectors	1980-2000	EC	LMDI-I – A
24.(Lise, 2006)	Economy wide with 4 sub-sectors	1980-2003	Emissions	R.Laspeyres-A
25.(Karakaya & Özçağ, 2003)	Economy wide	1973-1980	Emissions	R.Laspeyres-A

EC: Energy Consumption, EI: Energy Intensity, M: Multiplicative, A: Additive, R: Refined, C: Conventional and Emissions: CO2 or GHG

Table 2 summarises studies decomposing changes in energy – or emission-related aggregates in Turkey. To the best of the author's knowledge, (Karakaya & Özçağ, 2003) is among the first studies to use index decomposition to analyse Turkey's carbon emissions changes. The study uses a refined Laspeyres index in the additive form to see the driving factors of the changes in carbon emissions between 1973 and 1980. It was after 2011 that studies applying decomposition analysis became more widespread in Turkey, and the majority of studies focused on the changes in carbon emissions. It is also noticeable that most studies apply decomposition methods linked to the Divisa index in parallel with general literature. And the majority of these studies are based on the additive form of the LMDI-I method, whereas there are only two studies that analyse the changes in energy intensity of Turkey with the LMDI-II approach in the multiplicative form. Other studies using the decomposition technique linked to the Laspeyres index mainly use the refined Laspeyres index to overcome the residual problem. Furthermore, most studies deal with changes at the national level, while sectoral studies concentrate mainly on the industrial and manufacturing sectors.

In regards to studies focusing on energy consumption, Ediger & Huvaz (2006) utilises index decomposition to examine the changes in energy consumption in the Turkish economy between 1980-2000 with three sub-sector details covering agriculture, industry and services and find that the activity effect, i.e., economic growth is the major contributor to changes in energy consumption. Çermikli & Öztürkler (2009) focuses on changes in industrial energy consumption with seven sub-sector detail during five sub-periods between 1981-2000 and finds that the change in the structure and sub-sectoral intensity in the industrial sector led to significant savings in energy consumption in this period. Yilmaz & Atak (2010) is the only study that uses the conventional Laspeyres index as used in (Park, 1992). It is found that output effect has a dominant feature and structural effect has a positive contribution to the energy consumption in the entire period, energy intensity has a reducing impact, except in the period between 2000-2005. Yılmaz et al.,

(2016) analyse the changes in energy consumption in the industrial sector with 12 sub-sectors for the period 1981-2011 and find that, except in years of economic crisis and reduction in real added value, the activity effect contributes positively to energy consumption whereas the intensity and structural effects differ in contributions (positive or negative) in different years. Applying LMDI-I to the manufacturing industry with ten sub-sector details between 2005-2014, Akyürek (2020) finds few structural changes, so increasing production and changing energy intensity are dominant factors affecting manufacturing energy consumption. In the non-metallic minerals and primary metals sectors, structure and intensity effects were observed along with activity effects, while in other sectors, the activity effect dominated. Türköz (2021) analyses changes in national energy consumption with three sub-sector detail for the period between 1970-2018 using an additive form of LMDI. Energy consumption during this period was impacted mainly by increases in production, while structural changes (to a large extent) and intensity changes (to a smaller extent) had a reducing effect. It is also found that between 1970-1979 and 1980-1999, both activity and structural effects increased energy consumption, whereas, in the other sub-period covering 2000-2018, only activity effect led energy consumption to increase.

In all these studies, economic activity is found to be the main contributor to changes in energy consumption. It is not only because the aggregate of interest is a quantity indicator, which outweighs the impact of other indicators, but also because it is still hard to mention that there is a permanent resource decoupling between energy and growth.

Figure 2 illustrates the parallelism in changes between energy consumption and value-added. It is seen that energy consumption decreased in all recession years, namely 1994, 1999, 2001, 2008-2009, and 2019. In 2009 and 2019, only the industrial sector experienced negative growth, resulting in a decrease in industrial energy consumption. However, in some years, namely 1998, 2005, 2008, 2013, and 2018, energy consumption decreased independently from the value added, indicating a temporary decoupling between these two factors.

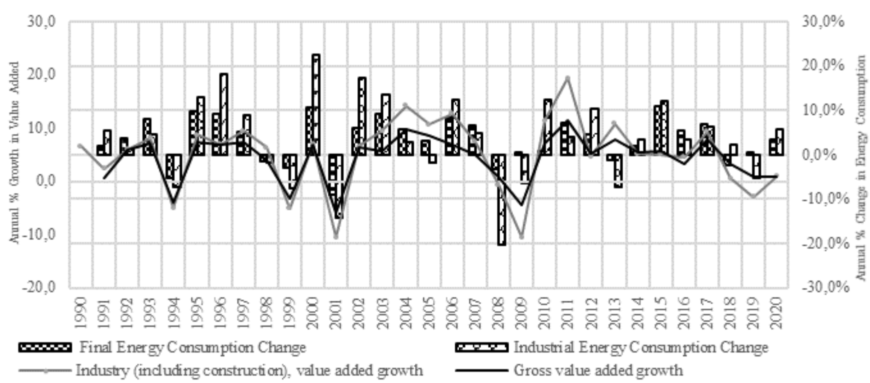

Figure 2: Annual Changes in Energy Consumption and Gross Value-Added, 1990-2020

Source: (MENR, 2022; World Bank, 2022)

