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METHODS IN FORECASTING CARBON DIOXIDE EMISSIONS: A DECADE REVIEW

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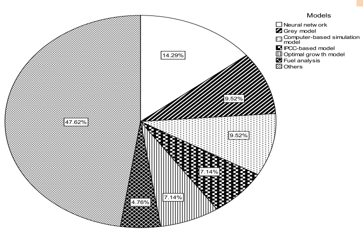
Graphical abstract



Abstract

Analyses and forecasts of carbon dioxide (CO_2) emissions is one of the key requirements to educate people about the issues of clean and healthy environment. Various methods have been proposed to forecast CO_2 emissions. This paper reviews the literature of the methods for the forecasting as well as estimatingCO_2 emissions. Related articles appearing in the international journals from 2003 to 2013 were gathered and analysed to find the answers for these two questions: (i) Which methods were prevalently applied? (ii) Which factors were regularly been investigated? Based on the overall observations on the journal articles some improvements and possible future works are recommended. This research not only provides evidence that the artificial intelligence methods are the most favour methods, but also aids the researchers and policy makers in applying the methods effectively.

Keywords: CO_2 emissions, forecasting, emission factors, review methods

Abstrak

Analisis dan ramalan pembebasan karbon dioksida (CO_2) adalah satu daripada syarat utama untuk mendidik orang ramai mengenai isu-isu persekitaran yang bersih dan sihat. Pelbagai kaedah telah dicadangkan untuk ramalan pembebasan CO_2. Artikel ini menilai kaedah-kaedah untuk peramalan dan penganggaran pembebasan CO_2 daripada artikel-artikel yang berkaitan daripada jurnal antarabangsa. Artikel-artikel tersebut yang diterbitkan daripada 2003 hingga 2013 dikumpul dan dianalisis untuk menjawab dua persoalanini: (i) Apakah kaedah yang sering diaplikasikan? (ii) Apakah faktor-faktor yang sering di teliti dalam peramalan ini? Berdasarkan pemerhatian secara keseluruhan, beberapa cadangan untuk kajian akan datang dicadangkan. Penyelidikan ini bukan sahaja menyediakan bukti bahawa kaedah kecerdikan buatan adalah kaedah yang paling banyak digunakan, tetapi juga dapat membantu pengkaji dan pembuat-pembuat dasar untuk memilih kaedah yang berkesan dalam membuat ramalan ini.

Kata kunci: Pembebasan CO_2, ramalan, faktor pembebasan, tinjauan kaedah

1.0 INTRODUCTION

Developments in environmental issues and energy consumptions have led to renewed interest in gas emissions forecasting. Forecast of CO_2 emissions has become a worldwide concern as the greenhouse gas (GHG) proved to contribute most impacts on environmental problems. Forecasting CO_2 emissions is also one important key to create awareness among public on how to solve environmental problems. There are considerable amounts of literature that discussed and reviewed the issue of CO_2 emissions such as mitigation CO_2 emissions. Ho *et al.*, [1] reviewed on the history and perspectives on microalgae CO_2-emission mitigation system to reduce the emission. Sauerbeck

[2] reviewed on agricultural factor to capture and minimize the production of CO_2 in the related area. Huaman and Jun [3] discussed in their about the massive development of carbon capture and storage (CCS) technologies in order to sustain a clean and safe environment. So far, however, there has been little discussion about methods used in CO_2 emissions forecasting. Choosing the right methods in forecasting the CO_2 emissions is depend on a wide range of factors which involved both qualitatively and quantitative. There have been many different methods of forecasting that available in the literature. It was due to the different locations, and factors of CO_2 emissions**.** The methods mostly based on artificial intelligence, traditional linear regression, computer based simulation, optimal growth model are among the popular approaches. In this paper, we comprehensively collected the literature associated with the descriptors 'CO_2 emissions', 'methods', 'forecasting' and 'prediction' from academic databases including IEEE, Science Direct, Taylor and Francis, Springer and also Wiley. Based on 42 journal articles collected, two issues are examined: (i) Which methods were prevalently applied? (ii) Which factors were regularly been investigated?

