Proceedings of the 3rd Indian International Conference on Industrial Engineering and Operations Management
New Delhi, India, November 2-4, 2023

Energy-Emission-Related Index Decomposition Analyses for the Period 2016-2020: A Systematic Review and Empirical Study

Jude James
Industrial Engineering Department, Durban University of Technology,
South Africa
Institute of Systems Science, Durban University of Technology, South Africa
judeosagie@ymail.com

Oludolapo Olanrewaju
Industrial Engineering Department, Durban University of Technology,
South Africa
oludolapoo@dut.ac.za

Kevin J. Duffy and Obiora C. Collins
Industrial Engineering Department, Durban University of Technology,
South Africa
Institute of Systems Science, Durban University of Technology, South Africa
Kevind@dut.ac.za and Obiora.c.collins@gmail.com

Abstract

This study reviewed and classified energy-emission-related IDA studies from 2016-2020 and assessed the relationship between the energy intensity of China and energy-emission-related IDA studies on China. Also, the study decomposed changes in China's industrial sector's energy consumption and emissions for 2016-2020 into contributing factors using Logarithmic Mean Divisia Index (LMDI). Findings show that of the three hundred and fifty-one energy-emission-related IDA studies, 66% of them were on China and the energy intensity of China decreased as energy-emission-related IDA studies on China increased with time within the study period indicating that research outcomes and recommendations were considered by policymakers. For the additive LMDI decomposition, results revealed that there was a decrease in energy consumption occasioned majorly by energy intensity followed by energy structure. Also, results showed that the increase in emissions was caused predominantly by the carbon emission factor, followed by overall industrial activity. Though the decrease in industrial energy consumption indicates the application of research outcomes and engagement of energy-efficient technologies, there is still need for more environmentally friendly policies. The innovation in this study is the assessment of the impact of energy-emission-related IDA studies in China on energy intensity, industrial energy consumption, and emissions in China.

Keywords
Energy, Emission, Index Decomposition Analysis, Logarithmic Mean Divisia Index, China

1. Introduction
One of the challenges faced by the world for many years is climate change, which is one of the consequences of excessive energy consumption. Extreme energy demand is challenging as the continuous increase in energy demand results in an ever-widening gap between energy demand and supply. This leaves researchers, practitioners, and policymakers with no other option than to seek ways to reduce energy consumption and emissions. Hence, countries have seen the need to reduce energy usage and CO_2 emissions (Inglesi-Lotz & Pouris, 2012). The reduction and eventually the elimination of incessant rises in energy consumption and emissions have been identified as the way to ensure sustainable economic development (Bekun, Emir, & Sarkodie, 2019), (Oladiran & Meyer 2007; Pollet;,

Staffell;, & Adamson 2015). To reduce energy consumption and related emissions, researchers and policy analysts needed to understand the driving forces behind change in energy consumption and emissions (Owusu & Asumadu-Sarkodie 2016). This understanding will aid the quantification of the factors responsible for changes in energy consumption and emissions in terms of magnitude and direction, thereby enhancing the management of energy consumption and emissions, and eventually the actualization of energy efficiency and emission reduction targets (Wang e al. 2017). Various analytical techniques have been employed by researchers for this purpose. According to Bekun, Emir, and Sarkodie (2019), specifically, there are four categories of analytical techniques reported in the literature for this purpose, and one of such techniques is decomposition analysis (Wang et al. 2017). The decomposition technique evaluates indicators of interest by sharing the change in the indicator amongst a number of pre-defined factors called drivers/effects, making it possible to know the different contributions of each determinant to the change in the indicator, thereby making it possible to have control over the change in the indicator (Wang et al. 2017). The IDA (disaggregation technique) and Structural Decomposition Analysis- (SDA) (input-output technique) are the two most extensively applied decomposition analytics tools. IDA is simpler, more flexible, and hence largely applied (Inglesi-Lotz & Blignaut, 2012; B. Mousavi, N. S. A. Lopez, J. B. M. Biona, A. S. F. Chiu, & M. Blesl, 2017; Oladiran & Meyer 2007). The simplest form of IDA model attributes changes in energy consumption to three factors, namely: effects related to activity output share, overall activity level and energy intensity. They explain change in any aggregate indicator over a particular time period (Beng W ah Ang & Zhang, 2000).

1.1 Objectives

To review and classify energy-emission-related IDA studies for the period 2016-2020, determine the impact of existing energy-emission-related IDA studies conducted in China on energy intensity. Finally, to quantify factors contributing to change in energy consumption and emission of China's industrial sector using additive and multiplicative LMDI.

2. Literature Review

Over the last three decades, decomposition analysis has been a useful technique for energy consumption and emission analyses (Inglesi-Lotz & Pouris, 2012). Studies using IDA were first implemented in the late 1970s and used to analyze the effect of structural changes of energy consumption in industry (B. Mousavi, N. Lopez, J. Biona, A. Chiu, & M. Blesl 2017). Then IDA's focus shifted from energy and the industrial sector to emissions and economy-wide studies in 1990. The Logarithmic Mean Divisia Index (LMDI) became the most preferred of all forms of IDAs as at mid-2000s (Wang et al., 2017). The application of IDA has increased exponentially. For instance, a survey by Huntington and Myers (1987) recorded eight (8) IDA-related publications. Subsequently, Ang (1995) recorded fifty-one (51) IDA related articles, Ang and Zhang (2000) recorded one hundred and nine (109) IDA-related studies, Mu (2012) recorded two hundred and eighty (280) IDA studies, while Wang, Ang and Su (2017) documented one hundred and twenty (120) IDA related scientific papers over the period 2010-2015. Since 2017 when the last survey which covered up to 2015 was done, the number of publications has tremendously increased and without doubt, application development has changed. Guided by the above, the 2017 survey, which is the latest survey, will not be able to provide detailed and up-to-date trends of energy-emission-related IDA studies, let alone ascertain the impact of energy-emissions-related IDA studies on energy consumption and emission's outlook of countries that mostly engage the technique, hence this study.