Another common point of these studies is that energy data are obtained from national energy balance tables using the territorial principle. In territorial principle, emissions and energy use of an economic actor are allocated to countries where these activities occur, regardless of whether their economic actors are residents or non-residents of these countries. On the other hand, the system of national accounts (SNA) is based on the residential principle, and economic units producing value added are required to be resident in countries engaged in production. In that light, the energy accounts of the World Input-Output Database (WIOD) (Timmer et al., 2015), an extensive database based on harmonised national input tables to analyse global production networks and their socio-economic and environmental impacts, aims to serve as a link between SNA and energy balance statistics by identifying and reconciling the differences between the two statistical systems. While the WIOD energy database is based initially on extended energy balances of the International Energy Agency (IEA), it has later been transformed to provide coherency between economic and energy information. The first transformation is realised by adding activities of residents operating abroad and reducing the activities of foreign entities operating in the national territory. The second transformation is performed by distributing some energy flows into related sectors in accordance with the classification used in SNA, as some energy flows in energy balance tables are categorised irrespective of the agent doing this transport. For example, "road transport" and "commerce and public services" items in energy balances are distributed across several industries, services, plus households in the WIOD energy accounts to set up a link between energy data and economic activities (Corsatea et al., 2019; Genty et al., 2012)

For these reasons, in this study, the analysis of energy consumption changes in Turkey [11] will be conducted with data obtained from the 2016 release of the WIOD using the additive form of the LMDI-I method. WIOD 2016 Release covers the 2000-2014 period with NACE Rev.2 sectoral classification. Gross energy use data in WIOD Environmental Accounts are used for energy consumption. Even though the gross energy concept implies double counting as intermediate energy inputs used for energy transformation are counted, it is considered useful for providing the total amount of consumed energy inputs and thus total energy intensity. Value-added is used as an indicator of production, and real value-added is obtained by deflating gross value added at current prices with the gross value-added price index (2010=100) in the WIOD Socio-Economic Accounts.

In this framework, following (Ang, 2005) the decomposition identity for change in energy consumption between 2000-2014 is set up as follows:

$$E = \sum_i^m E_i = \sum_i^m Q \frac{Q_i}{Q} \frac{E_i}{Q_i} = \sum_i^m Q S_i I_i \tag{17}$$

E = Total energy consumption in the economy

Q = Total activity level $(= \sum_i Q_i)$

11 As the study focuses on the production activities, final energy consumption by households is excluded.

S_i = Activity share ($^{Q_i}/_{Q}$) and

I_i = Energy intensity of the related sector ($^{E_i}/_{Q_i}$)

i refers to different sectors and m refers to the total number of these sectors. Energy consumption is measured in an energy unit (Joule), and output level is in a monetary unit (national currency).

The above identity divides the sources of changes in total energy consumption (ΔE_{tot}) between 2000-2014 into three categories: changes in total production (ΔE_{act}, activity effect) show the contribution of output change to the change in energy consumption. Changes in the shares of sectoral output (ΔE_{str}, structural effect) and changes in energy intensity (ΔE_{int}, intensity effect) reflect the role of structural and energy intensity changes in total energy consumption change.

Following Eq. (5), total energy consumption change in the additive analysis is demonstrated as follows:

$$\Delta E_{tot} = E^T - E^0 = \Delta E_{act} + \Delta E_{str} + \Delta E_{int} \tag{18}$$

And, to see the contribution of each of these components, the following LMDI-I formulae are applied.

$$\Delta E_{ACT} = \sum_i^m L(E_i^T, E_i^0) \ln\left(\frac{Q^T}{Q^0}\right) = \sum_i^m \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^O} \ln\left(\frac{Q^T}{Q^0}\right) \tag{19}$$

$$\Delta E_{STR} = \sum_i^m L(E_i^T, E_i^0) \ln\left(\frac{S_i{}^T}{S_i{}^0}\right) = \sum_i^m \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^O} \ln\left(\frac{S_i{}^T}{S_i{}^0}\right) \tag{20}$$

$$\Delta E_{INT} = \sum_i^m L(E_i^T, E_i^0) \ln\left(\frac{I_i{}^T}{I_i{}^0}\right) = \sum_i^m \frac{E_i^T - E_i^0}{\ln E_i^T - \ln E_i^O} \ln\left(\frac{I_i{}^T}{I_i^O}\right) \tag{21}$$

6. Results

Along with the results of the IDA analysis, it is considered useful and complementary to look at the sectoral shares and changes in total energy consumption, as given Table 3**.** According to the energy accounts provided in the WIOD tables, total energy demand related to production activities increased by 59% in this period, accounting for a total change of 2.35 million TJ. In 2000, total energy consumption was 3.9 million TJ, and 50% of total demand arose from manufacturing activities. Other industrial activities, covering mining and quarrying, and electricity, gas and water supply, turns out as another important sector in terms of energy consumption with a 28% share in total energy consumption in 2000 and is followed by the services sector with a 12% share. Between 2000-2014, the largest percentage increase in sectoral energy demand was realised in the services sector, leading to the share of services in total energy demand to rise to 19%. This increase constituted 32% of the total change in energy demand. However, the primary source of the rising energy demand was the other industrial activities comprising 45% of total change as the largest increase in absolute terms realised in this sector. And the second largest percentage increase occurred by 94% in the same sector resulting in a rise in its weight in total demand to 34% in 2014. In the manufacturing sector, on the other hand, energy demand increase stayed limited to 22%, constituting only 19% of the total increase in energy demand, and the share of the sector in total energy consumption decreased by 11 points to 39% in 2014 (Corsatea et al., 2019).

