Application of an Integrated Model to Manufacturing Sector's Carbon Emission

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Abstract

Based on a three-term plan, this study applied an integrated model (IPCC-RA-LMDI-TD) to analyse China's Carbon Emission from the manufacturing industries (CCEMI) for 2001-2020. Results revealed that for the long-term plan of CCEMI and decoupling analyses, the activity effect was the main enhancing factor while the intensity effect was the main limiting factor. For medium and short-term plans of CCEMI and decoupling analyses, the main enhancing factors are the activity effect followed by the carbon emission factor while the main inhibiting factors were structure effect, after intensity effect. In general, the sector's resultant decoupling status is mainly Expansive negative decoupling (2.22 in 2011-2015 and 1.27 in 2016-2020) followed by Expansive coupling (0.81 in 2001-2010). Nevertheless, the status is Expansive negative decoupling in the second half of the study period suggesting deterioration of the decoupling index of the sector over the study period. To actualize sustainable development, there is a need for environmentally friendly strategies such clean energy and technology deployment.

Keywords
Emissions, Intergovernmental Panel on Climate Change, Logarithmic Mean Divisia Index, Decoupling Analysis, China.

Introduction
Green House Gases (GHGs) have posed major threat to human existence, sustainable growth and development; hence, there is need to reduce GHGs (Olanrewaju and Mbohwa 2017). Countries from both Organization for Economic Cooperation and Development (OECD) & Brazil, Russia, India, China and South Africa (BRICS) emit about 80% of the world's GHGs(Olanrewaju and Mbohwa 2017). As one of the most industrialized countries in the world, energy is core to the manufacturing process in China; as energy is a key player in industrialization(Olanrewaju 2018b) which will result in high production of GHGs; particularly for the case of China due to population and manufacturing activities (Olanrewaju 2019; Khobai and Le Roux 2017). China is one of the highest CO_2 emitters in the world, next to the United States of America (Khobai and Le Roux 2017; Scientists 2022) as shown in Figure 1. China's GHG emission will continue to increase and probably increase to four-fold by 2050 as the country's economy grows and population increases, except carbon emission factors greatly improves and appropriate strategies are carefully employed (Winkler et al. 2011). Hence, carbon emission is one of the country's major problems. This has resulted in the development of various studies, policies and targets (Olanrewaju 2018a).

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1.1 Objectives

- To apply an integrated model to explore the dynamics of CCEMI.
- To quantify the contribution of pre-determined factors to change in CCEMI.
- To analyse the decoupling status of CCEMI from economic output

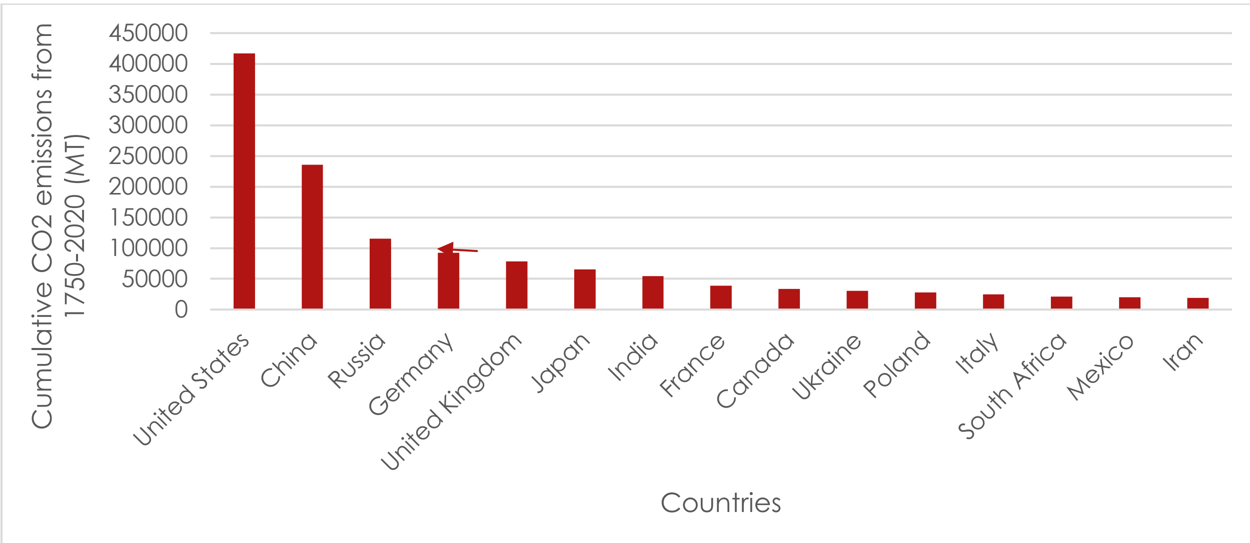

Figure 1. Cumulative CO_2 emissions from fossil fuels and cement only, for 1750-2020. MT = Metric megatons (Scientists 2022)