The paper is organized as follows: Sections 2 describes various kinds of methods. Section 3 analytically describes the observations out of the survey. Section 4 provides suggestion or recommendation for future work. Section 5 concludes this survey paper.

2.0 REVIEW OF METHODS

Considering the diversity and complexity methods used, we established the following list of methods

2.1 Neural Network

Radojevic *et al.,* [4] developed artificial neural network (ANN) for estimating CO_2 emissions in Serbia. They were trying to investigate and evaluate the possibility of using the technique for predicting the environmental indicators of sustainable development in the country. It was done in order to overcome the problem of incomplete data and to simulate various development scenarios and their environmental impact. The software tool NeuroShell 2 was used for neural network design and training. Data from 1999 to 2007 was considered. The share of renewable sources of energy, the gross domestic product (GDP), the gross energy consumption, and energy intensity were selected as the input parameters. Results from the training of EU countries and Bulgaria were compared with the result from Serbia. Bulgaria was selected as a country of special interest because its level of economic development, industry structure, climate, and energy intensity and consequently the input data are very similar to those of Serbia. In fact, ANN showed good results for Bulgaria even in predicting GHG emissions 5 years and more in the future, the relative errors were less than 10%. Therefore, good results for Serbia might be expected where at last the actual GHG emissions for Serbia were estimated as well. Based on the results obtained, it might be concluded that ANNs can be applied for modelling GHG emissions as one of the environmental parameters of sustainable development. Also, ANN models can be a useful tool to simulate various development scenarios, the impact of measures implemented by the government and industry and, hence, to support national and international-level decision-making on sustainable development.

Liu *et al.,* [5] proposed neural network model to forecast CO_2 emissions in China. Variables such as GDP, exports, CPI (consumer price index) data, investment in fixed assets and population were considered. First, the neural network was constructed for the time range 1990 to 2010. Carbon emission denotes CO_2 emission from fossil fuels and cement production. Then, considering the effect of subprime mortgage crisis and European debt crisis, the researchers forecasted the emissions in the next 10 years through the network. Relative error which was the percentage of the difference between the real emissions and the estimated emission were calculated. The values yielded were between 1% and -1%. So, the researchers concluded that the network was very good in forecasting. The result showed that China's emission would approach the turning point. From this point, if it is willing to produce less emission, China government should not enlarging investment in the fixed assets to spur GDP.

Yap and Karri [6] developed common feed forward neural network models to present a two-stage emissions predictive model. The first stage model involves predicting engine parameters power and attractive forces and the predicted parameters were used as inputs to the second stage model to predict the vehicle emissions. The second stage model predicted not only CO_2 emissions but also hydrocarbons (HC), carbon monoxide (CO) and oxygen (O_2). Three feed forward neural network models were investigated and compared in this study; back propagation, optimization layer-by-layer and radial basis function networks. Experimental data were obtained from the chassis dynamometer. An Auto Logic 5-gas analyzer was used to measure the emission levels for CO, CO_2, HC and O_2. Based on the experimental setup, the neural network models were trained and tested to accurately predict the effect of the engine operating conditions on the emissions by varying the number of hidden nodes. The selected optimization layer-by-layer network proved to be the most accurate and reliable predictive tool with prediction errors of 5%.