3. Methods

According to the Intergovernmental Panel on Climate Change's (IPCC) methodology (IPCC, 2006), industrial carbon emissions (ICE) can be quantified by the help of Reference Approach below:

$$TCE = \sum_{mn} C\, E_{mn}$$

$$TCE = \sum_{mn} E\, C_{mn} \,.NCV_n \,.\, CF_n \,.\, COF_n \,.\, \frac{44}{12} \quad (1)$$

$$C_{emf} = CF_n \,.\, COF_n \,.\, \frac{44}{12} \,.\, 1000 \quad (2)$$

$$TCE = \sum_{mn} E\, C_{mn} \,.NCVn \,.\, C_{emf} \,.\, 10^{-3} \quad (3)$$

For a country, aggregate energy consumption E in an industry is represented by a conventional three-factor IDA model as:

$$E = \sum_j \frac{E_j}{Q_j}\frac{Q_j}{Q} Q = \sum_j I_j S_j Q. \quad (4)$$

E represents aggregate energy consumption and Q represents the overall industrial activity. The variables denoted by subscript j stands for the industrial sector. I_j is the energy intensity of sector j, S_j is the activity share of sector j, also known as the industrial activity structure. Thus, energy intensity, activity structure (production value in a sector) and

Table 1: Description of variables & their units in equations 1-3

Variables	Description	Units
TCE	Total CO_2 emission of industrial sector	Gg CO_2
CE_{mn}	CO_2 emission of sector mth of fuel nth	Gg CO_2
M	Sector mth of industrial sector	--
N	Fuel nth of the energy consumed	--
EC_{mn}	Energy consumption of sector mth of fuel nth	Gg
NCV_n	Net caloric value of fuel nth	TJ/Gg
CF_n	Carbon content of fuel nth	Kg/GJ
COF_n	Carbon oxidation factor of fuel nth	1
C_{emf}	CO_2 emission factors for combustion	$(Kg/TJ)^2$
44/12	Molecular weights ratio of CO_2 to C	-

overall activity level (total production value) are the three factors that depict and explain the change in aggregate energy consumption. Activity effects indicate changes due to the scale of economic activities; structural effects show changes as a result of the contribution of each economic sector; and the intensity effect reveals changes due to the level of energy intensity . The absolute (associated additive decomposition) change and ratio (associated multiplicative decomposition) change in the aggregate energy consumption between periods 0 and T can be decomposed as:

$$E^T - E^0 = \Delta E_{int} + \Delta E_{str} + \Delta E_{act} \quad (5)$$

$$\frac{E^T}{E^0} = D_{int} D_{str} D_{act} \quad (6)$$

The subscripts int, str and act represent intensity effect, structural effect, and activity effect. Equations (5) and (6) are additive and multiplicative forms of Logarithmic Mean Divisia Index respectively. Note that the energy intensity indicator can also be decomposed in the same way the quantity indicator above has been decomposed. The intensity indicator is the ratio of energy used to production output, Q hence from the equation (4) above, the decomposition of intensity indicator gives two effects – . Ij is energy intensity of sector j and Sj is activity share of sector j, as shown below:

$$\text{Aggregate energy intensity, } I = \frac{E}{Q} = \sum_j I_j S_j \quad (7)$$

The breakdown of carbon emission is a continuation of the decomposition of energy consumption as carbon emission due to energy consumed are computed by multiplying energy consumption of fuels by various emission factors via the help of IPCC's Reference Approach above, equations (1-3). The factors in this case include effects due to sectoral fuel share, fuel emission factors, product mix and sectoral energy intensity (Beng Wah Ang & Zhang, 2000). Thus, a change in industrial carbon emission may be analyzed from the contribution of the following five factors: activity effect (overall industrial activity), structural effect (industrial activity mix), intensity effect (sectoral energy intensity), energy-mix effect (sectoral energy mix) and emission factor effect (carbon emission factor). Fuel type and industrial sectors are the sub-categories of the aggregates. The IDA identity for carbon emission may be written as:

$$C = \sum_{ij} C_{ij} = \sum_{ij} \frac{C_{ij}}{E_{ij}}\frac{E_{ij}}{E_j}\frac{E_j}{Q_j}\frac{Q_j}{Q} Q = \sum_j U_{ij} M_{ij} I_j S_j Q \quad (8)$$

C represents total carbon emission, C_{ij} represents carbon emission due to fuel i in industrial sector j, E_{ij} represents the consumption of fuel i in industrial sector j, $E_j = \sum_i E_{ij}$, $M_{ij} = \frac{E_{ij}}{E_j}$ represents the fuel-mix variable and $U_{ij} = \frac{C_{ij}}{E_{ij}}$ represents the carbon emission factor. Absolute (additive), equation (9) and ratio (multiplicative), equation (10) differences in carbon emission can be represented by

$$\Delta C_{tot} = C^T - C^0 = \Delta C_{emf} + \Delta C_{mix} + \Delta C_{int} + \Delta C_{str} + \Delta C_{act} \quad (9)$$

$$D_{tot} = \frac{C^T}{C^0} = D_{emf} D_{mix} D_{int} D_{str} D_{act} \quad (10)$$

Subscript act represents the overall activity effect, str represents the activity structural effect, int represents the sectoral energy intensity effect, mix represents the sectoral energy mix effect and emf represents the carbon emission factor.

