Assessing potential reduction in greenhouse gas: an integrated approach

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Abstract

Greenhouse gases remain as threat to the environment. Various models employed in greenhouse gases are either to determine the causative factors responsible for emission, forecast emission or to optimize. Integrating these models would reduce the limitations of individual models to better assess possible greenhouse mitigation. This paper addresses the management technique for analyzing, assessing and mitigating industry's carbon dioxide (CO_2) emission. The current work offers a different technique based on an integrated model utilizing the functions of Index Decomposition Analysis (IDA), Artificial Neural Network (ANN) and Data Envelopment Analysis (DEA) composed of activity, structure, intensity and energy-mix as inputs responsible for CO_2 emission. By considering how the three different models are integrated into one system, it will be demonstrated how much percentage of an industry's CO_2 can be reduced. The Canadian industrial sector was analyzed using the integrated model and it was discovered that 3.13% of emitted CO_2 from year 1991 to year 2035 could be mitigated.

Keywords: integrated model; industrial sector; carbon dioxide emission

1. Introduction

Carbon dioxide (CO2) has attracted worldwide concern because of their effects on the environment especially the climate (Aderemi et al., 2009). With the worldwide concern on the effects of greenhouse gases (GHGs) on our environment, it makes it very imperative to find ways of mitigating these gases to protect the future. Series of unpleasant impacts on the climate and air quality are due to atmospheric emissions (Amann et al., 2011). Climate change could be critical as it sabotages the security of the world economy and population. It is commonly agreed amongst scientists that most of the world's carbon dioxide emissions come from the way energy is produced and used. Consequently, energy policy has to undertake an exceptional participation in meeting this challenge (Nyamvumba et al., 2010). Thus, every establishment, either private or government owned has the obligation to control the fast growth of carbon dioxide emissions. To do that efficiently, research concerning which of the factors that has an impact on carbon dioxide emissions and the gravity of such impact has been of immense importance. These impact factors will directly influence the constitution of carbon dioxide abatement measures, policies and strategies

(Fan et al., 2006). Total gas emission can be decomposed into the following components: (1) activity effect, (2) structure effect, (3) intensity effect, (4) energy-mix effect and, (5) emission-factor effect. Similar to the Kaya identity which has carbon intensity of energy, energy intensity and affluence as three basic factors by which emission is decomposed into (Audretsch and Feldman, 1996). These components play unique functions in influencing the mitigation of total greenhouse gas emissions. It should be noted that other factors like environmental factors, economic and financial market, technological progress as well as difficulties and maintenance related issues responsible for plant performance are also important to be considered. However, those factors require high level of human resources and intense data input. Energy management and the reduction of carbon emission are concerns of the global village for environmental sustainability. This study is concerned with the dynamics of the five factors responsible for GHG emission in the industry and intends to quantify how many percentages could be mitigated.

Over the last few decades, a growing number of energy researchers and modelers have been analyzing CO2 for the purpose of its mitigation. Even though the objectives of these energy researchers and modelers are manifold, it is possible to split them in three broad categories: analyzing past emission of CO2 based on causative factors, CO2 baseline and CO2 optimization capability. Accordingly, this trend towards CO2 mitigation indicates that energy modelers and researchers have made relative decisions to protect the environment. Hence, it mirrors fundamental changes in energy models to the reduction of CO2, since it is necessary to think about the ways energy models can and should be integrated for the purpose of CO2 mitigation. Various models employed in greenhouse gases are either to determine the causative factors responsible for emission, forecast emission or to optimize. Integrating these models would reduce the limitations of individual models to better assess possible greenhouse mitigation. However, despite a recent evolution on energy models, particularly integrated models, the academic literature on the energy model concept has remained relatively scarce so far in relation to mitigating greenhouse gases. In particular, it seems that no study so far has tackled the role of the various categories of energy models integrated into a single model for the mitigation of greenhouse gases. Yet, it was deemed that it is essential to develop this kind of research, given the multiplication of empirical evidences of this evolution.

Numerous authors have based their study on GHG emissions, among them are the studies of (Liu et al., 2007) and (Hatzigeorgiou et al., 2008). The change of industrial carbon emissions from 36 industrial sectors in China over the period 1998-2005 was assessed based on time series decomposition of the logarithmic mean divisia index (LMDI) (Liu et al., 2007). The outcomes of their study showed that raw chemical materials and chemical products, non-metal mineral products and smelting and pressing of ferrous metals account for 59.31% of aggregate increased industrial carbon dioxide emissions. The great contributors to the change of China's industrial sectors' carbon emissions in that time were the industrial activity and energy intensity; the impact of emission coefficients of heat and electricity, fuel shift and structural shift was relatively small. Hatzigeorgiou et al., analyzed energy-related carbon dioxide emissions in Greece (Hatzigeorgiou et al., 2008) from 1990 to 2002. The Arithmetic Mean Divisia Index (AMDI) and LMDI methods were employed and changes in carbon dioxide emissions are decomposed into income effect, energy intensity effect, and fuel share effect. The period-wise and time series analyses show that the prime contributor to the rise in carbon dioxide emissions is the income effect; on contrary, the energy intensity effect is primarily accountable for the decrease in carbon dioxide emissions. Bohm (Bohm, undated) analyzed the relationship between emission growth and changes in underlying factors using LMDI method. The study covered the biggest carbon dioxide emitting countries and regions that together account for over 80% of total emissions worldwide in the period from 1971-2005. The results illustrate that gross domestic product (GDP) growth is by far the prime contributor to global emissions followed by an increasing population, whereas decreasing energy intensity was and still is the most vital factor to mitigate emissions. Torvanger (Torvanger, 1991) decomposed the change of carbon dioxide emissions related to energy consumption in nine Organization for Economic Cooperation and Development (OECD) countries. He employed the Divisia technique. He deduced that the reduction in energy intensity and the production allocation of energy intensive sectors contributed to the mitigation of carbon dioxide intensity in the OECD countries examined. Boqiang Lin and Xiaoling Ouyang (Lin and Ouyang, 2014) evaluated the CO_2 emissions change from energy consumption underlying the determinants of the emission in a Chinese non-metallic mineral industry from 1986 to 2010 based on LMDI. The result of their study indicated industrial activity as the leading force responsible for increase in emission while intensity is the focal contributor to its reduction. The contribution of the above mentioned studies was to use the proposed models to disintegrate the factors responsible for greenhouse gases and to identify which of the factors contributed more to its emission.