Behrang *et al.,* [7] applied an integrated multi-layer perceptron neural network and Bees Algorithm (BA) to forecast world CO_2 emissions. Twenty-seven years data (1980 to 2006) were used for developing both forms (linear and exponential) of BA demand estimation. In the first step, the BA was applied in order to determine the world's fossil fuels and primary energy demand equations based on socio-economic indicators. The world's population, gross domestic product (GDP), oil trade movement, and natural gas trade movement were used as socio-economic indicators in this study. There were two scenarios designed for forecasting each socio-economic indicator in a future time domain. For the Scenario I each socio-economic indicator, several polynomial trend lines were fitted to the observed data and the best fitted polynomial (highest correlation coefficient (R_2) value) for each socio-economic indicator was used for future forecasting. Then, in the Scenario II several neural networks were trained for the indicators mentioned and the best trained network for each socio-economic indicator was used for future forecasting. After that, the best results in the first step were used to project world CO_2 emission based on the oil, natural gas, coal, and primary energy consumption using BA. In conclusion, artificial intelligence techniques were successfully used to estimate world oil, natural gas, coal, and primary energy demand and CO_2 emission based on the structure of international industrial and economic conditions.

Li *et al.,* [8] also proposed a type of neural network which is called Radial Basis Function (RBF) combined with time series to forecast and analysed CO_2 emissions in China. It examines the rationality and flexibility of the RBF neural network used in prediction of CO_2 emissions. This paper converted total energy consumption to CO_2 emissions. Data were taken for the period between 1990 and 2010. The empirical result showed that RBF neural network was of superior function approximation capability and high predictive accuracy. The researchers believed that it is a valid method in forecasting CO_2 emissions by virtue of the above analysis and of reference value in actualizing sustainable development strategy.

Sozen *et al.,* [9] used artificial neural network to obtain equation in order to predict the greenhouse gases (GHGs) of Turkey using sectoral energy consumption as indicator. The equations obtained were used to determine the future level of the GHG and to take measures to control the share of sectors in total emission. The GHGs involved CO_2, carbon monoxide (CO), sulphur dioxide (SO_2), nitrous dioxide (NO_2) and emissions of non-methane volatile organic compound (E). The GHGs emissions were predicted from 2007 to 2020. Variants of the algorithm used in the study were scaled conjugate gradient and Levenberg-Marquadt (LM). To verify the estimation of the ANN approach, statistical error values such as R_2, root mean square (RMS) and MAPE of training and testing data were evaluated. R_2 values in this study were much higher than other studies and the values were in the acceptable range. Furthermore, the values of error were also small enough. The new formulation dependent on sectoral energy consumption of the output (GHG emissions) as the best algorithm was LM with 8 neurons. In conclusion, the results of this study showed that estimation capability of the ANN was very excellent especially when the test values were not used for training the ANN.

2.2 Grey Model

Pao *et al.,* [10] presented an improved GM model called nonlinear grey bernoulli model (NGBM) in their research. The model was developed to predict three indicators which were: carbon emissions, energy consumption and real output in China. This study collected annual data on energy consumption, CO_2 emissions, energy intensity, carbon intensity and the real GDP. It considered the data for the period between 1980 and 2009After that, the results were compared to the GM and ARIMA. For the purpose of evaluating the out-of-sample forecast capability, the forecasting accuracy is examined by calculating three different evaluation statistics: the root mean square error (RMSE), the mean absolute error (MAE) and the MAPE. The forecasting ability of NGBM with optimal parameter model, namely NGBM-OP has remarkably improved because it obtained robust results in terms of MAPE, RMSE and MAE, when compared with both ARIMA and GM models. The MAPEs of NGBM-OP for out-of-sample from 2004 to 2009 were ranging from 1.10 to 6.26. The prediction results showed that China's compound annual emissions, energy consumption and real GDP growth were set to 4.47%, 0.06% and 6.67%, respectively between 2011 and 2020. Meanwhile, the co-integration results showed that the long-run equilibrium relationship exists among these three indicators and emissions appeared to be real output inelastic and energy consumption elastic. The estimated values also could not support an EKC hypothesis, and real output was significantly negative impact on emissions.