4. Data Collection

Apart from the numerical values of energy intensity of China which is computed from the gross domestic product (GDP) and primary energy data extracted from the World Bank data (World bank, 2021) and BP's Statistical Review of World Energy (bp, 2021), all annual data covering a period of 5years from 2016-2020 were collected from the China Statistical Yearbook (CSY) [9]. Data for 2020 was not available at the time of this research, hence table 4 and figures (9-12) used data from 2015-2019.

5. Results and Discussion

5.1 Energy-emission-related IDA studies for the period 2016-2020

In this survey, a total of three hundred and fifty-one (351) energy-emission-related IDA studies for the period 2016-2020 were reviewed and classified systematically.

5.2 Main Features of the Studies

In this section, the major features of energy-emission-related IDA studies for the period 2016 - 2020 are discussed and shown in figures (1-6).

5.2.1. Area of Application

Energy and emission are the two major application areas of IDA. Figure 1 shows an increase in energy and emission-related IDA studies for the study period, except in 2017 and 2020. The decline in 2020 could be due to the global challenge of the COVID-19 pandemic. This result agrees with findings in energy and emission-related IDA studies from 2000s to before the study period, which showed that in each year, there were more emission studies than energy studies. A possible explanation for this could be due to increased attention on carbon emission reduction, specifically to ensure commitment to the delivery of the 2015 Paris Agreement on climate change, which originally stems from global concerns over sustainable growth and development as population and industrial activities increase.