Forecasting CO_2 emissions has been a critical subject in developing policies for climate change (Meng et al., 2014). Among these studies carried out in this field include (Sozen et al., 2007, Meng et al., 2014, Wu and Xu, 2013). A study on the prediction of greenhouse gas in Turkey was carried out by (Sozen et al., 2007). The results of the study of showed that the prediction formula of artificial neural network with high confidence dependent on sectoral energy consumption can use greenhouse gas emissions in Turkey in order to determine the future level of greenhouse gases. Meng et al (Meng et al., 2014) considered the design of a hybrid forecasting model integrating a non-homogenous experimental equation with a linear equation. The hybrid model was compared with linear model and grey model to forecast China's CO_2 emission from 1992 to 2011. The result showed that the hybrid model responds quickly to changes in the emission trends due to its specialized equation structure. Zhibin wu and Jiuping Xu (Wu and Xu, 2013) used a decision support model based on a fuzzy multiple objective programming model to predict CO_2 emissions in China during 2010-2020. The result revealed CO_2 emissions to increase dramatically with rapid economic growth. Considering the scenario of their study, 23.26% reduction in CO_2 emission intensity was discovered. The above mentioned predictive tools were successful in capturing the baselines for potential assessment of greenhouse gas study, however, they failed in optimizing the causes of emission.

All studies reviewed above contributed to identifying various factors that led to greenhouse gas emissions and its prediction. As much as various models are developed for different purposes, the concern of this study is to have a model responsible for total overhaul of greenhouse gas analysis to assist in its mitigation. As such, due to the merits of an integrated approach, the present study takes advantage of the best characteristics of various techniques to quantify the possible percentage of emission that could be mitigated. As identified by (Schwanitz, 2013), integrated assessment models of global climate change are important tools to study human feedbacks and influences on climate change and mitigation of greenhouse gases. Integrated models are generally developed to satisfy one of these – prediction, forecasting, management and decision-making under uncertainty, social learning, and developing system understanding/experimentation (Kelly et al., 2013). The proposed study satisfies prediction which estimates quantitative value (CO2 prediction) in a specified time, i.e., between 1991 and 2035. It also satisfies management and decision-making under uncertainty through optimization – based simulation.

It is worth noting that there is no technique which is absolutely reliable and suitable for all problem domains and types of data. This present study aims to assess quantitatively the percentage of carbon dioxide that could be mitigated in an industrial sector with the use of an integrated technique. This will allow policymakers and other stakeholders in climate change to concentrate on how best to mitigate CO_2 emissions. To establish a policy that leads to the safety of the environment, the relative contributions of factors that lead to CO_2 emissions will also be established. In achieving the objectives, integration of index decomposition analysis (IDA), data envelopment analysis (DEA) and artificial neural network (ANN) will be employed. Deterministic models based on fundamental mathematical descriptions can be used for this study, but those factors not easily acquired makes the application of deterministic models problematic (Abdul-Wahab and Al-Alawi, 2002) . The integrated method has been successfully utilized in the analysis and assessment of energy studies particularly energy consumption studies, including (Olanrewaju et al., 2012, Olanrewaju et al., 2013, Olanrewaju and Jimoh, 2014), but yet to be applied to CO_2 emission studies. This study will be the first application of the integrated model to CO_2 emissions. This study is to assist in achieving a set goal to what amount of greenhouse gas can be mitigated.

The overall objective is to quantify the possible percentage of CO_2 emissions that can be mitigated. Thus, the purpose of this study is to derive a model capable of advanced diagnosis and analysis of industry's CO_2 to determine the possible way of minimizing its emission through the following in a single model: analysis of industry's CO_2 historical data; prediction of industry's CO_2 baseline; and optimization of industry's CO_2 emission. The rest of this paper is organized as follows. Section 2 details the methodology with a background to the integrated model. Section 3 presents the data and the detailed application of the integrated model. In section 4, results and discussion of the application are presented. Conclusion is in Section 5.

2. Methodology

Although reducing carbon footprint realization is progressively being more accepted by policymakers globally as one of the most valuable means to tackling potential environmental risks and enhancing energy security (Sarkar and Singh, 2009), the right model that can analyze historical data, with prediction and optimization capability and compute efficiency continues to be a challenge. The aim of this study is to employ an integrated framework IDA-ANN-DEA for the analysis and assessment of industry's greenhouse gases for possible minimization. The schematic framework of the proposed methodology is given in Figure 1. The approach adopted by the study is the integration of Index Decomposition Analysis (IDA), Artificial Neural Network (ANN) and Data Envelopment Analysis (DEA) into a single model. This methodology combines modeling, which is at the core of an energy-management technique, with a wider interpretation of activity effect, structure effect, intensity effect, energy-mix effect and emission-factor effect which contribute to changes in greenhouse gases.