Pau and Tsai [11] applied Grey prediction model (GM) on three variables of CO_2 emissions, energy consumption and real GDP to investigate the dynamic relationships between the variables for Brazil. Data for the period between 1980 and 2007 were considered. The finding of the inverted U-shaped relationships of both emissions-income and energy consumption-income imply that both environmental damage and energy consumption firstly increase with income, then stabilize and eventually stabilize. Meanwhile, the causality results indicate that there was a bidirectional strong causality running between income, energy consumption and emissions. Autoregressive integrated moving average (ARIMA) model also was built in order to compare the forecasting ability of GM model. Both of the models have shown strong forecasting performance with MAPEs of less than 3%.

Lin *et al.,* [12] in their study applied the grey forecasting model to estimate future CO_2 emissions in Taiwan from 2010 until 2012.Variables considered were the CO_2 emissions related to the consumption of energy from coal, petroleum and natural gas in Taiwan. Training data from 2001 to 2006 was used for model fitting and data from 2007 to 2009 was reserved for validation. Then, the GM (1, 1) predicted further increases in CO_2 emissions over the next 3 years. To determine the accuracy of the proposed model, this study used the MAPE comparing the actual value and forecasted value to determine the forecasted error.

The proposed forecasting model yielded plausible prediction values when the MAPE was low. Values of residual error and average residual error also were calculated. The results showed that the average residual error of the GM (1, 1) was below 10%. This model revealed a high degree of prediction validity, presenting a clearly viable means of forecasting CO_2 emissions.

Lu *et al.,* [13] also presented GM model in their study to capture the development trends of the number of motor vehicles, vehicular energy consumption and CO_2 emissions in Taiwan during 2007 to 2025. The measure of transport CO_2 emissions, based on the Intergovernmental Panel on Climate Change (IPCC) guidelines principle was adjusted to Taiwan's fuel inventory that includes fuel density. In this study, the rolling grey prediction model (RGM) was further used to present more recent information of system behaviour and to compare the prediction results with the GM (1, 1) model. The difference between the GM (1, 1) and the rolling grey prediction model is that the rolling model avoids the accumulation of historical values by keeping a constant number of data points and adopting the recent data for model construction. That is, the rolling grey prediction model updates the input sequence in GM (1, 1) by discarding the oldest data point and adding the latest data point at the end of the original sequence for each cycling time. The comparisons between the grey forecast model GM (1, 1) and RGM (1, 1) indicated that the application of a rolling mechanism could not modify the higher growth rate that was forecasted by the GM (1, 1). Also, the results from GM (1, 1) were more consistent with the current transport policy for reducing motor vehicles. Thus, the GM (1, 1) model was adopted to predict the development trends under the different economic growth rate. After that, scenario analysis was made onto the three indicators by using the model built. The researchers also concluded that the grey forecasting model used in this study also can be applicable with modification to other sectors to forecast and analyse CO_2 reduction potential.

2.3 Computer-based Simulation Model

Feng *et al.,* [14] developed a system dynamics based computer simulation model, namely as Beijing-STELLA Model, for estimation and prediction of urban energy consumption trends and CO_2 emissions in for the City of Beijing over 2005 to 2030. In light of the research target and data availability, the structure of Beijing-STELLA Model was designed as a compound of six sub-models, i.e., socioeconomic, agricultural, industrial, service, residential, and transport sub-models. Results showed that the total energy demand in Beijing was predicted to reach 114.30 million tonnes coal equivalent (Mtce) by 2030, while that value in 2005 is 55.99 Mtce, which was 1.04 times higher than the level in 2005. The projected CO_2 emissions were estimated based on the energy demand and the carbon emission factors. Accordingly, the total CO_2 emissions in 2030 will reach 169.67 million tonnes CO_2 equivalent (Mt CO_2-eq), 0.43 times higher than that of 2005. The change of energy structure from carbon rich fuel as coal to low-carbon fuel as natural gas will play a very essential role in carbon emission reduction activities of Beijing. The modelling results also showed that the service sector will gradually replace the industrial dominant status in energy consumption as the largest energy consuming sector, followed by industrial and transport sector. The sensitive analysis suggested that change of economic development mode and control of rational population growth will have a far-reaching influence on energy consumption and on carbon emissions.