2. Literature Review

Manufacturing sector is a big player in GHGs emission. Hence, it has been the key focus for most countries attempting to reduce emission (Olanrewaju and Mbohwa 2017), especially in OECD and BRICS countries. Clearly, examination of manufacturing sector emissions is a good place to begin solving the problem of GHGs emission. This will expose abatement strategies as well as enable officials to set realistic emission targets. By extension, this will ensure right policies and practices for optimal production & minimal GHG emission(Olanrewaju and Mbohwa 2017). IDA has been applied greatly in energy and emissions studies, some of such studies in recent years are presented below. LMDI was used to investigate reasons for decoupling between economic growth and energy-related CO_2 emissions in BRICS countries by Dai et al. (2016). Under three scenarios, Liu et al. (2019) applied LMDI to carbon emission in a long-term examination of industrial systems in China to evaluate low carbon potentials; promote policies for regional substantial development and construction of eco-industry. (Wang et al. 2016) engaged LMDI method to examine changes in energy-related carbon emission at three different energy-consumption sectors and scenarios. A 2-level LMDI method framework was developed by Zhang and Mi (2016) to analyze the driving factors of CO_2 emission. Madaleno and Moutinho (2017) engaged a new LMDI decomposition approach to uncover emissions development in the EU. Using LMDI, decomposition and scenario analysis of CO_2 emissions in China's power industry were studied by Zhao et al. (2017).

3. Methods

CCEMI is examined by a unified-integrated model (Figure 2) - combining the strengths of individual models while making-up for the set-back(s) of each single model.

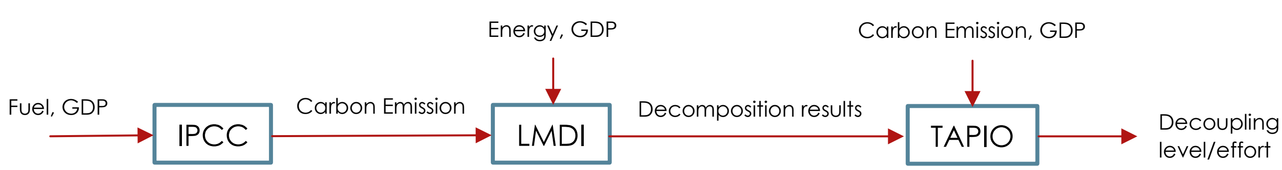

Figure 2. Conceptual framework

Intergovernmental Panel on Climate Change's (IPCC-RA) Reference Approach was engaged to compute energy emissions from primary energy consumed. LMDI analyses & disintegrate historical data of carbon emission into driving factors, Tapio decoupling (TD) index reveals the de-linking relationship between CCEMI and economic growth.

3. 1 IPCC's Reference Approach

According to the Intergovernmental Panel on Climate Change's (IPCC) methodology (IPCC 2006), Carbon Emission from the manufacturing industries (CCEMI) can be quantified by the help of Reference Approach below:

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

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

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

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

Table 1. Description of variables & their units in equations (1-3)

Variables	Description	Units
TCE	Total CO_2 emission of industrial sector	$MTCO_2$
CE_{mn}	CO_2 emission of sector mth of fuel nth	$MTCO_2$
M	Sector mth of industrial sector	--
N	Fuel nth of the energy consumed	--
EC_{mn}	Energy consumption in sector mth of fuel nth	MT of SCE
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	-

3.2 Logarithmic mean divisia index (LMDI)

From the traditional Kaya identity, I = PAT
Impact = Technology (Intensity) x Affluence (structure) x Population
Thus, total CCEMI, C_{T_n} is expressed thus:

$$C_{T_n} = \frac{CO_2}{GDP} \text{ x } \frac{GDP}{Pop} \text{ x } pop$$

$$C_{T_n} = \frac{CO_2}{E} \text{ x } \frac{E}{GDP} \text{ x } \frac{GDP}{Pop} \text{ x } pop$$

$$C_{T_n} = \sum_{ij} C_{ij} = \sum_{ij} \frac{C_{ij}}{E_{ij}} \frac{E_{ij}}{E_j} \frac{E_j}{Q_j} \frac{Q_j}{Q} Q = \sum_j U_{ij} M_{ij} I_j S_j Q \quad (4)$$

C_{T_n} represents total CO_2 emission of manufacturing sector, C_{ij} represents the CO_2 emission of jth manufacturing industrial sector of ith fuel , 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, I_j is energy intensity of sector j and S_j is the activity share of sector j and Q (GDP) is overall industrial activity. Absolute and ratio differences in carbon emission can be represented by

$$\Delta C_{tot} = C^T - C^O = \Delta C_{emf} + \Delta C_{mix} + \Delta C_{int} + \Delta C_{str} + \Delta C_{act} \tag{5}$$

$$D_{tot} = \frac{C^T}{C^0} = D_{emf}D_{mix}D_{int}D_{str}D_{act} \tag{6}$$

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 emission factor (Lin and Agyeman 2020; Zhang et al. 2020; Inglesi-Lotz 2017).

The respective effects of Additive decomposition are as follows:

$$\Delta C_{emf} = \Sigma_{ij} W.\log(U_i^T/U_i^0) \tag{7}$$

$$\Delta C_{mix} = \Sigma_{ij} W.\log(M_i^T/M_i^0) \tag{8}$$

$$\Delta C_{int} = \Sigma_{ij} W.\log(I_i^T/I_i^0) \tag{9}$$

$$\Delta C_{str} = \Sigma_{ij} W.\log(S_i^T/S_i^0) \tag{10}$$

$$\Delta C_{act} = \Sigma_{ij} W.\log(Q^T/Q^0) \tag{11}$$

$$W = \Sigma_{ij}[(C_{ij}^T - C_{ij}^0)/(\log(C_{ij}^T) - \log(C_{ij}^0))] \tag{12}$$