In this study, modeling will be used to explore the implications of industry's greenhouse gases in a quantitative framework. Decomposition analysis will be employed as the first step to understand the factors that influence greenhouse gases.

ANN will be used to capture the non-linear relationship so as to make accurate forecasting of the greenhouse gases, considering factors that led to the changes as the input factors. As production and carbon data become available, prediction is accomplished as a check on the industrial sector in terms of the factors specified through decomposition. The ANN methodology enables reliable prediction which consequently allows for planning and conducting necessary measures to reach specified objectives (Kljajic et al., 2012). Among the justification of ANN to this approach is the complex nature of the input factors for this study. Statistical methods sometimes have limitations when variables interact a complex way (Mas et al., 2004), to avoid such limitation, ANN is employed.

DEA is based on a linear programming that produces a single measure of efficiency using the greenhouse gas result calculated from IDA and the predicted greenhouse gas result from ANN as variables. DEA is a powerful data analytic tool that is widely used by researchers and practitioners alike to assess relative performance of Decision Making Units (DMUs).

The theoretical framework towards this study combines various energy models labeled "integrated IDA-ANN-DEA Model". The integrated model relies on available literature on IDA, ANN and DEA. In the integrated model, energy mix, intensity, structure and activity are considered inputs, with total CO_2 emission as the output. To analyze and assess the CO_2 emission, the algorithm serves as a management technique to mitigate CO_2.

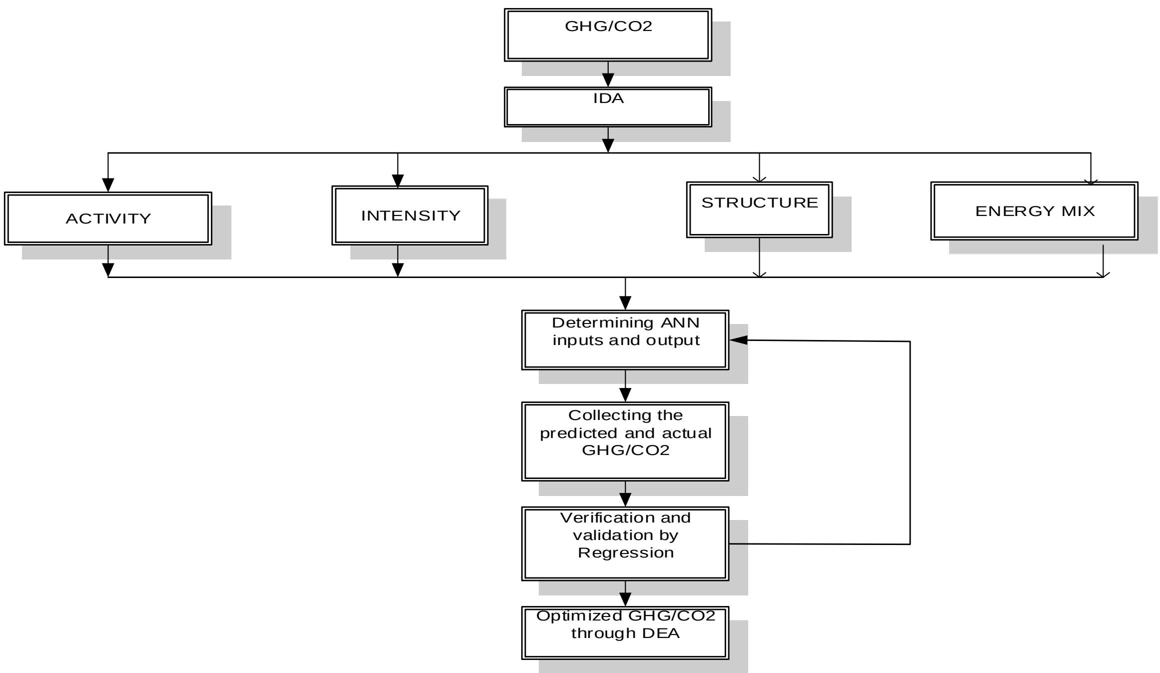

Figure 1: Schematic framework of the proposed method

Background to the integrated model

Index decomposition analysis is designed to understand energy mix, emission factor, intensity, structure and activity factors that have a bearing on CO_2 emission. It is derived from index numbers used to link the contributions of price and quantity levels to changes in aggregate commodity consumption (Fengling, 2004). To understand the importance for GHG mitigation, it is imperative to first understand the underlying factors which led to the historic increases in GHGs. For this reason, decomposition analysis which separates changes in GHGs over time into the driving factors was employed. The use of IDA which evaluates CO_2 emission patterns and identifies the dynamic factors leading to changes in emission is important to the realization of possible mitigation techniques to factors responsible for emission. This study implements IDA for the purpose of understanding changes that lead to CO_2 emission.

Since IDA cannot be used for prediction (Olanrewaju et al., 2012), ANN was used to determine the relationship between CO_2 emission and its driving factors. This network is able to forecast CO_2 accurately, while taking into consideration the responsible input factors leading to the emission. The accuracy of ANN model used in this study is measured by performing a linear regression analysis between the measured emission (output from the neural network) and the predicted emission. The general purpose of regression is to learn more about the relationship between a predictor variable and a dependent or criterion variable (Yilmaz and Kaynar, 2011).

For this study, DEA requires only the measured quantities of CO_2 emitted as an input and predicted CO_2 emitted as an output. DEA is most considered among other non-parametric methods especially for its homogenous nature. The DMUs use the same type of resources to produce the same kind of output (Coli et al., 2010). DEA has also gained acceptance as an efficient optimization tool (Olanrewaju et al., 2012), which led to its use in this study. DEA is employed to determine the optimal CO_2 emission to ensure the safety of the environment from the present and future emission. For this study, it is postulated that the integration of IDA, ANN and DEA will result in the optimization of possible CO_2 that can be emitted to the environment.