Zhao *et al.,* [15] proposed a MapReduce framework for on-road mobile fossil fuel combustion CO_2 emissions estimation. Data of the Intelligent Traffic System (ITS) were collected from Shanghai that from June 1st to June 15th of 2009. They implemented the emission estimation tool suite of their prototype based on Hadoop. The emission estimation system had a three-layer architecture that consisted of infrastructure layer, distributed computing platform and application layer. The application layer contained modules of emission estimation tool suite where they have designed four modules for the emission estimation tool suite: data cleaning module, emission estimation module, cluster analysis module and graphics rendering module. The data cleaning module was responsible to eliminate those ITS records that contained outliers that were used in the retreatment of emission calculation. In emission estimation module, they implemented the estimation model to get the amount of emission. The cluster analysis module organized road sections into groups according to the amount of emissions. Deep analysis can be carried based on the cluster result. Graphics rendering module generated the emission distribution map. The module was implemented in a distributed way to make the rendering fast. From this map, it was clear that the amount of CO_2 emissions were various with the level of the road. Express roads inside the city have higher emissions than normal roads. Emissions of trunk roads around the city are also higher. One of the reasons was that these roads took the responsibility of logistics transportation that connected surrounding urban areas so that the flow of the transport vehicles was heavier than roads inside the urban. By comparing the estimation data with the data published in the annual report, this estimation was higher. In conclusion, the experiment result showed that the system was efficient and suitable for this kind of applications.

Kean *et al.,* [16] developed a System Dynamics based computer simulation model known as FML Model, to forecast city level CO_2 emission trends, based on the case study of Iskandar Development Region (IDR) of Malaysia, in order to promote data accessibility, synthesis and analysis for evaluating emissions, as CO_2 emissions related database in developing countries was generally either unavailable or not yet mature. In this study, a computer programming software known as STELLA was used to construct the System Dynamics model to represent the complicated urban energy consumption and CO_2 emission system. Subsequently, simulation results of energy consumptions and CO_2 emissions for IDR up to 2050 were presented. Energy consumptions were estimated based on GDP values. Other variables that also were considered: vehicle population, travel distance and energy consumption rate. The results showed that, if the current 'Business as Usual' trend of socio-economic development continues to prevail, emissions from IDR was possible to increase to about 44 million tons by 2050, over seven times of 2005 level of 5.6 million tons.

Coelho *et al.*, [17] developed and applied a traffic and emission decision support (TEDS) tool to urban highway corridors. This model simulated traffic while predicting time elapsed, energy consumed, and pollutants emitted to the atmosphere by vehicles on the corridor. This approach yielded a numerical predictive model, based on experimental measurements and concepts of traffic flow theory, which explained the interaction between the system operational variables of each traffic interruption and the environmental and traffic performance variables. In particular, the focus was on carbon monoxide (CO), carbon dioxide (CO_2), nitric oxide (NO), and hydrocarbons (HC) emissions and their relation to queue length and stops. TEDS model was developed in Visual Basic programming language. It was composed of a core module that simulated traffic using a zonal method (where traffic volume and average speed of vehicles were assumed constant within each zone) and several sub modules. The method was applied for two linear access corridors to the city of Lisbon (Portugal), namely Freeway A5 and Highway N6. These corridors were chosen because of their importance in terms of access to Lisbon and because they have different characteristics and encounter different types of traffic interruptions. A detailed statistical analysis (namely by Student's t-tests and residuals analyses) was performed to derive suitable numerical equations that characterize the traffic performance in each traffic interruption. Emissions were estimated based on the concept of Vehicle Specific Power (VSP), a proxy variable for the engine load. In conclusions, as expected, traffic interruptions contributed the greatest percentage of emissions for a vehicle travelling through a corridor, namely due to the final acceleration back to cruise speed and to stop-and-go cycles. In relation to CO_2 emissions (similar to fuel consumption), the pay toll in the segment of Freeway A5 was responsible for more than 20% of overall CO_2 emissions, and other traffic interruptions in the segment of Highway N6 were responsible for more than 50% of CO_2 emissions.