Table 3: Energy Consumption Change, 2000-2014

	2000		***2014***		***2000-2014***	
	*E*_Tot	Sectoral Shares in *E*_Tot	*E*_Tot	Sectoral Shares in *E*_Tot	% Δ*E*_Tot	Sectoral Share in Δ*E*_Tot
Total	3,999.8		6,348.4		59%	
Agriculture	227.6	6%	323.0	5%	42%	4%
Manufacturing	2,014.2	50%	2,450.7	39%	22%	19%
Other industry	1,123.7	28%	2,182.7	34%	94%	45%
Construction	152.9	4%	166.1	3%	9%	1%
Services	481.4	12%	1,225.9	19%	155%	32%

Source: (Corsatea et al., 2019)

Notes: Energy consumption values are given Thousand TJ
Other Industry includes Mining and quarrying and Electricity, gas and water supply.

Applying the additive form of IDA to the change in energy consumption shows that the increase in total energy demand mainly arisen from the activity and structural effect. In contrast, the intensity effect has a reducing impact on total change. Figure 3 shows the driving factors of this change, and it is seen that if energy intensity had stayed the same during this period, the total increase in energy consumption would be 26% higher than the actual change, reaching 2,962 thousand TJ, instead of staying at the level of 2,348 thousand TJ.

According to the WIOD database, the overall value added increased by 75% in this period, causing an activity effect of 2,838 thousand TJ. In other words, without structural and intensity impact, increase in total energy demand would be 71%, instead of the actual increase of 59%. Since the activity effect equals the weighted sum of the difference change in total output by changes in sectoral energy consumption, as shown in Eq. (19), it is not possible to see the contribution of changes in sectoral value added to changes in total energy demand [12]. However, in other driving factors showing the structural and intensity effects, it is possible to see the impact of changes in

12 Without taking into consideration the structure of the formula, activity affect can easily be interpreted as the effect of change in sectoral value added on the aggregate indicator (total energy demand, emissions, etc.), which could be misleading. The structural effect also needs to be interpreted carefully, since it shows only the impact of changes in sectoral shares on the aggregate indicator rather than the impact of sub-structural changes on these sectoral indicators (sectoral energy demand, emission etc.)

sectoral shares and intensities on the total change in energy demand which is shown in detail in Table 4.

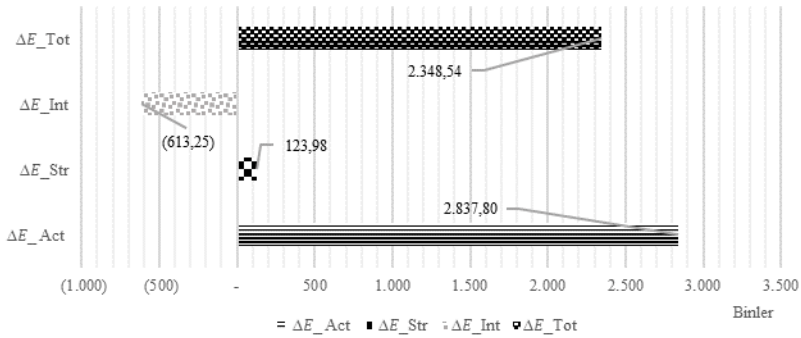

Figure 3: Decomposition of Total Energy Consumption Change, 2000-2014

As seen in Figure 3, the change in the economic structure, reflected by the total impact of each change in sectoral shares of production activities, contributed to the increase in total energy consumption by 123.98 thousand TJ, equalling 5% of the total change in energy demand.

Components of structural and intensity effects are shown in Table 4. The first column (A) shows the % change in the sectoral value-added shares through which the structural impact is calculated in IDA. And the next column (B) gives the structural effect (ΔE_Str) associated with each sector, and the sum of these effects gives the final structural effect. The following column (C) shows the contribution of changes in sectoral shares to total energy demand, which is measured by the percentage of the sectoral structural effect in total energy demand change. In column (D), the % change in sectoral energy intensity is given, and the sectoral intensity effects sum of which equals the total intensity effect is provided in column (E). And the last column (F) shows the contribution of sectoral intensity effects to total energy demand change, equalling to the share of sectoral intensity effect in total energy demand change.

It is seen that a 13% increase in the weight of manufacturing in total value added resulted in 265 thousand TJ increase in energy consumption, accounting for 11% of the total energy demand change. And despite the increase in its weight in total value added, the share of the sector in total energy demand decreased, as stated before, mainly resulting from the gains from improvements in energy efficiency. Another structural change causing an increase in energy demand came from the rise in services and construction sectors' shares. The 3% increase in the share of the services in total value-added resulted in 22 thousand TJ increase in energy demand, equalling the 1% of the total rise in total energy consumption. On the other hand, 29% and 4% decrease in the shares of agricultural and other industries in total value added, respectively, had a reducing impact on energy demand equalling 7% of total change.