The model derivation follows. The input data obtained from the industry using multiplicative decomposition method is given below:

The variables used for the decomposition analysis

C – Total CO_2 emission

C_{ij} – CO_2 emissions arising from fuel j in industrial sector i

E_{ij} – Consumption of fuel j in industrial sector i, where $E_i = \sum_j E_{ij}$

$M_{ij} = E_{ij} / E_j$ – The fuel-mix variable

Q_i - Value of production in sector i

Q - Total value of production $(Q = \sum_i Q_i)$

S_i - Production share of sector i $(S_i = \frac{Q_i}{Q})$

I_i - Intensity of energy consumption in sector $(I_i = \frac{E_i}{Q_i})$

$$C = \sum_{ij} Q \frac{Q_i}{Q} \frac{E_i}{Q_i} \frac{E_{ij}}{E_i} \frac{C_{ij}}{E_{ij}} = \sum_{ij} Q S_i I_i M_{ij} \quad (1)$$

$$\frac{C^T}{C^0} = D_{tot} = D_{act} D_{str} D_{\text{int}} D_{mix} \quad (2)$$

Where D_{tot} is the total CO_2 emission, D_{act} is the activity, D_{str} is the structure, D_{int} is the intensity and D_{mix} is the sectoral energy mix.

$$D_{act} = \exp\left(\sum_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{Q^T}{Q^0}\right)\right) \quad (3)$$

$$D_{str} = \exp\left(\sum_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{S_i^T}{S_i^0}\right)\right) \quad (4)$$

$$D_{\text{int}} = \exp\left(\sum_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{I^T}{I^0}\right)\right) \quad (5)$$

$$D_{mix} = \exp\left(\sum_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{M_{ij}^T}{M_{ij}^0}\right)\right) \quad (6)$$

$$D_{tot} = D_{act} D_{str} D_{\text{int}} D_{mix} \quad (7)$$

The multiplicative decomposition variables serve as input to ANN, whose equation is given by

$$y_j = f\left(\sum_i w_{ij} x_{ij}\right) \quad (8)$$

Substituting the variables (equations (3) – (6)) as input values and equation (7) as the output value into equation (8) becomes

$$U_{tot} = f(\sum_i w_{ij} \{D_{act(ij)}, D_{str(ij)}, D_{\text{int}(ij)}, D_{mix(ij),}\}) \quad (9)$$

The goal is to minimize the average sum of the errors between the decomposed total CO_2 (output to the neural network) and the target total CO_2 (predicted CO_2). Thus,

$$mse = \frac{1}{Q}\sum_{K=1}^{Q}[U_{tot}t(k) - U_{tot}a(k)]^2 \quad (10)$$

Where $U_{tot}t$ is the predicted total CO_2 and $U_{tot}a$, the decomposed total CO_2.

From the DEA, interested readers can refer to (William et al., 2006); substituting $U_{tot}(t)$ as the output variable and $U_{tot}(a)$ as the input variable gives

$$\text{Max } \frac{\sum_{r=1}^{s} U_{tot}(t)_{ro} u_r}{\sum_{i=1}^{m} U_{tot}(a)_{io} v_i}$$

$$\text{such that} \quad \frac{\sum_{r=1}^{s} U_{tot}(t)_{ro} u_r}{\sum_{i=1}^{m} U_{tot}(a)_{io} v_i} \leq 1, \text{j} = 1\ldots\text{n} \quad (11)$$

$$v_i \geq 0, i = 1,\ldots, m;$$
$$u_r \geq 0, r = 1,\ldots, s.$$

Where the $U_{tot}(t)_{ro}, r = 1,..s$ represent outputs and the $U_{tot}(a)_{io}, i = 1,..m,$ represent inputs for each of $j = 1,\ldots n$, DMUs and $j = 0$ identifies DMUj to be evaluated. μ_r is the output weight while V_i is the input weight. Transforming equation (11) into an ordinary linear programming problem;

$\boldsymbol{\mu}_r = \beta\, \boldsymbol{\mu}_r$, $v_i = \beta\, v_i$ is obtained with the same optimum value as equation (11)

$$\text{Max } \varphi = \sum_{r=1}^{s} \mu_r U_{tot}(t)_{ro}$$

$$\text{Such that} \quad \sum_{i=1}^{m} v_i U_{tot}(a)_{io} = 1,$$

$$-\sum_{i=1}^{m} U_{tot}(a)_{ij} + \sum_{r=1}^{s} \mu_r U_{tot}(t)_{rj} \leq 0, \ j = 1,...n, \tag{12}$$

$$v_i \geq 0, i = 1,..m,$$
$$\mu_r \geq 0, r = 1,...s.$$

Equation (12) has a dual form that can be written as

Min η_o

Such that $\sum_{j=1}^{n} U_{tot}(a)_{ij} \lambda_i \leq U_{tot}(a)_{io} \eta_o, i = 1,..., m$ (13)

$$\sum_{j=1}^{n} U_{tot}(t)_{ij} \lambda_j \geq U_{tot}(t)_{ro}, r = 1,...s$$

$$\lambda_j \geq 0, j = 1,...,n$$

Equations (12) and (13) will allow the accountability for the extra CO_2 emission while keeping the expected CO_2 emission at the baseline level.