2.4 Tier 1 and Tier 2 Method-Intergovernmental Panel on Climate Change (IPCC) Method

Borgen et al., [18] developed the Intergovernmental Panel on Climate Change (IPCC) methodology, a Tier 2 method for estimating CO_2 emissions from cropland on mineral soils in Norway and the results were compared with those of the default Tier 1 method. A soil C balance model, the introductory carbon balance model (ICBM) was used to calculate country-specific soil organic carbon (SOC) stock change factors for cropland management systems for the Tier 2 method. Climate data, that was, air temperature, precipitation and potential evaporation transpiration (Penman-Monteith equation) for 1980 to 2009, were estimated for 32,000 grid points covering arable land, applying the spatial interpolation approach. Meanwhile, a database holding approximately 600,000 soil samples were used to calculate the distribution of soil textures. Areal statistics for major crop types were collected for 1999 and 2009. Results showed annual CO_2 emissions from cropland management were substantially higher when estimated by the default Tier 1 method (313 Gg CO_2 per year) compared with Tier 2 (149 Gg CO_2 per year). The differences between the results were mainly due to the default Tier 1 stock change factors for crop rotations without manure application, which led to greater CO_2 emissions compared with the ICBM-based factors.

Liao *et al.*, [19] estimated the CO_2 emissions from inland container transport in Taiwan during the period between 1998 and 2008 and predicted the trend of these emissions based on the IPCC Guidelines (Tier-1 IPCC methodology). Then, a regression model with ordinary least squares (OLS) was used to identify the drivers that influence the CO_2 emissions. All analyses were conducted with SPSS 16.0 for Windows. The analyses showed that the CO_2 emissions from inland container transport in 1992 reached 1.03 million tonnes, and the figure drastically increased by 89.3% to 1.95 million tonnes in 2008. Using a multiple regression model, GDP and oil price were found to be the key drivers for CO_2 emissions. The CO_2 mitigation strategies were discussed in the policy suggestions given that Taiwan was warming at twice global average rate.

Olivier and Peters [20] used IPCC Tier 1 reference calculation using IEA/UN data for 1970 to 1995 to estimate CO_2 emissions related to non-energy use (NEU) of fuels as part of the construction of the EDGAR (Emission Database for Global Atmospheric Research) version 3.2 information system. Thus, they also showed the trends of these shares as well as the type of non-energy source (chemical feedstock, industry in general, transport, other sectors) and the fuel type (solid, liquid, gaseous). Their general approach for EDGAR was to estimate emissions per source sector at country level with activity data and so-called emission factors at national level. Emission factors were selected mostly from 'international' publications to ensure a consistent approach across countries. For emissions from fuel combustion they had used the sectoral approach, i.e. sectoral fuel consumption statistics, whereas for the CO_2 from NEU they used the simple (Tier 1) method. For EDGAR 3, production and use data of fossil fuels for 112 countries were taken from the IEA energy statistics for OECD and non-OECD countries. For the countries of the former Soviet Union (SU), they used a modified dataset to achieve a complete time series for the new countries of which the sum converges to the older dataset for the total former SU. For another 71 countries, the aggregated IEA data for the regions 'Other America', 'Other Africa' and 'Other Asia' have been split using the sectoral IEA data per region and total production and consumption figures per country of hard coal, brown coal, gas and oil from UN energy statistics. The share of CO_2 from NEU was increasing over time. Expressed as fraction of total CO_2 emissions from the industry sector, the shares were about 4% in 1970, 7% in 1990 and 12% in 1995 for global total emissions. In most regions chemical feedstock emissions of CO_2 had become increasingly important. The share of CO_2 from feedstocks in total CO_2 from NEU also had increased globally. This large increase was largely responsible for the increasing share of total CO_2 NEU emissions.