While the respective effects of Multiplication decomposition are as follows:

$$D_{emf} = \exp(\Sigma_{ij} W1.\log(U_i^T/U_i^0)) \tag{13}$$

$$D_{mix} = \exp(\Sigma_{ij} W1.\log(M_i^T/M_i^0)) \tag{14}$$

$$D_{int} = \exp(\Sigma_{ij} W1.\log(I_i^T/I_i^0)) \tag{15}$$

$$D_{str} = \exp(\Sigma_{ij} W1.\log(S_i^T/S_i^0)) \tag{16}$$

$$D_{act} = \exp(\Sigma_{ij} W1.\log(Q^T/Q^0)) \tag{17}$$

$$W_I=\exp((C_{ij}^T-C_{ij}^0)/(\log(C_{ij}^T)-\log(C_{ij}^0)))/((C^T-C^0)/(\log(C^T)-\log(C^0))) \tag{18}$$

3.2 Decoupling analyses

Tapio (2005) defined decoupling index as the ratio of share of change in emission to share of change in economic output expressed below.

$$D_{C,GDP} = \frac{\Delta C/C^0}{\Delta GDP/GDP} = \frac{\Delta C/C^0}{\Delta Q/Q} \tag{19}$$

$$\text{Decoupling elasticity}=\varepsilon = \frac{\Delta C_{emf}/C^0}{\Delta Q/Q^0} + \frac{\Delta C_{mix}/C^0}{\Delta Q/Q^0} + \frac{\Delta C_{int}/C^0}{\Delta Q/Q^0} + \frac{\Delta C_{str}/C^0}{\Delta Q/Q^0} + \frac{\Delta C_{act}/C^0}{\Delta Q/Q^0} \tag{20}$$

$$= \varepsilon_{emf} + \varepsilon_{mix} + \varepsilon_{int} + \varepsilon_{str} + \varepsilon_{act} \tag{21}$$

ε_{str} (energy structure effect), ε_{int} (energy intensity effect), ε_{act} (activity level effect), ε_{mix} (sectoral energy mix effect) & ε_{emf} (carbon emission factor effect) on ε (decoupling elasticity index)(Wang and Wang 2019; Wang et al. 2018; Wang and Li 2019; Wan et al. 2016).

4. Data Collection

Annual data covering a period of 20 years from 2001 to 2020 were applied in this study. With the exception of density, data for all variables were collected from China Statistical Yearbook (CSY) which is compiled and housed by the National Bureau of Statistics of China (National Bureau of Statistics of China 2012). Density of natural gas was gotten from Engineering Tool Box(Engineering ToolBox 2003). For 2002 and 2020, manufacturing industrial sector's energy consumption data were not available, hence they were computed by the help of trend function in Microsoft Excel.

5. Results and discussion

5.1 Change in historic data and their ratios

Figure 3 shows the behaviour of CCEMI (C_{ij}), China's manufacturing industrial sector's GDP (Q_{ij}), China's Manufacturing sector energy consumption (E_{ij}), and China's overall carbon emission (C), China's overall energy consumption (E) and GDP(Q). CCEMI and China's overall carbon emission rose, though not steadily from 5.08MT and 6.37MT in 2001 to 42.8MT and 64.95MT in 2020 with an increase of 743% and 920% respectively. Q_{ij} and Q increased, again not steadily from 4386Billion-Yuan and 11,086Billion-Yuan in 2001 to 32,730Billion-Yuan and 98,232Billion-Yuan in 2020 with an increase rate of 647% and 786% respectively. China's manufacturing industrial sector's energy consumption and overall energy consumption rose slightly, also not constantly from 0.923Billion Tons of SCE and 1.349Billion Tons of SCE in 2001 to 3.49Billion Tons of SCE and 5.217Billion Tons of SCE in 2020 with growth rate of 278% and 287% respectively. Also, from Figure 3., GDP, China's overall carbon emission and CCEMI experienced a downward trend from 98.652Billion-Yuan, 67.366 MT and 46.4MT in 2019 to 98.232Billion-Yuan, 64.951MT and 42.8MT in 2020 at a reducing rate of 0.4%, 3.5% and 7.76% respectively perhaps due to Covid-19 pandemic.