Table 4: Components of Structural and Intensity Effects

	% Changes in Sectoral Value – Added Shares *(A)*	***ΔE_Str*** *(B)*	***% Contribution to ΔE_tot through ΔE_Str*** *(C)*	***% Changes in energy intensity*** *(D)*	***ΔE_Int*** *(E)*	***% Contribution to ΔE_Tot through ΔE_Int*** *(F)*
Agriculture	-29%	(93.89)	-4%	14%	36.07	2%
Manufacturing	13%	264.98	11%	-38%	(1,079.24)	-46%
Other Industry	-4%	(71.56)	-3%	16%	234.00	10%
Construction	1%	2.04	0.1%	-39%	(78.52)	-3%
Services	3%	22.41	1%	41%	274.45	12%
Total Effects (Str.& Int.)	-	**123.98**			**(613.25)**	

Source: (Corsatea et al., 2019)

Notes: Energy consumption values are given Thousand TJ

Other Industry includes Mining and quarrying and Electricity, gas and water supply

As mentioned before, the total impact of changes in sectoral energy intensities led to a decrease in the total energy demand during this period. Looking at these sectoral components of total intensity effect, it is seen that the significant decline in energy intensity occurred in manufacturing activities with 38% and had a reducing impact on energy demand by 1.08 million TJ, equalling 46% of total change. In other words, if there had not been any improvement in energy efficiency in the manufacturing sector, the total energy consumption increase would be 46% higher than its actual level. However, the impact of this energy saving was lessened by the rise in sectoral energy intensities in other industrial activities and the service sector. The %41 increase in sectoral energy intensity of services resulted in 274.4 thousand TJ rise in total energy demand, equalling 12% of total energy demand change, whereas only a 16% increase in energy intensity of other industrial activities led to a rise in total energy demand by 234 thousand TJ, constituting the 10% of total change. On the other hand, in the construction sector the impact of the 39% decrease in energy intensity led to a relatively small reducing impact on total energy demand by only 3%, equalling 78.5 thousand TJ, and in the agricultural sector, energy intensity increased by 14% leading to 36 thousand TJ rise in total energy demand, equalling to 2% of total change.

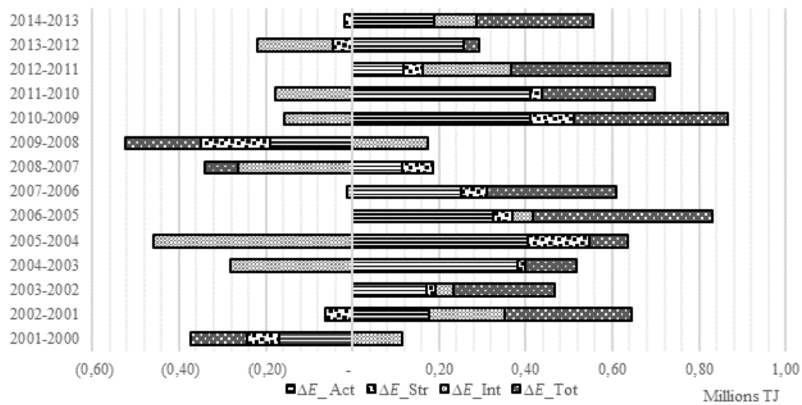

Figure 4: Decomposition of Annual Changes in Energy Consumption, 2000-2014

Figure 4 shows the decomposition of annual changes in total energy consumption in this period. It is seen that in three recession years, total energy consumption declined and only in 2008 energy intensity decrease was the primary source of this decline, while in other years, 2001 and 2009, structural change and decrease in total value added were the main driving factors behind this change. Similar to the analysis of the whole period, structural changes had relatively limited effects in each year and only in 2001, 2002, 2009, 2013 and 2014 it had a reducing impact on total energy demand. A detailed analysis of (Corsatea et al., 2019) depicts that in 2001, 2002 and 2009, the decline in the weight of manufacturing activities was the main source of this structural effect, whereas in 2013 and 2014, it mainly arose from the decrease in the weight of other industrial activities. On the other hand, in half of the analysed years, namely in 2004, 2005, 2007, 2008, 2010, 2011, and 2013 energy intensity had a reducing effect on energy demand and changes in manufactural energy intensity (in 2004, 2005, 2007, 2008 and 2011) and other industrial activities (in 2010 and 2013) was the main source of this impact.

7. Discussion

Findings of the decomposition of both period-wise and annual changes in energy consumption in Turkey are coherent with previous studies, showing that the activity effect is the main contributing factor to the increase in energy demand during this period. As stated previously, this finding can be attributed to two factors: Firstly, decomposing a difference change of an aggregate results in a disproportionately significant impact of an additional variable. Additionally, there is still a strong relationship with the production and energy consumption, as seen in Figure 2 while only in some years a temporary decoupling is observed due to the substantial decrease in energy intensity as annual decomposition analysis demonstrates for 2005,2008 and 2013.

It is also worth emphasising that structural effect generally has a very limited impact on changes in energy consumption, in contrast to the intensity effect which turns out to be the main reason behind the large amount of energy savings during this period. For the annual analysis, this finding can be explained by the low-level sub-sectoral detail of the study, as significant shifts in the shares of these main sectors are less likely to happen annually. Instead, these structural changes are more likely to be observed in the medium and/or long term. In Table 4, we can see a shift from both other industries and agriculture to manufacturing during the entire period. However, the impact of this change was also limited, and this can be explained by the indirect effect of the decrease in sectoral energy intensity. Nevertheless, the effect of structural changes on total energy consumption, while limited, differs from the finding of Türköz (2021) for the sub-period covering 2000-2018, which may be due to differences in the data source as well as sub-sectoral details.

In both period-wise and annual analyses, the primary energy-saving source is the decrease in energy intensity, consistent with the findings of other studies. This is due to a 38% reduction in the sectoral energy intensity of the manufacturing sector, which led to an energy savings of 1.079 thousand TJ, 46% of the overall energy consumption change.