3. Data

Due to the inability of getting most recent data, this method was applied to data from Granel's thesis on the decomposition result on the Canadian industrial data from 1991 to 2000 (Granel, 2003). In his thesis, he applied the LMDI on the data to get the results presented in Table 1 below. As indicated by Granel, CO_2 based on final energy consumption is considered whereas that induced by electricity production is not reported. Fuel considered are coal, coke, coke oven gas, petroleum coke, natural gas, heavy fuel oil, lpg/propane, and waste fuels consumption. It should be noted that 52 sectors and subsectors including mining and all manufacturing industries excluding oil and gas extraction, forestry and construction were observed for this study. The data was extended to year 2035 by a computed least square trend line equation. Least squares was employed because it makes good interpolated predictions under the right circumstances (Burger and Repisky, 2012). The years are replaced by coded values, that is, year 1991 was replaced by 1, 1992 by 2, and so forth to year 2035 which is coded by 45. This is called the coded method. With the least square trend equation, the following were obtained for the various factors responsible, the *t* in the equations below represent the coded values for the years

$$energy\ mix = 0.987 + 0.000315\ t \tag{15}$$

$$\text{int}\ ensity = 1.025 - 0.00477\ t \tag{16}$$

$$structure = 1.0169 - 0.00571t \tag{17}$$

$$activity = 0.982 + 0.00954\,t \qquad (18)$$

Table 1: multiplicative decomposition on Canada's greenhouse gas from 1991 to 2000 (Granel, 2003) and calculated values from 2001 to 2035 using least square trend equation

Year	Total CO_2 emission	Energy mix	Intensity	Structure	Activity
1991	0.99	1.00	1.04	1.03	0.94
1992	0.98	0.97	1.00	1.00	1.01
1993	1.03	1.02	0.97	1.01	1.04
1994	1.02	0.96	1.02	0.97	1.07
1995	1.02	0.96	1.05	0.98	1.04
1996	1.02	1.01	1.00	1.00	1.01
1997	1.01	1.00	0.98	0.97	1.06
1998	0.99	0.99	0.98	0.97	1.04
1999	1.01	0.99	0.98	0.98	1.07
2000	0.99	0.99	0.98	0.95	1.07
2001	1.00	0.99	0.97	0.95	1.09
2002	1.00	0.99	0.97	0.95	1.10
2003	1.00	0.99	0.96	0.94	1.11
2004	0.99	0.99	0.96	0.94	1.12
2005	0.99	0.99	0.95	0.93	1.13
2006	0.99	0.99	0.95	0.93	1.14
2007	0.99	0.99	0.94	0.92	1.15
2008	0.98	0.99	0.94	0.91	1.15
2009	0.98	0.99	0.93	0.91	1.16
2010	0.98	0.99	0.93	0.90	1.17
2011	0.98	0.99	0.92	0.90	1.18
2012	0.97	0.99	0.92	0.89	1.19
2013	0.97	0.99	0.92	0.89	1.20
2014	0.97	0.99	0.91	0.88	1.21
2015	0.96	0.99	0.91	0.87	1.22
2016	0.96	1.00	0.90	0.87	1.23
2017	0.95	1.00	0.90	0.86	1.24
2018	0.95	1.00	0.89	0.86	1.25

2019	0.95	1.00	0.89	0.85	1.26
2020	0.94	1.00	0.88	0.85	1.27
2021	0.94	1.00	0.88	0.84	1.28
2022	0.93	1.00	0.87	0.83	1.29
2023	0.93	1.00	0.87	0.83	1.30
2024	0.93	1.00	0.86	0.82	1.31
2025	0.92	1.00	0.86	0.82	1.32
2026	0.92	1.00	0.85	0.81	1.33
2027	0.91	1.00	0.85	0.81	1.34
2028	0.91	1.00	0.84	0.80	1.35
2029	0.90	1.00	0.84	0.79	1.35
2030	0.90	1.00	0.83	0.79	1.36
2031	0.89	1.00	0.83	0.78	1.37
2032	0.89	1.00	0.82	0.78	1.38
2033	0.88	1.00	0.82	0.77	1.39
2034	0.88	1.00	0.82	0.77	1.40
2035	0.87	1.00	0.81	0.76	1.41

Application of the integrated model

The general proposed model can be summarized as follows:

I. LMDI based on IDA was performed to assess the respective contribution of energy-mix, emission factor, intensity, structure and activity. This was successfully achieved from Granel's thesis (Granel, 2003) from 1991 to 2000 and extended to year 2035 by a computed least square trend line equation coded method.

II. Total CO_2 emission, energy-mix, emission factor, intensity, structure and activity are selected as ANN inputs and output indicators. Total CO_2 emission indicator is the output and energy-mix, emission factor, intensity, structure and activity are the input indicators.

III. The predicted results of ANN are verified and validated by the result of regression analysis.

IV. With the aid of DEA sub-model, efficient computation for CO_2 emission was obtained.

V. Optimization suggestions for the CO_2 emission are proposed for each year for the Canadian industrial sectors to determine the possible percentage mitigation.

Addressing uncertainty

Estimating greenhouse gases has been one of the subjects of uncertainty (Ballantyne et al., 2012, Rodrigues, 2015). To address the uncertainty using the proposed model, (Johnson et al., 2011) explained in their study the guidelines for addressing model uncertainties. Among the guidelines is that models are expected to disaggregate and spatially until they have reached the practical limits of the availability of data. In this study, disaggregation was successfully achieved as stipulated using IDA from Granel's study eliminating any possible uncertainty. To address the uncertainty in the data from IDA as well as the extended data through the least square method, the data was reported to two significant figures. The uncertainty bound by reporting to two significant figures thus represents 1% of the value reported (Johnson et al., 2011). The bounding of the uncertainty to the model assists in understanding the range of results that will be attributed to estimating the possible greenhouse gas mitigation.