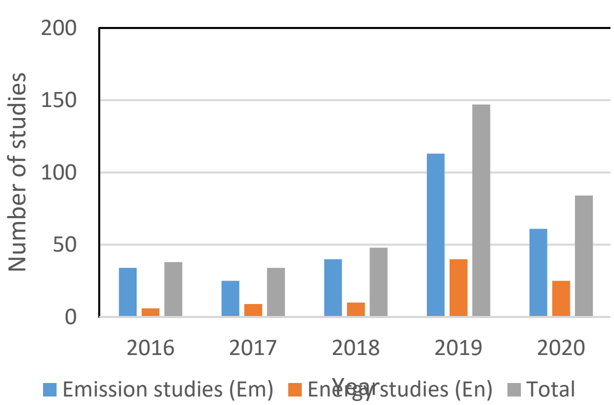


Figure 1. Classification by area of application

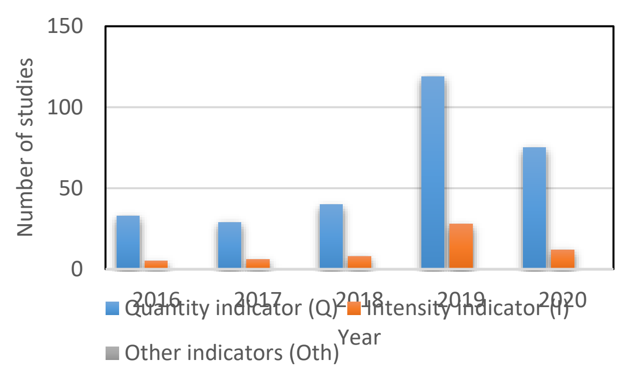


Figure 2. Classification of studies by types of indicator

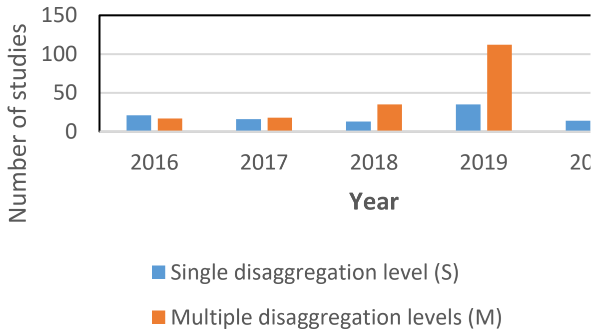


Figure 3. Classification by disaggregation level

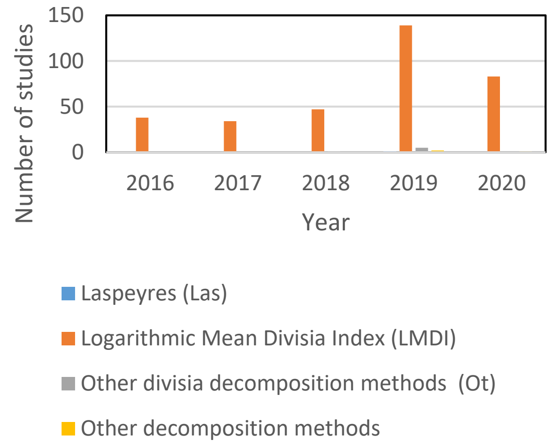


Figure 5. Classification by decomposition method

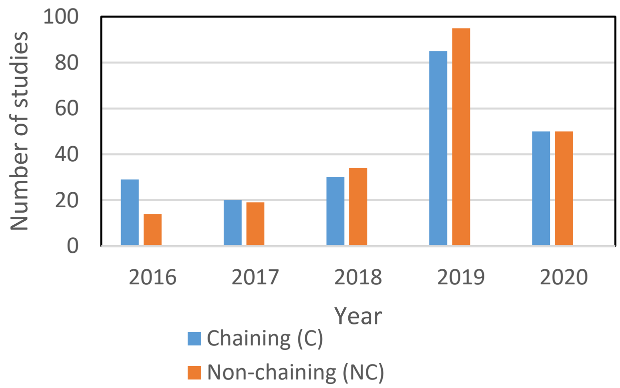


Figure 4. Classification of studies by time treatment

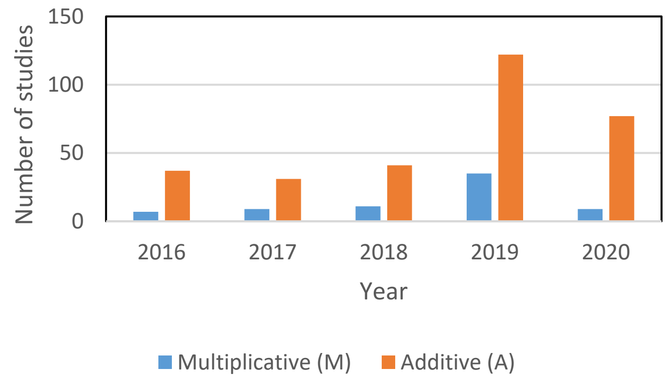


Figure 6. Classification of studies by decomposition approach

Figures (1-6). Features of energy-emission-related the 351 IDA studies for the period 2016-2020: (1) Classification of studies by area of application; (2) Classification of studies by types of indicators; (3) Classification of studies by disaggregation level; (4) Classification of studies by time treatment; (5) Classification of studies by decomposition method; and (6) Classification of studies by decomposition approach. Source: Authors' computation

5.2.2 Types of Indicators

Figure 2 is a classification of studies by types of indicator. For this study, types of indicators have been classified into the following two categories: quantity indicator and ratio indicator. Figure 2 further shows that most of the studies applied quantity indicator and the rate of application varies directly with the number of studies per year. This could be because of the ease of application and interpretation for quantity indicator, as opposed to intensity (ratio) indicator.

5.2.3. Level of Disaggregation

Figure 3 is a classification of studies by disaggregation level. The degree to which the entire economy/industry is broken down in terms of sector/sub-sector is referred to as the disaggregation level. Usually, the higher the level of disaggregation, the better the results from the survey, and the better the evaluations of the factors of the IDA. However, prominent levels of disaggregation are difficult to apply because of the nature of data required. In this study, the disaggregation level is divided into two (2) categories – single disaggregation and multiple disaggregation. Figure 3 shows a decrease in the application of the single disaggregation level and an increase in the multiple disaggregation level from 2016 to 2018. In 2019, both disaggregation levels increased but the multiple disaggregation level increased more rapidly within the same study period. Finally, in 2020, studies applying both types of disaggregation levels decreased, but the single disaggregation level decreased more. Overall, the multiple disaggregation level has been applied more in studies in the period.

5.2.4. Time Treatment

Figure 4 is the classification of the studies by time treatment. The two methods of time treatment in IDA studies are the chaining and non-chaining approaches. The non-chaining approach is used when a study has only two years data. This approach only considers what happens in the two years without considering what happens in any year(s) in between. On the other hand, the chaining approach considers data for more than two years. It considers what happens in the first year, last year and the year(s) in between. This means that the non-chaining approach results can be extracted from the chaining approach results, but not vice versa. Figure 4 shows a number of studies by time treatment. There has been a substantial application of both the chain and non-chain approaches in the studies. There is a slight difference in the level of application of both approaches, particularly from 2017-2020, except for 2019. Specifically, in 2017, the chaining approach was applied more than the non-chaining approach; while in 2018, the non-chaining approach was applied more than the chaining approach. In 2019, non-chaining was somewhat more applied compared to 2018. Finally, in 2020, the two methods were equally applied. This alternating and seemingly equal level of applications of both approaches suggest the same degree of data requirement, suitability, relevance, and exposition. Hence, no approach clearly dominates the other in the study period.

5.2.5. Methods of Decomposition

Figure 5 shows the classification of the studies by decomposition method. There are many decomposition methods such as: Divisia-based IDA, Laspeyres-based IDA, and other IDA methods. For this study, we considered the following decomposition methods: Laspeyres (Las), Logarithmic Mean Divisia Index (LMDI), Other divisia decomposition methods (Ot) and other decomposition methods only. From Figure 5, one can see that there has been a significant increase in the application of LMDI compared to the application of Laspeyres, Other divisia decomposition methods and other decomposition methods. This can be due to the ease of application of LMDI and its robustness. This aligns with the findings of other similar studies covering the periods prior to 2016.

5.2.6. Decomposition Approach

Figure 6 shows the classification of studies by decomposition approach. In decomposition analysis, there are two types of decomposition approaches, namely the additive and multiplication approaches. Figure 6 shows that there has been a greater application of the additive decomposition approach than the multiplicative decomposition approach in each year and increasingly so, except in 2017 and 2020, which experienced some form of decrease in the number of studies that employed the additive approach compared to the previous years. The behaviour of this feature of the IDA studies for the period 2016-2020 is to a significant extent consistent with that of pre-2016 IDA studies.

5.2.7. Classification of IDA studies by region/country

Table 2 shows the classification of energy-emission-related IDA studies by country/region for the period 2016-2020. The table shows that China is the country with the highest number of energy-emission-related IDA studies, comprising 66% (232 studies) of the entire 351 studies. This was followed by the USA and Pakistan, 13% of the studies were conducted across countries and/or at a global level; while 87% were studies conducted on a single country, province, city, or region. six (6) studies were conducted on South Africa; three (3) studies were conducted on Cameroon; and one (1) study each on Ethiopia and Madagascar, making it a total of eleven (11) studies conducted on African countries. This shows that China is dominating in energy-emission-related IDA studies.