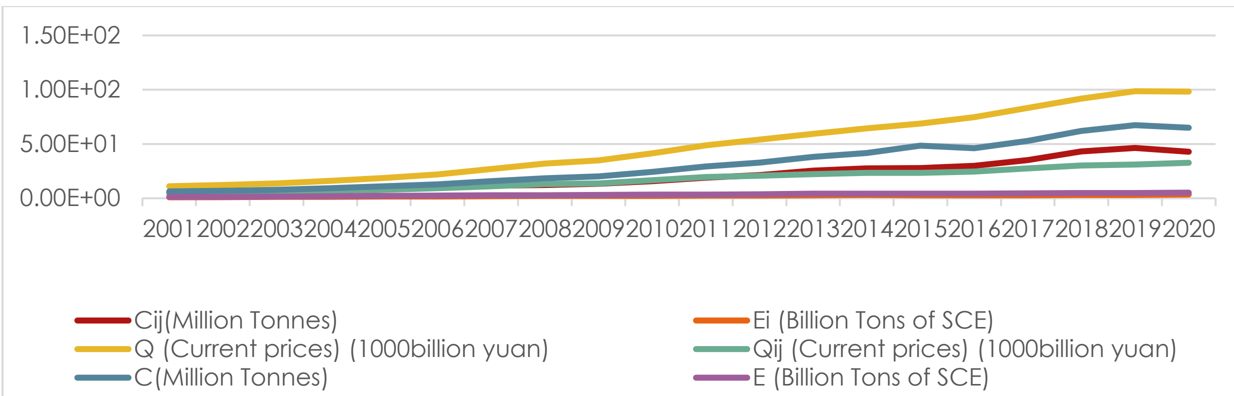

Figure 3. Change in historic data of China and their ratios, 2001-2020

Figure 4 shows the changes in activity share of the sector ($S_i=Q_i/Q$), energy intensity of the sector j ($I_j=E_i/Q_i$), fuel mix variable ($M=E_{ij}/E$) and carbon emission factor ($U=C_{ij}/E_{ij}$). Specifically, M and S_i experienced a downward trend, not at same rate though, from 0.697 and 0.398 in 2001 to 0.668 and 0.333 in 2020, respectively. U increased from 0.0055 in 2001 to 0.0123 in 2020, while I_i decreased from 0.021 in 2001 to 0.010 in 2020. On one hand, the increase in carbon emission factor implies increase in carbon emissions released per unit energy consumed in the sector which means there is need for non-fossil fuel consumption; on the other hand, the decrease in energy intensity, suggests that policies and technologies for improved energy efficiency are being developed and implemented in the study period. Also in the study period, activity share of the sector was minimal in 2019, perhaps, due to lock-down because of Covid-19 pandemic.

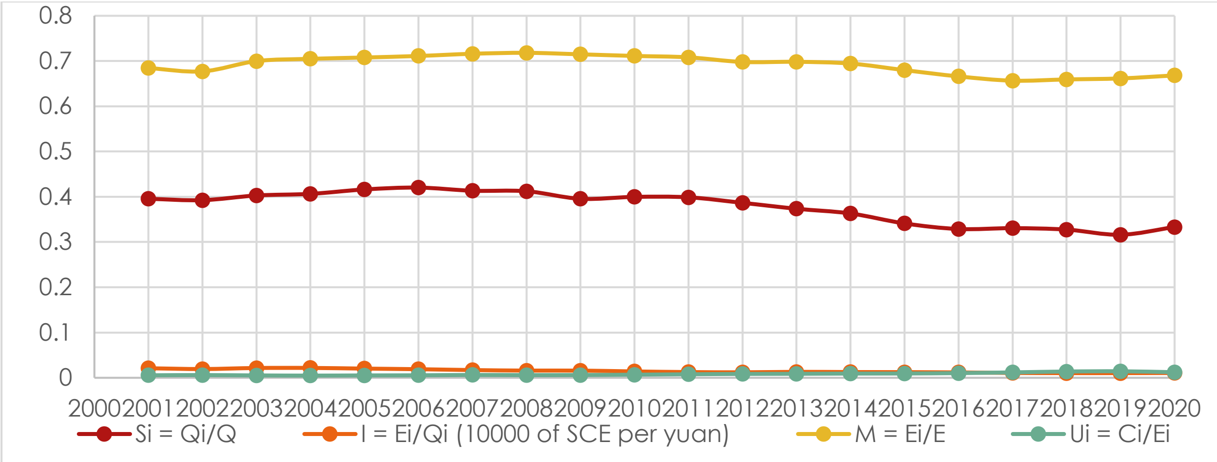

Figure 4. Ratios of historic data of CCEMI, 2001-2020

5.2 Decomposition of change in CCEMI (2001-2020) based on long-term plan.

From Figure 5, over the study period, the total change in CCEMI without considering the years in between, is 3.75Million Tonnes. The increase was caused mainly by activity effect, followed by energy structure effect and sectoral energy mix effect contributed the least to the increase. On the other hand, energy intensity effect limited the increase in CCEMI the most followed by carbon emission factor effect which contributed the least to the limitation. Generally, across the study period, from this long-term plan decomposition analysis, to reduce CCEMI, there is need for the use of non-fossil fuel, renewable energy, and development of policies that inhibit increase in GHGs emission.