It is noticeable that the impact of changes in the sectoral shares or energy intensities on the total change in energy consumption is related to the percentage of this economic activity in total energy demand. For example, the change in the share of agriculture in total value added (-29%) is more than two times the change in manufactural shares (13%), but its impact on change in total energy demand (-4%) was significantly lower than the impact of manufactural change (11%). Similarly, almost equal reductions in energy intensities of construction (-39%) and manufacturing activities (-38%) had different impacts on change in total energy demand. This indicates that structural changes and energy improvements in sectors of which shares in total energy consumption are higher than others have a larger impact on total energy demand than those with a small weight in total energy consumption.

8. Conclusion

Not only the biophysical limits on natural resources and climate-related concerns but also the distribution of these resources makes continuous access to energy more critical than ever as fossil fuels continue to dominate the world economy. And with the growing energy demand triggered by growth-oriented economic policies and increasing population, analysis of energy consumption becomes more important to understand its driving factors truly and thus establish efficient demand-oriented energy policies to achieve a sustainable level of consumption within supply constraints.

In that regard, the primary aim of this study was to provide an informative framework for IDA, index decomposition analysis, a methodology that has become a widely accepted tool in energy and emission studies and is also being tested in other areas. It is explained that, since its emergence in the 1980s, this methodology transformed substantially through the development of several methods and the improvement of existing ones to carry out more insightful and accurate analyses. Consequently, the methods linked to the Divisia index have emerged as the most preferred methods for various reasons. Among them, LMDI-I was used in this study to analyse the changes in energy consumption from 2000-2014.

While many other studies examining the energy consumption changes in Turkey have utilised the same method, this study differs from them and contributes to a few existing studies by using the WIOD as the sole data source for energy and value-added variables in a county level study. As energy accounts in the WIOD database have been transformed from extended energy balance tables of IEA to achieve the same recording principle and sectoral classification with the national accounting framework, decomposition analysis of the change in energy consumption is considered to be more coherent as energy data is based on the same statistical approach and sectoral classifications with value-added. However, the restriction with using the WIOD database was the limited time period. This issue remains one of the improvement areas depending on the enhancements of WIOD with up-to-date data.

As the analysis shows, IDA can be a very beneficial tool to distinguish the impacts of different factors on the change in energy consumption from each other. Knowing the extent of changes in value-added share and energy intensity of an analysed sector affect total energy demand would provide valuable input in establishing sectoral energy policies. In that regard, a multilevel analysis showing the impact of changes in value-added shares and energy intensity of sub-sectors at the lower hierarchical level on total demand can be more beneficial for in determination of targeted sectors. In addition, as the climate-related concerns are as critical as the supply constraints on energy resources, a study combining the findings of the decomposition of changes in emissions and energy consumption would also be a valuable guide for energy policies.

References

Agnolucci, P., Ekins, P., Iacopini, G., Anderson, K., Bows, A., Mander, S., & Shackley, S. (2009). Different scenarios for achieving radical reduction in carbon emissions: A decomposition analysis. *Ecological Economics*, *68*(6), 1652–1666. https://doi.org/10.1016/j.ecolecon.2007.09.005

Akbostancı, E., Tunç, G. İ., & Türüt-Aşık, S. (2011). CO2 emissions of Turkish manufacturing industry: A decomposition analysis. *Applied Energy*, *88*(6), 2273–2278. https://doi.org/10.1016/j.apenergy.2010.12.076

Akbostancı, E., Tunç, G. İ., & Türüt-Aşık, S. (2018). Drivers of fuel based carbon dioxide emissions: The case of Turkey. *Renewable and Sustainable Energy Reviews*, *81*, 2599–2608. https://doi.org/10.1016/j.rser.2017.06.066

Akyürek, Z. (2020). LMDI decomposition analysis of energy consumption of Turkish manufacturing industry: 2005–2014. *Energy Efficiency*, *13*(4), 649–663. https://doi.org/10.1007/s12053.020.09846-8

Albrecht, J., François, D., & Schoors, K. (2002). A Shapley decomposition of carbon emissions without residuals. *Energy Policy*, *30*(9), 727–736. https://doi.org/10.1016/S0301-4215(01)00131-8

Alkan, A., & Binatlı, A. O. (2021). Is Production or Consumption the Determiner? Sources of Turkey's CO2 Emissions between 1990-2015 and Policy Implications. *Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 359–378. https://doi.org/10.17065/huniibf.823845

Ang, B. W. (1994). Decomposition of industrial energy consumption-The energy intensity approach. *Energy Economics*, *16*(3), 163–174. https://doi.org/10.1016/0140-9883(94)90030-2

Ang, B. W. (1995a). Decomposition methodology in industrial energy demand analysis. *Energy*, *20*(11), 1081–1095. https://doi.org/10.1016/0360-5442(95)00068-R

Ang, B. W. (1995b). Multilevel decomposition of industrial energy consumption. *Energy Economics*, *17*(1), 39–51. https://doi.org/10.1016/0140-9883(95)98905-J

Ang, B. W. (2004a). Decomposition Analysis Applied to Energy. In C. J. Cleveland & R. U. Ayres (Eds.), *Encyclopedia of Energy: Vol. I* (pp. 761–769). Elsevier Academic Press.

Ang, B. W. (2004b). Decomposition analysis for policymaking in energy: which is the preferred method? *Energy Policy*, *32*(9), 1131–1139. https://doi.org/10.1016/S0301-4215(03)00076-4

Ang, B. W. (2015). LMDI decomposition approach: A guide for implementation. *Energy Policy*, *86*, 233–238. https://doi.org/10.1016/j.enpol.2015.07.007

Ang, B. W., & Choi, K.-H. (1997). Decomposition of Aggregate Energy and Gas Emission Intensities for Industry: A Refined Divisia Index Method. *The Energy Journal*, *18*(3), 59–73.