Table 2. Classification of energy-emission-related IDA studies by country/region for the period 2016-2020
Source: Authors' computation

Country/Region	Number of Studies	Share of Studies
China	232	66%
International and/or Global	46	13%
Bangladesh, Czech Republic, Ethiopia, Finland, Germany, Greece, Poland, Hungary, Kazakhstan, Madagascar, Malaysia, Philippines, Taiwan, Thai, Australia	1 study per country = 15	4%
Korea, South Africa	6 studies per country = 12	3%
Turkey, Portugal, Japan, Italy, Iran, Columbia	2 studies per country = 12	3%

Spain, Indonesia	5 studies per country = 10	3%
Canada, India, Cameroon	3 studies per country = 9	3%
USA	8	2%
Pakistan	7	2%
Total	**351**	**100%**

5.3 Energy Intensity vs Energy-emission-related IDA Studies: A Case Study of China

In this section, we explore the energy intensity improvement in China over the study period to determine if it corresponds with the level of energy-emission-related IDA studies conducted on China.

5.3.1. Energy Intensity Calculation

Energy intensity can be understood as the energy required to produce 1unit of economic output. It is often calculated by taking the ratio of energy consumption to gross domestic product (GDP) (or production output). High-energy intensity indicates high energy consumption to produce a unit of economic output and vice versa. Thus, the lower the energy intensity implies higher energy efficiency, and by extension better energy systems and economy.

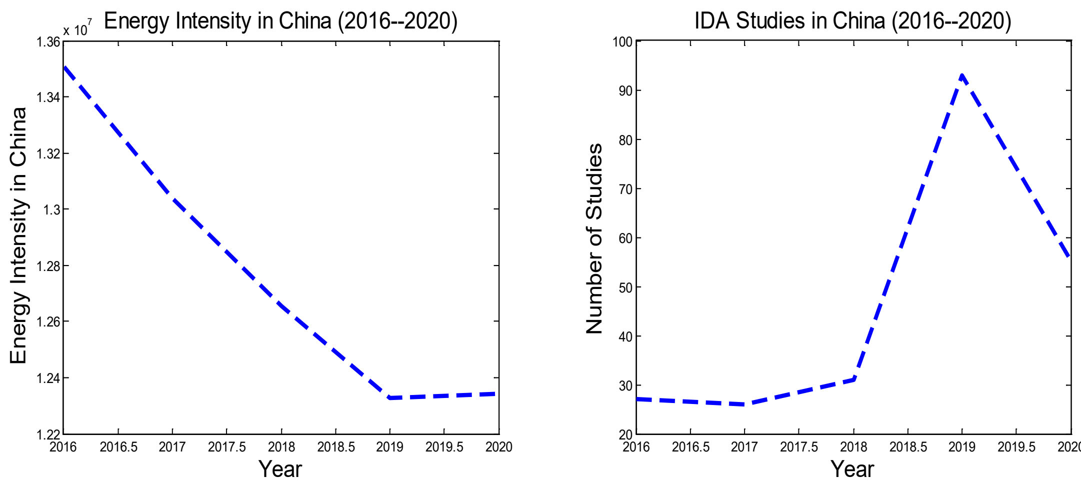


Figure 7. Energy Intensity vs Energy-emission-related IDA Studies on China,2016-2020
Source: Authors' computation

5.3.2. Energy Intensity vs Energy-emission-related IDA Studies on China

China has recorded the highest level of energy-emission-related IDA studies globally being about 66% of the entire studies for the period 2016-2020. A positive correlation between energy intensity and energy-emission-related IDA studies on China suggests effective implementation of research findings of energy-emission-related IDA studies by policymakers. Consequently, we present a numerical comparison of energy intensity and energy-emission-related IDA studies on China for the period 2016-2020. Figure 7 is a numerical representation of China's energy intensity and energy-emission-related IDA studies on China for 2016-2020. The figure shows that energy intensity is decreasing continuously over the period 2016 to 2019 while it experienced a slight rise towards 2020. This indicates better energy performance for China most part of the period. The number of IDA studies in China increased until 2019, afterwards a sharp decrease to the end of the study period. This shows a positive correlation between the theoretical energy-related IDA studies on China and the country's energy intensity. This decrease in energy intensity of China within the study period validates the massive investment of resources in energy-emission-related IDA studies on China. From the above findings, a possible recommendation for China would be to at least maintain its investment in IDA energy-emission-related studies and other related studies as well as use findings and recommendations of the studies as these have capacity to ensure that the energy and emission targets of the country are achieved.

5.3.3 Decomposition of China's Industrial Energy Consumption, 2016-2020

Table 3 below shows the determinant of change in China's industrial energy consumption, their contributions, and the value of the change in China's total industrial energy consumption in the study period, calculated using additive LMDI. In this study, China's Industrial Energy is measured in Million Tons of Standard Coal Equivalent (MTSCE). As shown, there is decrease of 6.9156MTSCE in China's total industrial energy consumption in the study period which is caused majorly by intensity effect (-865.971MTSCE) followed by structural effect (-415.619MTSCE).

Table 3: Summary of the factors responsible for change in China's industrial energy consumption (2016-2020) based on additive LMDI calculation.
Source: Authors' computation

Determinants of change in China's industrial energy consumption and total change in China's industrial energy consumption	Eint	Estr	Eact	Etot
Contribution to change in China's industrial energy consumption and total change in China's industrial energy consumption (MTSCE)	-865.971	-415.619	1274.7	-6.9156

Also, Table 4 below shows the computation of annual change in China's industrial energy consumption and the contribution of its determinants, using multiplicative LMDI.