4. Results and Discussion

4.1. ANN Results

To attain the specified objectives of the study, the baseline was predicted using a reliable prediction technique, ANN. For the prediction technique; activity effect, structure effect, intensity effect, energy-mix effect and emission-factor effect were the inputs while the target CO_2 emission was the output. Table 2 shows the target and predicted result. The number of hidden neurons was determined by comparing the performance of different cross-validated networks, with 1–15 hidden neurons, and choosing the number that produced the greatest network performance. This resulted in a network with '6' hidden neurons. Years 1991, 1993, 1995, 1997, 1999, 2001, 2003, 2005, 2007, 2009, 2011, 2013, 2015, 2017, 2019, 2021, 2023, 2025, 2027, 2029, 2031, 2033 and 2035 were used for training; years 1992, 1996, 2000, 2004, 2008, 2012, 2016, 2020, 2024, 2028 and 2032 for testing; and years 1994, 1998, 2002, 2006, 2010, 2014, 2018, 2022, 2026, 2030 and 2034 for validation. In the analyses, network parameters of learning rate and momentum were set at 0.06 and 0.7, respectively with activation functions of purelin and tansig under Matlab 2010a software. Purelin and tansig gave the best fit compared to other activation functions. It was discovered that a strong correlation exists between the baseline (predicted CO_2 emission) and the target CO_2 emission from the visual inspection as presented in Figure 2.

Table 2: predicted result from ANN

Year	Target CO2	Predicted CO2	Error (Target-Predicted)
1991	0.99	1.02	-0.03
1992	0.98	1.02	-0.04
1993	1.03	1.02	0.01
1994	1.02	1.02	0.00

1995	1.02	1.02	0.00
1996	1.02	1.01	0.01
1997	1.01	1.00	0.01
1998	0.99	1.00	-0.01
1999	1.01	1.02	-0.01
2000	0.99	1.00	-0.01
2001	1.00	1.00	0.00
2002	1.00	1.00	0.00
2003	1.00	1.00	0.00
2004	0.99	1.00	-0.01
2005	0.99	0.99	0.00
2006	0.99	1.00	-0.01
2007	0.99	0.99	0.00
2008	0.98	0.98	0.00
2009	0.98	0.98	0.00
2010	0.98	0.97	0.01
2011	0.98	0.97	0.01
2012	0.97	0.97	0.00
2013	0.97	0.97	0.00
2014	0.97	0.96	0.01
2015	0.96	0.95	0.01
2016	0.96	0.95	0.01
2017	0.95	0.95	0.00
2018	0.95	0.95	0.00
2019	0.95	0.94	0.01
2020	0.94	0.94	0.00
2021	0.94	0.93	0.01
2022	0.93	0.92	0.01
2023	0.93	0.93	0.00
2024	0.93	0.92	0.01
2025	0.92	0.92	0.00
2026	0.92	0.91	0.01
2027	0.91	0.92	-0.01
2028	0.91	0.91	0.00
2029	0.9	0.90	0.00
2030	0.9	0.90	0.00
2031	0.89	0.89	0.00
2032	0.89	0.89	0.00
2033	0.88	0.89	-0.01
2034	0.88	0.89	-0.01
2035	0.87	0.89	-0.02

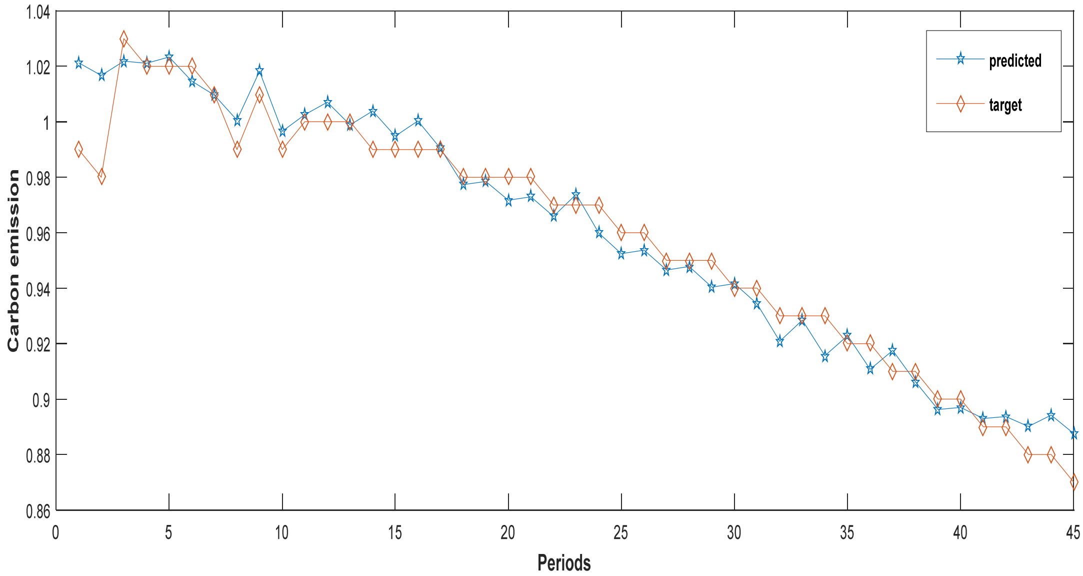

Figure 2: prediction result for CO_2 emission baseline

Regression validation

To confirm and validate the ANN's result, linear regression analyses is a likely confirmation method to the neural network model between the predicted and corresponding target CO_2 emission values. The analyses lead to a straight line equation $y = a + bx$ with a correlation coefficient of R^2. Figure 3 below shows the regression results signaling a good prediction.