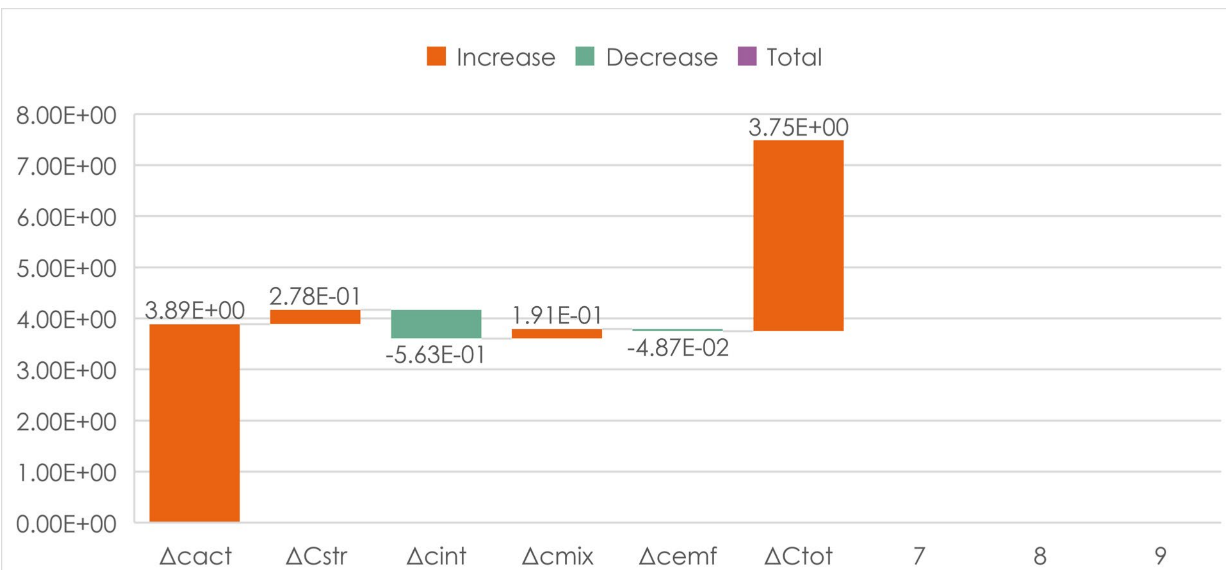

Figure 5. Contribution of driving factors to change in CCEMI (2001-2020) based on long-term plan using additive LMDI calculation.

5.3 Decomposition of change in CCEMI (2001-2020) based on medium-term plan.

Figure 6. shows that for each of the 4, 5-year periods (2001-2005, 2006-2010, 2011-2015, 2016-2020), carbon emission increased mainly due to activity effect followed by carbon emission factor effect in 2011-2015 and 2016-2020. Also, in 2011-2015 and 2016-2020, energy structure, energy intensity and sectoral energy mix had reducing effect on CCEMI. In 2006-2010, increase in CCEMI was due to activity effect, carbon emission factor effect and sectoral energy mix while structure effect and energy intensity had reducing influence. In 2001-2005, increase in CCEMI was caused by increase in activity.

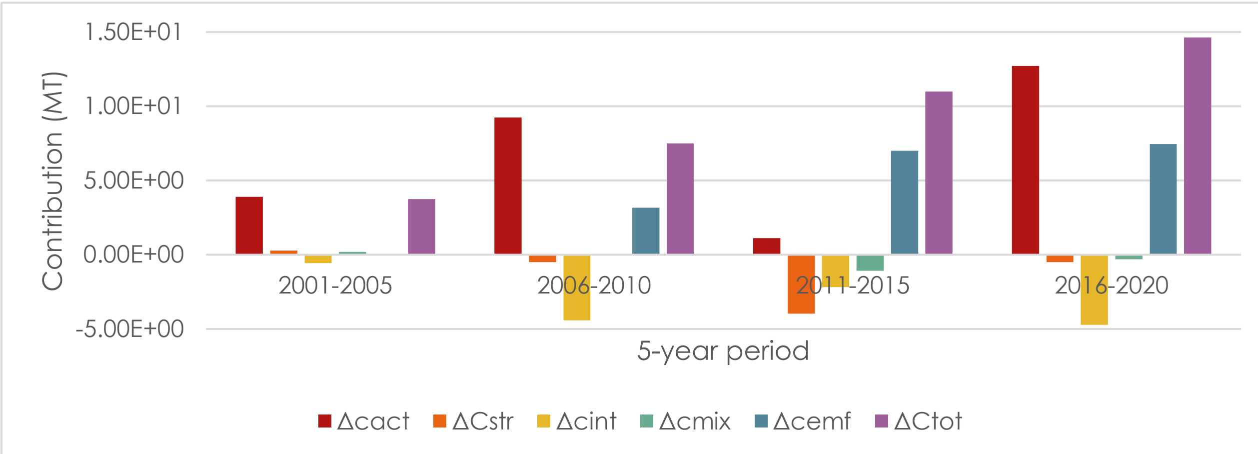

Figure 6. Contribution of driving factors to change in CCEMI (2001-2020) based on medium-term plan, using additive LMDI calculation.

effect, energy structure effect, sectoral energy mix and carbon emission effect while energy intensity has impeding impact. Overall, the entire 4, 5-year periods, 2001-2020, the increase in CCEMI is caused mainly by activity effect, followed by carbon emission factor effect while decrease in CCEMI is caused primarily by energy intensity, followed by energy structure, sectoral energy mix. This suggests engagement of energy efficient policies and technology, hence the dividends.

5.4 Decomposition of change in CCEMI, 2001-2020 based on short-term plan.

To examine the magnitude and direction of change in CCEMI and its contributing factors in adjacent years as well as compare with earlier achieved results above, the study period, 2001-2020 was divided into twenty time-period with each representing one year. The results are presented in Figure 7. Activity effect caused increase in CCEMI except for 2020 where it has a decreasing effect. Activity effect has the greatest impact on CCEMI. Also, carbon emission factor has an increasing effect on CCEMI except in 2003, 2004, 2008 and 2020. Energy structure has a decreasing effect on CCEMI except in 2003, 2004, 2013 and 2020. Sectoral energy mix has a reducing effect on CCEMI except in 2003-2008, 2013 and 2018-2020. However, sectoral energy mix has the least influence on CCEMI. The driving factors that cause increase in CCEMI are primarily activity effect, followed by structure effect and then sectoral energy mix, while energy intensity followed by carbon emission effect cause decrease in CCEMI. This indicates the effect of technological progress on CCEMI affirming the findings of the study by Chen et al. (2018).