Table 4. Summary of the factors responsible for change in China's industrial energy consumption (2016-2020) based on multiplicative LMDI calculation.
Source: Authors' computation

Year	**Dint**	**Dstr**	**Dact**	**Dtot**
2014-2015	0.9612	0.9581	1.0474	0.9646
2015-2016	0.9564	0.9754	1.0555	0.9846
2016-2017	0.9484	1.0038	1.0745	1.0229
2017-2018	0.9680	0.9936	1.0678	1.0270
2018-2019	0.9754	0.9769	1.0477	0.9983
2014-2019	0.8209	0.9105	1.3350	0.9979

As shown in Table 5, in years 2014-2015, 2015-2016 and 2018-2019, there were decreases in China's annual total industrial energy consumption, Dtot and they were caused by decreases in intensity effect, Dint supported by decrease in structural effect, Dstr. While in years 2016-2017 and 2017-2018, there were increases in China's annual total industrial energy consumption, Dtot and they were caused by increase in activity effect for both years, supported by increase and decrease in structural effect for years 2016-2017 and 2017-2018 respectively. Overall, there were a decrease in China's total industrial energy consumption over 2014-2019 without considering the years in between, and this was caused by decrease in intensity effect, Dint supported by decrease in structural effect, Dstr. There was consistency in the results from the computation of change in China's total industrial energy consumption and their corresponding effects (intensity, structural and activity) for both additive and multiplicative forms of LMDI calculations. The results indicated a decrease in China's total industrial energy consumption which was cause by decrease in intensity effect and supported by decrease in structural effect. These results suggest that China's investment in IDA energy-emission-related studies was profitable and that recommendations by researchers for improved policies on energy efficiency and energy mix were implemented.

5.3.4 Decomposition of China's Industrial Emission, 2016-2020

Additive LMDI technique was applied to compute emission change in China's industrial sector and its contributing factors. Change in emission in China's industrial sector was decomposed into five factors - activity effect (C_{act}), structural effect (C_{str}), intensity effect (C_{int}), energy-mix effect (C_{mix}) and carbon emission factor (C_{emf}). Unfortunately, we do not have data for emission for China industrial sector; hence China's industrial emissions were calculated with the help of the International Panel on Climate Change (IPCC) guidelines for National Green House Gas Inventories(Eggleston, Buendia, Miwa, Ngara, & Tanabe, 2006). The results are shown in Figure 8 below. First, the carbon emission effect(15.175MTCO_2) was the factor that was most responsible for increase in China's industrial emissions and, this was closely followed by the overall industrial activity effect(14.7613MTCO_2). The other three effects were negative, which means that together, they were responsible for reduction in China's industrial emission with intensity factor(-9.7347MTCO_2) having the largest reducing effect. Structural effect (-4.5701MTCO_2) contributed about half the reducing effect whilst energy-mix effect (-1.3345MTCO_2) contributed the least reducing effect.

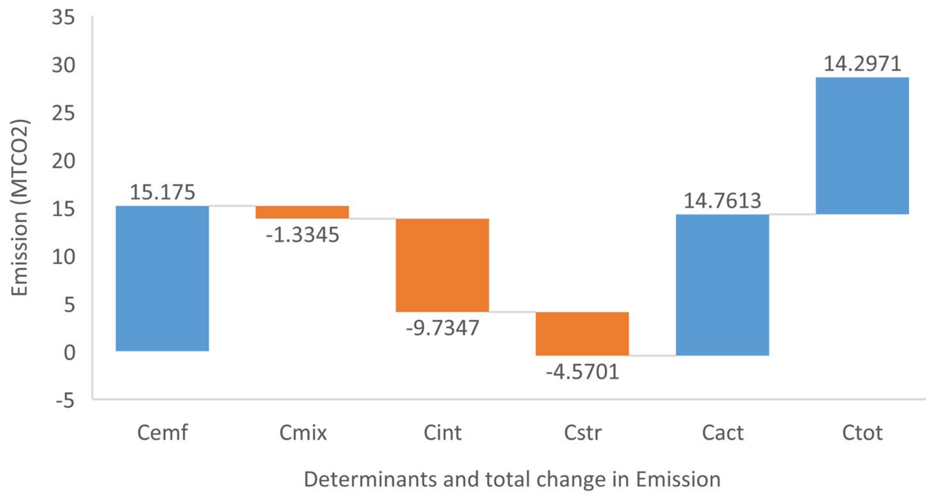
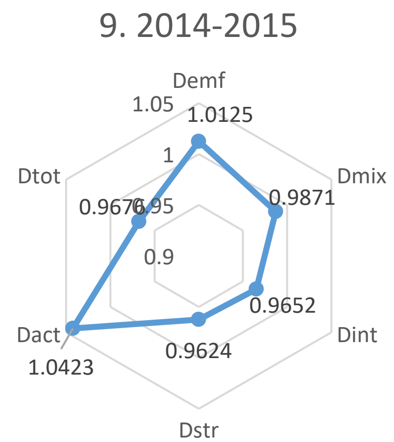
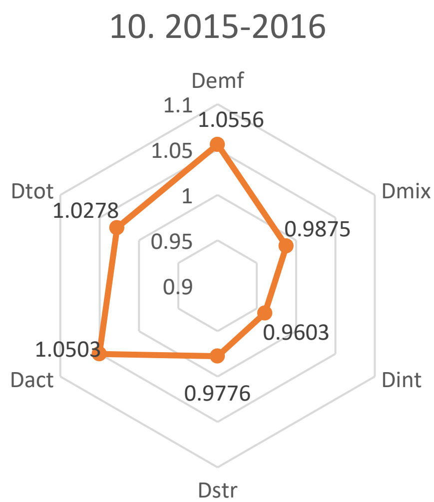
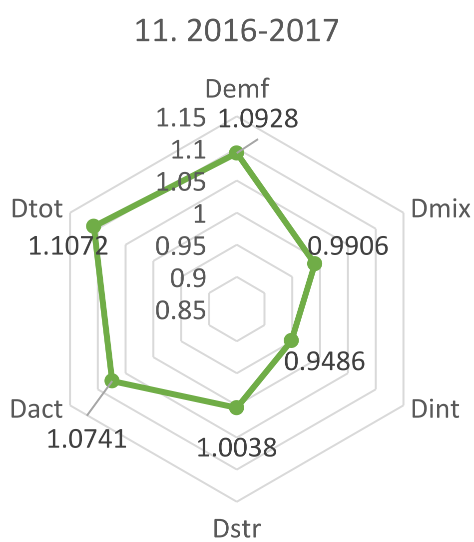