Ang, B. W., & Goh, T. (2019a). *Routledge handbook of energy economics* (U. Soytaş & R. Sarı, Eds.). Routledge.

Ang, B. W., & Goh, T. (2019b). Index decomposition analysis for comparing emission scenarios: Applications and challenges. *Energy Economics*, *83*, 74–87. https://doi.org/10.1016/j.eneco.2019.06.013

Ang, B. W., Huang, H. C., & Mu, A. R. (2009). Properties and linkages of some index decomposition analysis methods. *Energy Policy*, *37*(11), 4624–4632. https://doi.org/10.1016/j.enpol.2009.06.017

Ang, B. W., & Lee, S. Y. (1994). Decomposition of industrial energy consumption: Some methodological and application issues. *Energy Economics*, *16*(2), 83–92. https://doi.org/10.1016/0140-9883(94)90001-9

Ang, B. W., & Liu, F. L. (2001). A new energy decomposition method: perfect in decomposition and consistent in aggregation. *Energy*, *26*(6), 537–548. https://doi.org/10.1016/S0360-5442(01)00022-6

Ang, B. W., Liu, F. L., & Chew, E. P. (2003). Perfect decomposition techniques in energy and environmental analysis. *Energy Policy*, *31*(14), 1561–1566. https://doi.org/10.1016/S0301-4215(02)00206-9

Ang, B. W., Liu, F. L., & Chung, H.-S. (2004). A generalized Fisher index approach to energy decomposition analysis. *Energy Economics*, *26*(5), 757–763. https://doi.org/10.1016/j.eneco.2004.02.002

Ang, B. W., & Liu, N. (2007a). Handling zero values in the logarithmic mean Divisia index decomposition approach. *Energy Policy*, *35*(1), 238–246. https://doi.org/10.1016/j.enpol.2005.11.001

Ang, B. W., & Liu, N. (2007b). Negative-value problems of the logarithmic mean Divisia index decomposition approach. *Energy Policy*, *35*(1), 739–742. https://doi.org/10.1016/j.enpol.2005.12.004

Ang, B. W., & Wang, H. (2015). Index decomposition analysis with multidimensional and multilevel energy data. *Energy Economics*, *51*, 67–76. https://doi.org/10.1016/j.eneco.2015.06.004

Ang, B. W., Zhang, F., & Choi, K. (1998). Factorizing changes in energy and environmental indicators through decomposition. *Energy*, *23*(6), 489–495. https://doi.org/10.1016/S0360-5442(98)00016-4

Ang, B. W., & Zhang, F. Q. (2000). A survey of index decomposition analysis in energy and environmental studies. *Energy*, *25*(12), 1149–1176. https://doi.org/10.1016/S0360-5442(00)00039-6

Bektaş, A. (2021a). Decomposıtıon of Energy-Related Co2 Emission Over 1998-2017 In Turkey. *Environmental Engineering & Management Journal (EEMJ)*, , *20*(12), 1981–1998.

Bektaş, A. (2021b). The Impact of European Green Deal on Turkey's Iron and Steel Industry: Decomposition Analysis of Energy-Related Sectoral Emissions. *Celal Bayar Üniversitesi Fen Bilimleri Dergisi*. https://doi.org/10.18466/cbayarfbe.823265

Bossanyi, E. (1979). UK primary energy consumption and the changing structure of final demand. *Energy Policy*, *7*(3), 253–258. https://doi.org/10.1016/0301-4215(79)90068-5

Boyd D., McDonald J.F., Ross M., & Hanson D.A. (1987). Separating the Changing Composition of U.S. Manufacturing Production from Energy Efficiency Improvements: A Divisia Index Approach. *The Energy Journal*, *8*(2), 77–96.

Boyd, G. A., Hanson, D. A., & Sterner, T. (1988). Decomposition of changes in energy intensity. *Energy Economics*, *10*(4), 309–312. https://doi.org/10.1016/0140-9883(88)90042-4

Boyd, G. A., & Roop, J. M. (2004). A Note on the Fisher Ideal Index Decomposition for Structural Change in Energy Intensity. *EJ*, *25*(1). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol25-No1-5

Chen, J., Gao, M., Li, D., Song, M., Xie, Q., & Zhou, J. (2020). Extended Yearly LMDI Approaches: A Case Study of Energy Consumption. *Mathematical Problems in Engineering*, *2020*, 1–13. https://doi.org/10.1155/2020/9207896

Choi, K.-H., & Ang, B. W. (2003). Decomposition of aggregate energy intensity changes in two measures: ratio and difference. *Energy Economics*, *25*(6), 615–624. https://doi.org/10.1016/S0140-9883(03)00038-0

Choi, K.-H., & Ang, B. W. (2012). Attribution of changes in Divisia real energy intensity index — An extension to index decomposition analysis. *Energy Economics*, *34*(1), 171–176. https://doi.org/10.1016/j.eneco.2011.04.011

Chung, H.-S., & Rhee, H.-C. (2001). A residual-free decomposition of the sources of carbon dioxide emissions: a case of the Korean industries. *Energy*, *26*(1), 15–30. https://doi.org/10.1016/S0360-5442(00)00045-1