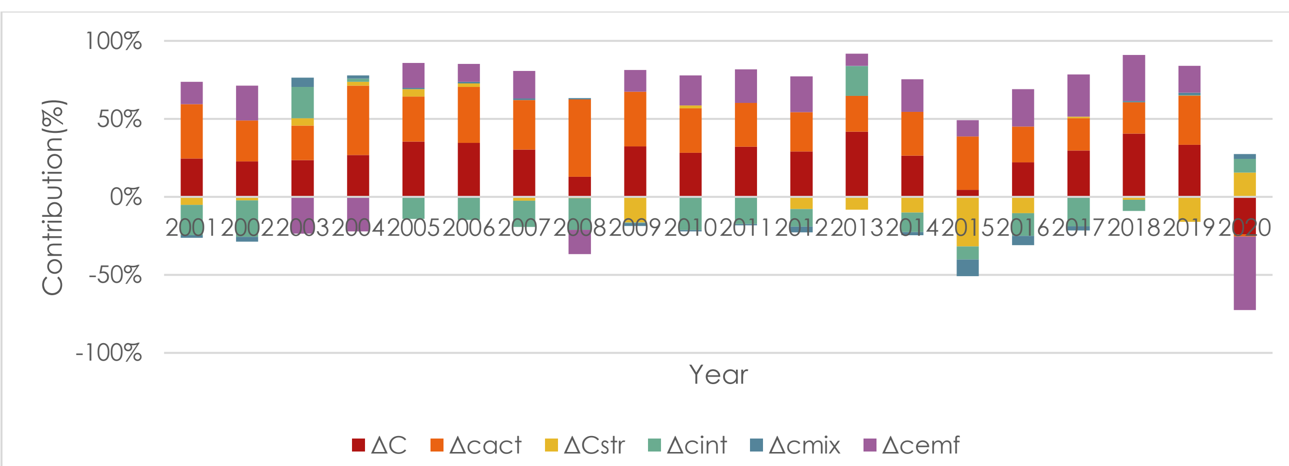

Figure 7. Contribution of driving factors to change in CCEMI (2001-2020) based on short-term plan using additive LMDI calculation.

5.5 Decoupling analyses of CCEMI from GDP (2001-2020) based on long-term plan.

From Table 2, the total decoupling index for the study period is 1.15 which is equivalent to Expansive Coupling. Based on the range of values for Expansive Coupling, 1.15 is much closer to Expansive Negative Decoupling which is at worse decoupling level than weak decoupling. This implies that for every unit increase in GDP in China's manufacturing industrial sector, there will be much more increase in CCEMI indicating that the decoupling relationship between the economic growth and carbon emissions in the sector is worsening. This proposes the need for environment-friendly energy sources and technologies.

Table 2. Decoupling state of CCEMI from GDP based on long-term plan, 2001-2020

Long term period	Decoupling index	State
2001-2020	1.15	EC

Note the eight decoupling states are Strong negative decoupling, SND (worst decoupling), Strong decoupling, SD (best decoupling), all other decoupling states (Expansive negative decoupling, END; Expansive coupling, EC; Weak decoupling, WD; Weak negative decoupling, WND; Recessive coupling, RC and Recessive decoupling, RD) are intermediate(Hang et al. 2019; Khan and Majeed 2019).

5.6 Decoupling analyses of CCEMI from GDP (2001-2020) based on medium-term plan.

According to Table 3, the decoupling analyses of CCEMI from GDP based on medium term plan for 2001-2005 and 2006-2010 are each Expansive coupling while the rest of the study period, 2011-2020 is Expansive negative decoupling. This indicates decrease in the decoupling level in the second half of the study period compared to the first half as decoupling level decreases with increase in decoupling indexes values. Furthermore, this implies that based on medium term plan, the decoupling level of CCEMI experienced a downward trend from the first two 5-year plans to last two 5-year plans.

Table 3. Decoupling state of CCEMI from GDP based on medium-term plan, 2001-2020

Medium term plan	2001-2005	State	2006-2010	State	2011-2015	State	2016-2020	State
Decoupling elasticity	0.811	EC	0.81	EC	2.22	END	1.27	END

5.7 Decoupling analyses of CCEMI from GDP (2001-2020) based on short-term plan.

From Figure 8, the decoupling states of CCEMI from GDP based on short-term plan are mainly Expansive negative decoupling, END; followed by Expansive coupling, EC and then finally Weak decoupling, WD. Expansive negative decoupling occurred around 2009, and from 2011 to 2019; Expansive coupling occurred in 2001-2003, 2005-2007, just before 2009, 2009-2011 and early 2019-2020. And finally, Weak decoupling occurred around 2003-2005, 2007-2009 and later part of 2019-2020. Generally, the decoupling status is END, though it improved from 2019-2020.