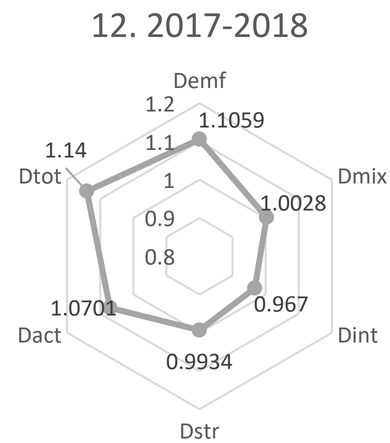
Figure 8. Summary of the factors responsible for change in China's industrial emissions (2016-2020) based on additive LMDI calculation.
Source: Authors' computation

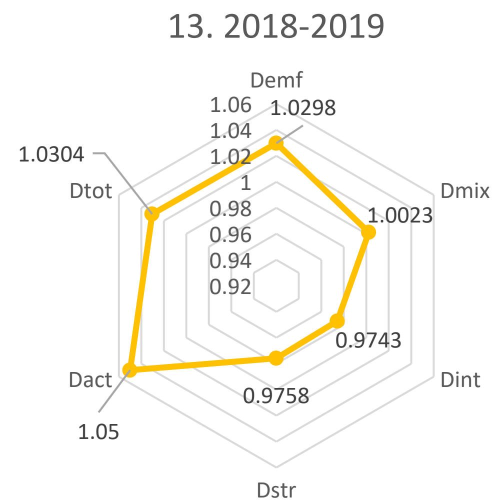
Using multiplicative LMDI technique, expressed in the equation (10) above, change in China's industrial emissions is decomposed into five factors - Dact(overall activity effect), Dstr(structural effect), Dint(sectoral energy intensity effect), Dmix(sectoral energy mix effect) and Demf(emission factor) and the results are shown in Figures (9-14) below. Figures (9-13) are the results of the examination of annual change in China's industrial emission from 2015-2019, while Figure 14 is the result of the examination of change in China's industrial emission from 2015 to 2019 without considering the years in between. From the figure, the emission factor made the highest contribution to change in China's industrial emission in 2015-2016(1.0556), 2016-2017(1.0928), 2014-2019(1.341) and 2017-2018(1.1059), while the overall activity effect made the largest contribution in 2014-2015 (1.0423) & 2018-2019(1.05). Whereas the variable that made the least contribution to change in China's industrial emissions were Dstr in 2014-2015(0.9624) and Dint in 2015-2016(0.9603), 2016-2017(0.9486), 2017-2018(0.967), 2018-2019(0.9743) and 2014-2019(0.8213).

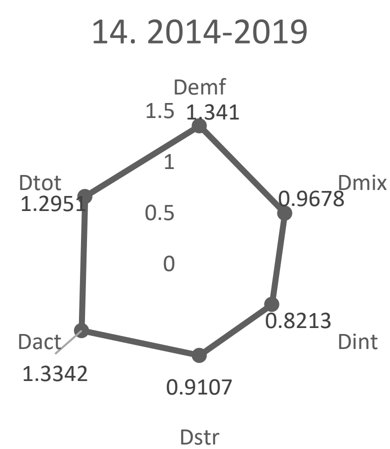












Figures (9-12).: Summary of the factors responsible for change in China industrial emission (2016-2020) based on multiplication LMDI calculation.
Source: Authors' computation

The results from the additive and multiplicative LMDI's computation of factors responsible for change in China's industrial emission show that China needs to make further investment in environmentally friendly initiatives, make policies that support the use of non-fossil fuel, payment of carbon tax and invest more in IDA emissions studies on China, its sectors and regions while effectively implementing the recommendations from .

6. Conclusions

In this study, over three hundred and fifty (350) energy-emission-related IDA studies for the period 2016-2020 were reviewed and classified. More than a decade before the study period, focus was increasingly on emission studies and pollutants, particularly with the aid of LMDI. About 75% of the studies were on emission and the focus on emission increased rapidly, perhaps due to the increased global attention on CO_2 emission reduction and efforts to achieve Paris Agreement targets by 2030. As a result, there is increased attention specifically on prospective studies of emissions, energy efficiency, de-coupling of economic growth from emissions and the decomposition of de-coupling efforts using the LMDI-based hybrid method to ensure more exposition of the future.