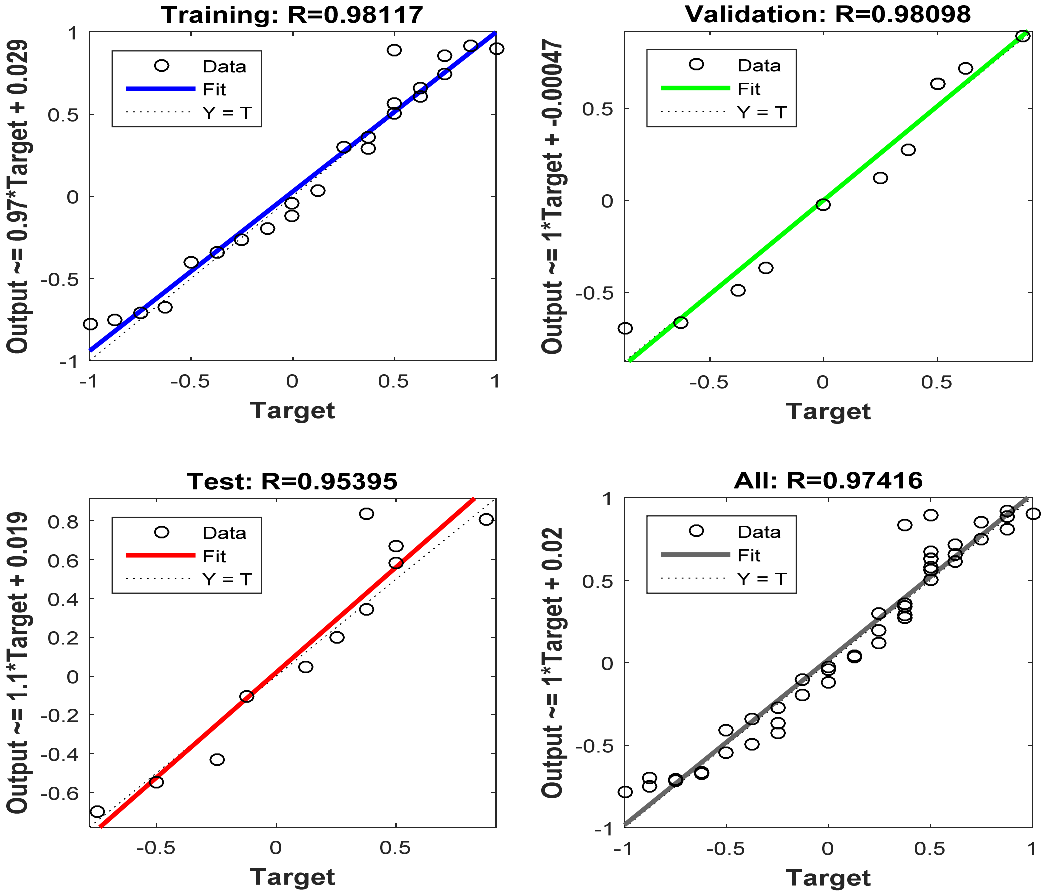

Figure 3: Regression validation

4.2. DEA Results

To be able to determine the possible percentage CO_2 mitigation for the period of study, DEA analysis was carried out. DEAFrontier software package on excel has been employed to carry out the DEA analyses. The target CO_2 emission was selected as the input whereas the predicted CO_2 emission was selected as the output data for the analyses. The efficiency scores in different years (DMUs) are shown in Table 3. These efficiency scores are relative to the best performing years, to determine how best quantitatively the CO_2 emission could be reduced.

With benchmarking based on the year of CO_2 emission, 1992 was discovered to have the optimal performance of 100% and can serve as the only benchmark to the other periods considered. The remaining years have the rating of 96% - 98.8%. Table 3 presents the efficiency scores based on the comparison of the years following the Constant Returns to Scale assumption. For this case study, the year 1992 was considered to have the lowest CO_2 emission in comparison to the others. The other years would consider the year 1992 as a peer to enable them efficient. To be able to register the CO_2 emission that will enable the inefficient years optimal, they must emulate the efficient year. The efficiency score of each year is a coefficient that indicates how optimal and efficient the operations leading to CO_2 can be.

Table 3: efficiency scores based on benchmarking

DMU No	DMU Name	Efficiency
1	1991	0.96788
2	1992	1.00000
3	1993	0.96325
4	1994	0.97585
5	1995	0.96691
6	1996	0.96492
7	1997	0.96863
8	1998	0.96160
9	1999	0.97770
10	2000	0.96749
11	2001	0.97310
12	2002	0.97253
13	2003	0.97205
14	2004	0.97148
15	2005	0.97081
16	2006	0.97013
17	2007	0.96945
18	2008	0.96867
19	2009	0.96789
20	2010	0.96700
21	2011	0.96611
22	2012	0.96521
23	2013	0.96430
24	2014	0.96349
25	2015	0.96268
26	2016	0.96195
27	2017	0.96132
28	2018	0.96069
29	2019	0.96036
30	2020	0.96012
31	2021	0.96009
32	2022	0.96037
33	2023	0.96076
34	2024	0.96146
35	2025	0.96237
36	2026	0.96362
37	2027	0.96508

38	2028	0.96689
39	2029	0.96903
40	2030	0.97152
41	2031	0.97426
42	2032	0.97735
43	2033	0.98082
44	2034	0.98454
45	2035	0.98865