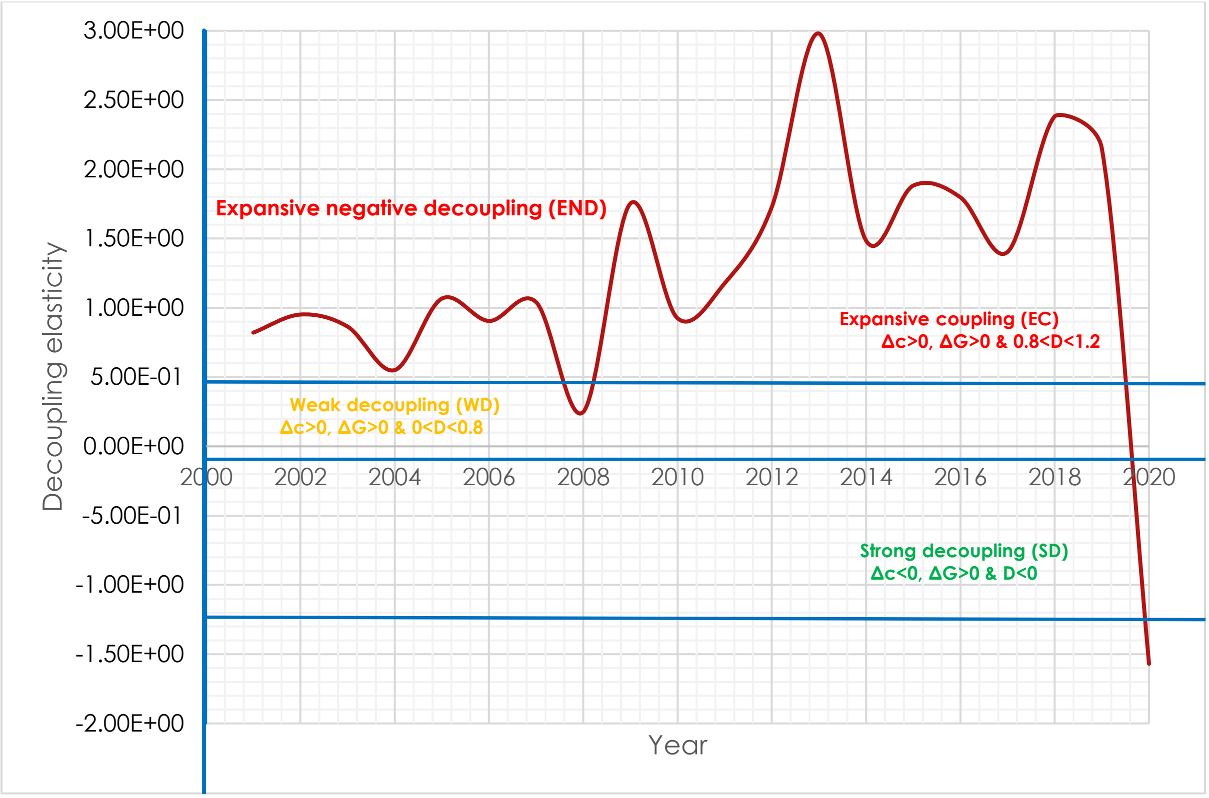

Figure 8. Decoupling state of CCEMI from GDP based on short-term plan, 2001-2020

5.8 Decoupling effects of decomposition results of change in CCEMI (2001-2020) based on long-term plan.

Figure 9 below shows the decoupling indexes of the decomposition results of change in CCEMI based on

Figure. 9 Decoupling efforts of decomposition results of change in CCEMI based on long-term plan, 2001-2020

long-term plan. It shows the resultant decoupling effect of all the decoupling factors across the study period. From the figure, all decoupling factors put together, energy intensity and carbon emission factor have negative effect (enhancing influence) on the decoupling process while overall industrial activity, energy structure and sectoral energy mix have positive effect (impeding influence) on the decoupling process. Whilst energy intensity has the highest enhancing impact on the decoupling process, overall, industrial activity has the highest impeding influence. The resultant decoupling effect of all decomposition factors based on long-term plan for the study period is impeding effect. At this rate sustainable development cannot be achieved without environmentally friendly policies and technology being deployed.

5.9 Decoupling effects of decomposition results of CCEMI (2001-2020) based on medium-term plan.

From Figure10, overall, all decoupling factors put together have restrictive impact on the decoupling process

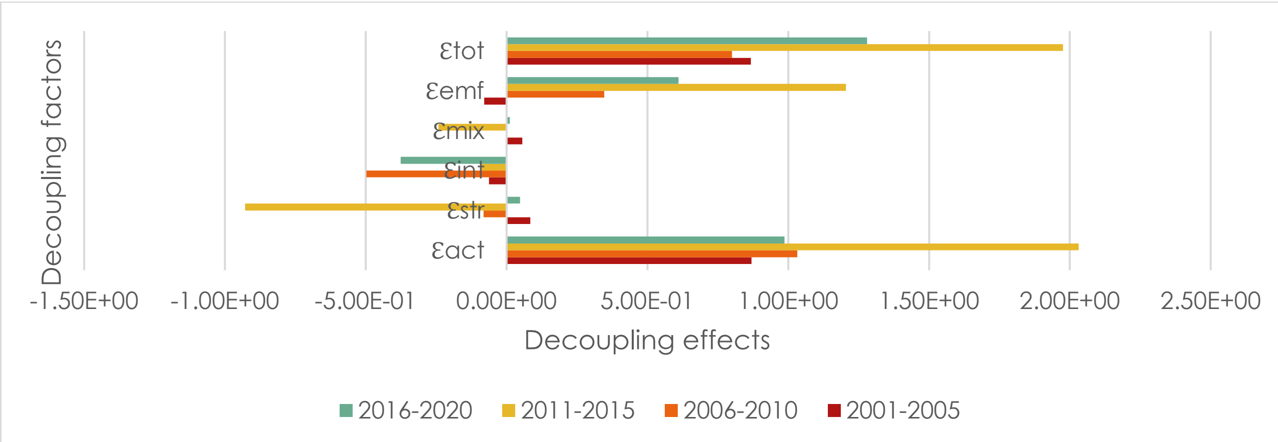

Figure 10. The decoupling analysis of the decomposition factors of change in CCEMI, 2001-2020 based on medium-term plan is presented above.

of CCEMI from GDP. At this rate, for this plan, sustainable economic growth is not achievable in the sector. Industrial activity and carbon emission factor have limiting influence on the decoupling process with industrial activity being the main limiting factor on the decoupling process followed by carbon emission factor. Energy intensity and structure effect have supportive effect on the decoupling process, however, energy intensity has more supportive effect. Though energy structure had limiting effects on the decoupling process for 2001-2005 and 2016-2020, sectoral energy mix had negligible alternating influence on the decoupling process. To realise stronger decoupling and sustainable development, there is need for considerable reduction of the enhancing decoupling factors – energy intensity and structure effects. The impact of energy intensity effect on the decoupling process affirms the findings of study by Li et al. (2019).