China is the most studied country with respect to energy-emission-related IDA studies. Reviewed studies could not tell whether China will achieve emissions targets on or before 2030. The good news, however, is that at various levels, sectors, regions, provinces, and cities, the most-intense energy-emission-related IDA research ever are ongoing in China, the world's highest CO_2 emitter. As a result, the impact of the energy-emission-related IDA studies on energy intensity of China was examined. The results showed that energy-emission-related IDA studies of China have a positive correlation with energy intensity of China over the study period. This suggested that policymakers in China are taking into consideration the findings from the researchers for better policy analyses and development. The additive and multiplicative LMDI calculations of change in China's industrial energy and its determinants show that there is decrease in industrial energy consumption in China over the study period caused by intensity effect and structural effect which proposes that investment on energy-emission-related IDA studies in China are yielding dividends. It also proposes that China is engaging energy-efficient technologies and policies. LMDI computations for both additive and multiplication forms revealed that carbon emission factor, followed by overall industrial activity are the key factors responsible for increase in emission. Specifically, for additive form of LMDI, carbon emission effect and industrial activity effect; while for multiplicative form of LMDI, carbon emission factor in [2015-2016, 2016-2017, 2014-2019 and 2017-2018], as well as overall activity effect in [2014-2015 & 2018-2019] are the highest contributors to increase in emission. The above reducing and increasing agents of China's industrial emission were partly consistent with the findings of Shi, Han, Zafar, and Wei (2019) and Xie, Shao, and Lin (2016). Although, there were indications that policy recommendations from energy-emissions-related IDA researchers were implemented, China's industrial emissions increased as energy-emissions-related IDA studies increased over the studies period. Hence, China needs to make further investment on IDA emission studies with the view to seek options to mitigate emissions, achieve peak carbon emission before 2030, as planned.

References

Ang, B. W., Decomposition methodology in industrial energy demand analysis. *Energy*, 20 (11): 1081-1095,1995.

Ang, B. W. and Zhang, F. Q. , A survey of index decomposition analysis in energy and environmental studies. *Energy*, 25 (12): 1149-1176,2000..

Eggleston, S., Buendia, L., Miwa, K., Ngara, T. and Tanabe, K. 2006. IPCC guidelines for national greenhouse gas inventories.

Huntington, H. and Myers, J. 1987. *Sectoral Shift and industrial energy demand: what have we learned. The changing structure of American industry and energy use patterns. A. Farunqui, J. Broehl und CW Gellings. Colombus, OH*: Battelle Press.

Mu, A. , Index Decomposition Analysis: Some Methodological Issues,2012.

Shi, Y., Han, B., Zafar, M. W. and Wei, Z. 2019. Uncovering the driving forces of carbon dioxide emissions in Chinese manufacturing industry: An intersectoral analysis. *Environmental Science and Pollution Research*, 26 (30): 31434-31448,2019.

Wang, H., Ang, B. W. and Su, B. 2017. Assessing drivers of economy-wide energy use and emission: IDA versus SDA. *Energy Policy* 05 (034): 586 -599.

Xie, X., Shao, S. and Lin, B. 2016. Exploring the driving forces and mitigation pathways of CO2 emissions in China's petroleum refining and coking industry: 1995–2031. *Applied energy*, 184: 1004-1015.

Bekun, F. V., Emir, F., & Sarkodie, S. A. (2019). Another look at the relationship between energy consumption, carbon dioxide emissions, and economic growth in South Africa. *Science of the Total Environment, 655*, 759-765.

Eggleston, S., Buendia, L., Miwa, K., Ngara, T., & Tanabe, K., IPCC guidelines for national greenhouse gas inventories, 2006.
Inglesi-Lotz, R., & Pouris, A., Energy efficiency in South Africa: A decomposition exercise. *Energy, 42*(1), 113-120,2012.
Oladiran, M. T., & Meyer, J. P., Energy and Exergy analyses consumptionin the Industrial sector in South Africa. *Applied energy, 84*, 1057-1067,2007.
Owusu, P. A., & Asumadu-Sarkodie, S. (2016). A review of renewable energy sources, sustainability issues and climate change mitigation. *Cogent Engineering, 3*(1), 1167990, 2016.
Pollet;, B. G., Staffell;, I., & Adamson;, K. A. , Current energy landscape in the Republic of South Africa. *International Journal of Hydrogen Energy 40*, 16685-16701,2015.
Shi, Y., Han, B., Zafar, M. W., & Wei, Z. (2019). Uncovering the driving forces of carbon dioxide emissions in Chinese manufacturing industry: An intersectoral analysis. *Environmental Science and Pollution Research, 26*(30), 31434-31448, 2019. doi:10.1007/s11356-019-06303-7
Xie, X., Shao, S., & Lin, B. (2016). Exploring the driving forces and mitigation pathways of CO2 emissions in China's petroleum refining and coking industry: 1995–2031. *Applied energy, 184*, 1004-1015, 2016. doi:10.1016/j.apenergy.2016.06.008

Biographies

Jude James is a D. Eng. student in the Department of Industrial Engineering, Durban University of Technology, South Africa. His research interest includes energy management and carbon emissions mitigation.

Oludolapo Akanni Olanrewaju is currently a Senior Lecturer and Head of Department of Industrial Engineering, Durban University of Technology, South Africa. He earned his BSc in Electrical Electronics Engineering and MSc in Industrial Engineering from the University of Ibadan, Nigeria and his Doctorate in Industrial Engineering from the Tshwane University of Technology, South Africa. He has published journal and conference papers. His research interests are not limited to energy/greenhouse gas analysis/management, life cycle assessment, application of artificial intelligence techniques and 3D Modelling. He is an associate member of the Southern African Institute of Industrial Engineering (SAIIE) and NRF rated researcher in South Africa.

Prof. Kevin Duffy has a PhD from the University of Virginia in the United States. He was recently awarded a South African National Research Foundation Chair in ‘Applying Mathematics to Human and Natural Systems’. Along with his research group at the Durban University of Technology he attempts to connect mathematics to answering real world questions in science, engineering, and development.

O.C. Collins hold a PhD in applied mathematics from the University of Kwazulu -Natal, South Africa. His research interests include application of Mathematical tools for solving real world problems.