Reduction of CO_2 emission

Figure 4 shows the years of operation of industrial sectors for reduction in greenhouse gas. The most reduction in the greenhouse gas from the sectors will take place in years 2020 and 2021. Apart from the most efficient year of 1991, year 2035 will be the least in the reduction of greenhouse gas. Figure 4 is a normal graph in nature from year 2001 to year 2035. The normal graph nature is similar to the carbon dioxide emission of Indonesia, Brazil and India from year 1971 to year 2050 according to Global Commons Institute as depicted from the study of (Kuntsi-Reunanen and Luukkanen, 2006). This is also similar to the reduction in Thailand's carbon dioxide emission intensity from year 1971 to year 2050 according to 'contraction and convergence' approach. The year 1991 will encounter a reduction in emission of (100-96.788 = 3.212) % compared to the most optimal practice in 1992 (efficiency of 1). Industrial sectors in 1991 can reduce their emission by 3.212% and be an efficient industrial sector. Figure 4 relates the emission to the percentage amount of CO_2 that would have been reduced if the periods emulated 1992 practice. In summary, the amount of CO_2 that can be possibly mitigated from year 1991 to year 2035 is 3.13% of the total CO_2 that can be emitted for the whole period under study.

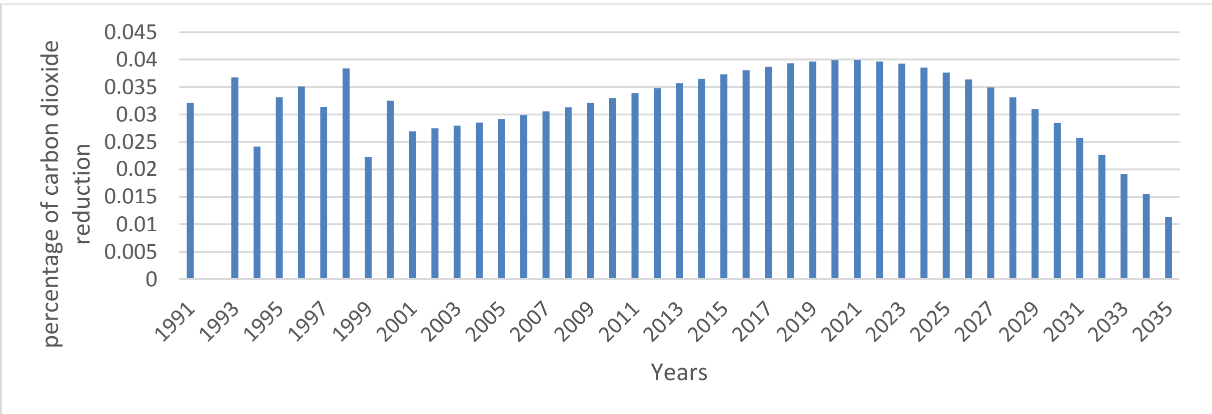

Figure 4: percentage reduction in CO_2

5. Conclusion

The improvements to be obtained in the reduction of CO_2 emission requiring efficiency computation, analyzed historical data, predicted and optimized reduction of CO_2 emitted in an integrated system is advantageous. Various contributions of the key drivers to the emission of CO_2 were determined through the use of Index Decomposition Analysis. Predicting the CO_2 emission baseline after the determination of the pattern of the various drivers responsible for the emission was successfully demonstrated with the use of Artificial Neural Network. Possible reduction of CO_2 emission was achieved using Data Envelopment Analysis. Thus, by determining the analysis and assessments of CO_2 with an accommodative tool like that proposed for this study, CO_2 can be mitigated efficiently to the benefits of the global society. The combined advantages of IDA, ANN and DEA have greatly expanded the research horizons in the field of energy studies. Model development to assessing and mitigating CO_2 for this study successfully captured the analysis of historical data, CO_2 baseline prediction, CO_2 efficiency computation and the possible reduction of CO_2 emission in a combined model as opposed to single models. The approach can assist to make long-term planning which involves developing a view of the possible future mitigation of GHGs. Without proper analysis of the causal effects and its baseline determination, it becomes difficult to have an effective assessment for the reduction of CO_2 emission. It should be noted that due to the unavailability of data at the time of research and the high probability of not getting data from year 2001 to the year of study, data was projected for this study. The result of this study projects a least target that is possible for mitigation in the future putting in mind the present scenario, using scenario of year 1991 to 2000 as the baseline.

It is also worth noting that the 52 sectors definitely could change or improve practices before the end of year 2035, however, this study has only considered year 1991 to 2000 as a baseline (due to data unavailability), leading to the assumption that all practices within the stipulated available data was constant throughout the years predicted. Comparing the efficiency of the practices using the DEA singled out 1992 as the best practice. This probably wouldn't be so should there be more availability of data. It can also be argued as well that any of the years 1998, 1999 or 2000 should have been the most efficient instead of the 1992 practices. However, it is worth noting that the efficiency of 1992 is not only due to the lower intensity in comparison to the later years but also due to the amount of activities. Improved technologies and practices in the later years could only mean increased activities leading to more consumption of energy and automatically to more emission. Computing the efficiency and minimizing CO_2 emissions are very useful to understanding how best emission could be mitigated. When compared to the single models, DEA computes efficiency and optimizes, ANN computes efficiency and predicts, and IDA analyzes and disintegrates historical data, whereas the proposed algorithm integrates all the features.

However, future work will focus on the following areas (1) creating a single platform for the operations of IDA, ANN and DEA that leads to model simplicity (2) application of the model to up-to-date data including data of environmental, technological progress, economic and financial market factors. When such factors are included, it will definitely change the dynamics of the equation especially that of IDA. (3) Research to explore the most appropriate technique to calculate the uncertainty associated to mitigating CO2 emission. Results are based on limited data, which may not allow generalization of the findings regarding technical progress from 1992 to 2035. Nonetheless, the findings of this study together with the arguments provide key insights to assessing potential reduction in greenhouse gases.

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