Corsatea, T., Román, M., Amores, A., Neuwahl, F., Velázquez Afonso, A., Rueda-Cantuche, J., Arto, I., & Lindner, S. (2019). *World Input-Output Database Environmental Accounts : Update 2000-2016*. Publications Office. https://doi.org/doi/10.2760/024036

Çermikli, H., & Öztürkler, H. (2009). Türkiye'de 1981-2000 döneminde sanayi kesiminde enerji tüketiminin ayrıştırılması. *TİSK Akademi*, *4*(8), 63–79.

de Boer, P., & Rodrigues, J. F. D. (2020). Decomposition analysis: when to use which method? *Economic Systems Research*, *32*(1), 1–28. https://doi.org/10.1080/09535.314.2019.1652571

Ediger, V. Ş., & Huvaz, O. (2006). Examining the sectoral energy use in Turkish economy (1980–2000) with the help of decomposition analysis. *Energy Conversion and Management*, *47*(6), 732–745. https://doi.org/10.1016/j.enconman.2005.05.022

Förster, H., Schumacher, K., de Cian, E., Hübler, M., Keppo, I., Mima, S., & Sands, R. D. (2013). European Energy Efficiency and Decarbonization Strategies Beyond 2030—A Sectoral Multi-Model Decomposition. *Clim. Change Econ.*, *04*(supp01), 1340004. https://doi.org/10.1142/S201.000.7813400046

Genty, A., Arto, I., & Neuwahl, F. (2012). *Final Database of Environmental Satellite Accounts: Technical Report on Their Compilation*.

Hankinson, G. A., & Rhys, J. M. W. (1983). Electricity consumption, electricity intensity and industrial structure. *Energy Economics*, *5*(3), 146–152. https://doi.org/10.1016/0140-9883(83)90054-3

Hasanbeigi, A., Jiang, Z., & Price, L. (2014). Retrospective and prospective analysis of the trends of energy use in Chinese iron and steel industry. *Journal of Cleaner Production*, *74*, 105–118. https://doi.org/10.1016/j.jclepro.2014.03.065

Hoekstra, R., & van den Bergh, J. C. J. M. (2003). Comparing structural decomposition analysis and index. *Energy Economics*, *25*(1), 39–64. https://doi.org/10.1016/S0140-9883(02)00059-2

Howarth, R. B., Schipper, L., Duerr, P. A., & Strøm, S. (1991). Manufacturing energy use in eight OECD countries. *Energy Economics*, *13*(2), 135–142. https://doi.org/10.1016/0140-9883(91)90046-3

IEA. (2021). *Turkey 2021*.

Isik, M., Ari, I., & Sarica, K. (2021). Challenges in the CO2 emissions of the Turkish power sector: Evidence from a two-level decomposition approach. *Utilities Policy*, *70*, 101227. https://doi.org/10.1016/j.jup.2021.101227

Isik, M., Sarica, K., & Ari, I. (2020). Driving forces of Turkey's transportation sector CO2 emissions: An LMDI approach. *Transport Policy*, *97*, 210–219. https://doi.org/10.1016/j.tranpol.2020.07.006

Jenne, C. A., & Cattell, R. K. (1983). Structural change and energy efficiency in industry. *Energy Economics*, *5*(2), 114–123. https://doi.org/10.1016/0140-9883(83)90018-X

Karakaya, E., Bostan, A., & Özçağ, M. (2019). Decomposition and decoupling analysis of energy-related carbon emissions in Turkey. *Environmental Science and Pollution Research*, *26*(31), 32080–32091. https://doi.org/10.1007/s11356.019.06359-5

Karakaya, E., & Özçağ, A. G. M. (2003). Türkİye Açisindan Kyoto Protokolü'nün Değerlendİrİlmesİ Ve Ayriştirma (Decomposition) Yöntemİ İle Co2 Emİsyonu Belİrleyİcİlerİnİn Analİzİ. *METU International Conference in Economics VII*.

Köne, A. Ç., & Büke, T. (2016). The impact of changing energy mix of Turkey on CO2 emission intensities. *Environment Protection Engineering*, *42*(3), 85–93.

Köne, A. Ç., & Büke, T. (2019). Factor analysis of projected carbon dioxide emissions according to the IPCC based sustainable emission scenario in Turkey. *Renewable Energy*, *133*, 914–918. https://doi.org/10.1016/j.renene.2018.10.099

Kumbaroğlu, G. (2011). A sectoral decomposition analysis of Turkish CO2 emissions over 1990–2007. *Energy*, *36*(5), 2419–2433. https://doi.org/10.1016/j.energy.2011.01.027

Lescaroux, F. (2013). Industrial energy demand, a forecasting model based on an index decomposition of structural and efficiency effects. *OPEC Energy Review*, *37*(4), 477–502. https://doi.org/10.1111/opec.12023

Lise, W. (2006). Decomposition of CO2 emissions over 1980–2003 in Turkey. *Energy Policy*, *34*(14), 1841–1852. https://doi.org/10.1016/j.enpol.2004.12.021

Liu, F. L., & Ang, B. W. (2003). Eight methods for decomposing the aggregate energy-intensity of industry. *Applied Energy*, *76*(1–3), 15–23. https://doi.org/10.1016/S0306-2619(03)00043-6

Liu, X. Q., Ang, B. W., & Ong, H. L. (1992). The Application of the Divisia Index to the Decomposition of Changes in Industrial Energy Consumption. *EJ*, *13*(4). https://doi.org/10.5547/ISSN0195-6574-EJ-Vol13-No4-9

MENR. (2022). National Energy Balance Tables 1990-2022. In *Reports of Directorate General of Energy Affairs*. https://enerji.gov.tr/eigm-raporlari

O'Mahony, T. (2010). *Energy-Related Carbon Emissions in Ireland: Scenarios to 2020*. https://doi.org/10.21427/D79895

Özçağ, M., Yılmaz, B., & Sofuoğlu, E. (2017). Türkiye'de Sanayi ve Tarım Sektörlerinde Seragazı Emisyonlarının Belirleyicileri: İndeks Ayrıştırma Analizi . *Uluslararası İlişkiler*, *14*(54), 175–195.