5.10 Decoupling effects of decomposition results of CCEMI (2001-2020) based on short-term plan.

From Figure 11, across the study period, energy intensity and structure effects support the decoupling process of CCEMI from GDP. However, energy intensity has a stronger decoupling effect compared to energy structure. Overall, industrial activity, and carbon emission factor, have inhibitory effect on the decoupling process while industrial activity has more constraining effect than carbon emission factor. Sectoral energy mix has supporting and limiting effect on the decoupling level all through the study period. The effect of all decoupling factors put together is an inhibitory influence except around 2015 and 2020. Hence, to realise sustainable development and strong decoupling, energy intensity and structure should be further reduced. Energy intensity and structure have same influence on the decoupling process as in the study by Khan and Majeed (2019).

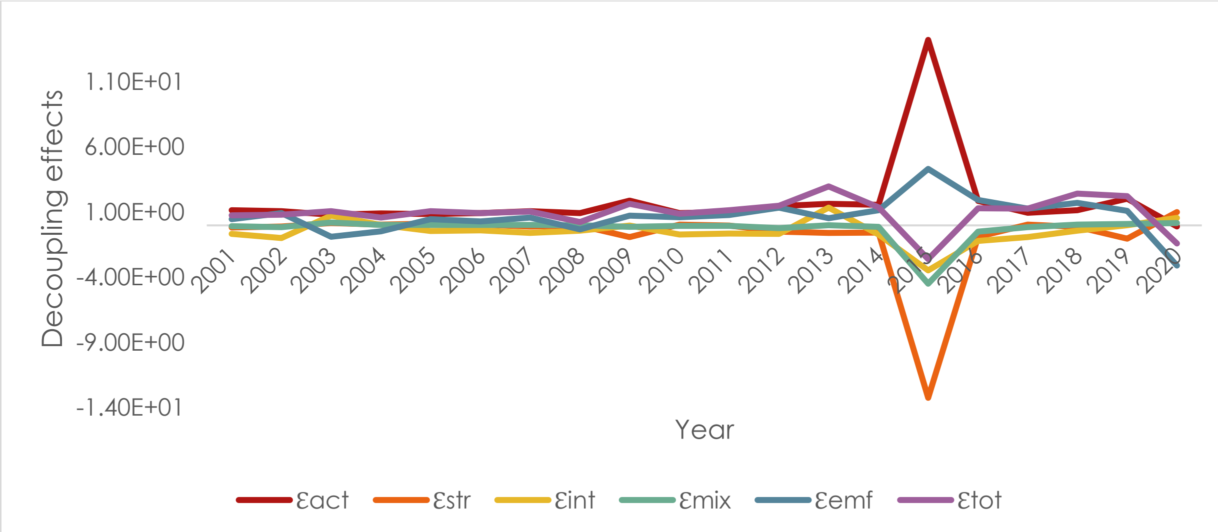

Figure 11. Decoupling efforts of decomposition results of change in CCEMI based on short-term plan, 2001-2020

5.11 Proposed Improvements

In the next phase of this study, scenario analyses will be conducted to examine prospective characteristics of the CCEMI from 2021 to 2035. Another future study could be sensitivity analyses across three-time ranges, before the study period, during the study period and after the study period. Also, Data Envelopment Analyses could be conducted to assess reduction potential of CCEMI. Finally, Artificial Neural Network could be introduced into the study to further deepen analyses. Any of the following analyses or combination will serve as a good improvement on this work.

6. Conclusion

With the help of IPCC's Reference Approach and primary energy consumption data of China's Manufacturing sector, CCEMI, 2001-2020 is computed. The five (5) factors driving CCEMI are quantified by additive LMDI decomposition method. Next, the decomposition of Tapio decoupling analyses of CCEMI from GDP is conducted. To deepen the study, both analyses are done based on a three terms plan: long, medium, and short. From the results in Figure 5 and Figure 9, activity effect is the main enhancing factor while energy intensity is the main inhibiting factor to change in CCEMI and its decoupling from GDP. On the other hand, from the results of Figures. 6, 7, 10 and 11, the main enhancing factor of CCEMI and its decoupling are activity effect and carbon emission factor while the main inhibiting factors are intensity effect and structure effect. From Figures. 7 and 11, 2020 experienced a downward trend in CCEMI and an improved decoupling level due to COVID-19. The sector's decoupling status is Expansive Coupling that is much closer to Expansive negative decoupling compared to Weak decoupling as depicted in Table 2. Also, the results in Table 3 shows a deteriorating decoupling level in the first three 5-year plans and improved a bit in the last 5-year plan, however it is still at Expansive negative decoupling status; and from Figure 8, decoupling level is mainly Expansive negative decoupling, followed by Expansive coupling and Weak decoupling across the study period. Overall, CCEMI and decoupling are deteriorating, especially during the second half of the study period. To improve on the declining environmental condition for sustainable development, there is need for policy to reduce fossil-fuel share in the energy mix, this will substitute fossil-fuel with clean and renewable energy.

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