Özşahin, G. (2019). Decomposition of Industrial Energy Consumption in Turkey. *Journal of Research in Economics*, *3*(2), 192–211. https://doi.org/10.35333/JORE.2019.55

Park, S.-H. (1992). Decomposition of industrial energy consumption: An alternative method. *Energy Economics*, *14*(4), 265–270. https://doi.org/10.1016/0140-9883(92)90031-8

PSB. (2019). *11. Development Plan of Turkey (2019-2023)*. Turkish Presidency of Strategy and Budget .

Reitler, W., Rudolph, M., & Schaefer, H. (1987). Analysis of the factors influencing energy consumption in industry. *Energy Economics*, *9*(3), 145–148. https://doi.org/10.1016/0140-9883(87)90019-3

Rüstemoğlu, H. (2016). Ekonomik Büyümenin Çevresel Maliyeti: Türkiye ve İran Ölçeğinde CO2 Emisyonlarının Belirleyicileri. *Journal of the Human & Social Science Researches*, *5*(7).

Rüstemoğlu, H. (2021). Environmental analysis of Turkey's aggregated and sector-level CO2 emissions. *Environmental Science and Pollution Research*, *28*(45), 63933–63944. https://doi.org/10.1007/s11356.020.11895-6

Saygin, D., Wetzels, W., Worrell, E., & Patel, M. K. (2013). Linking historic developments and future scenarios of industrial energy use in the Netherlands between 1993 and 2040. *Energy Efficiency*, *6*(2), 341–368. https://doi.org/10.1007/s12053.012.9172-8

Selçuk, I. Ş. (2018). Energy Efficiency of Turkish Energy Sector: Extended Analysis of Logarithmic Mean Divisia Index Decomposition. *Sosyoekonomi*, 127–145. https://doi.org/10.17233/sosyoekonomi.2018.03.07

Shenning, Q. (2020). The Decomposition Analysis of Carbon Emissions: Theoretical Basis, Methods and Their Evaluations. *Chn. J. Urb. Environ.Stud*, *08*(04), 2050020. https://doi.org/10.1142/S234.574.8120500207

Smit, T. A. B., Hu, J., & Harmsen, R. (2014). Unravelling projected energy savings in 2020 of EU Member States using decomposition analyses. *Energy Policy*, *74*, 271–285. https://doi.org/10.1016/j.enpol.2014.08.030

Su, B., & Ang, B. W. (2012). Structural decomposition analysis applied to energy and emissions: Some methodological developments. *Energy Economics*, *34*(1), 177–188. https://doi.org/10.1016/j.eneco.2011.10.009

Sun, J. W. (1998). Changes in energy consumption and energy intensity: A complete decomposition model. *Energy Economics*, *20*(1), 85–100. https://doi.org/10.1016/S0140-9883(97)00012-1

Timmer, M. P., Dietzenbacher, E., Los, B. , Stehrer R., & de Vries, G. J. (2015). An Illustrated User Guide to the World Input–Output Database: the Case of Global Automotive Production. *Review of International Economics*, *23*, 575–605.

Tunç, İ. G., Türüt-Aşık, S., & Akbostancı, E. (2009). A decomposition analysis of CO2 emissions from energy use: Turkish case. *Energy Policy*, *37*(11), 4689–4699. https://doi.org/10.1016/j.enpol.2009.06.019

Türköz, K. (2021). Türkiye'de Sektörel Enerji Kullanımındaki Değişimlerin İtici Güçleri: Ayrıştırma Analizi. *MANAS Sosyal Araştırmalar Dergisi*, 1038–1052. https://doi.org/10.33206/mjss.853348

Wang, H., Ang, B. W., & Su, B. (2017a). Multiplicative structural decomposition analysis of energy and emission intensities: Some methodological issues. *Energy*, *123*, 47–63. https://doi.org/10.1016/j.energy.2017.01.141

Wang, H., Ang, B. W., & Su, B. (2017b). Assessing drivers of economy-wide energy use and emissions: IDA versus SDA. *Energy Policy*, *107*, 585–599. https://doi.org/10.1016/j.enpol.2017.05.034

World Bank. (2022). *World Development Indicators*.

Xu, X. Y., & Ang, B. W. (2014). Multilevel index decomposition analysis: Approaches and application. *Energy Economics*, *44*, 375–382. https://doi.org/10.1016/j.eneco.2014.05.002

Yilmaz, M., & Atak, M. (2010). Decomposition Analysis of Sectoral Energy Consumption in Turkey. *Energy Sources, Part B: Economics, Planning, and Policy*, *5*(2), 224–231. https://doi.org/10.1080/155.672.40802533203

Yılmaz, A., Ürüt Kelleci, S., & Bostan, A. (2016). Türkiye İmalat Sanayiinde Enerji Tüketiminin İncelenmesi: Ayrıştırma Analizi. . . *Uşak Üniversitesi Sosyal Bilimler Dergisi*, *9*(1), 205-224 .