2.5 Optimal Growth Model

Hui *et al*., [21] used optimal economic growth model to predict net carbon emissions of Yunnan, China from 2007 to 2050 through energy consumption carbon emissions. Then they used CO2FIX to estimate forest carbon sinks. They studied carbon emissions from all aspects including carbon emissions intensity, the carbon emissions, the declining rate of carbon emissions intensity, and the per capita net carbon emissions. Finally they found that carbon emissions was more than carbon sinks by forests, and the net carbon emissions inevitably increased due to the high-speed development of the economy. Further finding were the percentage of coal energy structure of Yunnan decreased year by year, while oil, natural gas and non-carbon energy were rising slowly but non-carbon increase relatively faster among the three. Energy structure of Yunnan will reach to a steady state in 2042. Meanwhile, under all effects of various factors, carbon emissions of energy consumption peak at 2035 and similarly to net carbon emissions of Yunnan peak at 2035.

Huang and Wang [22] adopted the optimal growth model proposed by Yongbin and Zheng [23] to investigate Shanghai's energy consumption and carbon emissions. In allusion to urban problems, the author used the Logistic curve to approach urban population growth rate and employed Nonlinear Economic Dynamics to predict Shanghai's economic growth rate before 2050. In this paper the researcher first calculated the rate of economic growth of Shanghai under the circumstance of stable economy development, and obtained the GDP and energy consumption of different years. Then according to the energy structure and the coefficients of the sub-energy carbon emissions in the next few years, the researchers could get the carbon emissions of each year before 2050 in Shanghai. Economic variables such as GDP, energy consumption and labour force from 1998 to 2005 were used as sample data. The results showed that Shanghai's energy consumption and carbon emission increased in the curve of inversed "U". The peak of energy consumption and carbon emissions will be in 2040. The value of reaching peak in Shanghai was a little bigger than other provinces relatively, reflecting that reducing CO_2 in Shanghai still has a long way to go.

Huang et al., [24] again discussed the method of urban carbon emissions prediction in this paper. Using Yongbin and Zheng's optimal growth model [23], to study the energy carbon emissions of cities under steady economic growth and getting forest carbon sinks of cities with CO2FIX model, they could get the result in net carbon emissions of cities. In this paper, the labour force, demographic data and gross output, and data for energy consumption were considered for the period between 1995 and 2005. The results showed that in Beijing, Tianjin and Shanghai, net carbon emissions presented inverted U-curve of growth, but were not very different from the situation when they did not consider forest carbon sinks. Scenarios showed that speeding up technological progress in Beijing and Shanghai to reduce energy carbon emissions had no significant effect, but in Tianjin it had an obvious effect.

2.6 Linear Regression

Murad *et al.,* [25] used ordinary least squares methods to estimate parameters in three linear regression models involved in the research. The purposes of the paper were actually to identify and analyse the link between climate change and agricultural growth in Malaysia, and pursue three sub-objectives: to determine and analyse the link between agricultural growth rate and climate change score; to determine and analyse the link between per capita CO_2 emissions and agricultural production index; and to determine and analyse the link between per capita agricultural production index and per capita CO_2 emissions. The data for agricultural growth rate and climate change score for Malaysia were found to be available only for the four recent years from 2006 to 2009. The data for other variables such as per capita agricultural production index and per capita CO_2 emissions have been standardized covering the period from 1990 to 2004. Findings of the research revealed three important observations for Malaysia: the link between agricultural growth rate and climate change score was proven to be negative, but insignificant; the link between per capita CO_2 emissions and agricultural production index was found to be direct and highly significant; and the link between per capita agricultural production index and per capita CO_2 emissions was proven to be positive and highly significant. Also, an increasing level of per capita CO_2 emissions in the country was proven to have both detrimental and beneficial effects on its agricultural growth.

2.7 Trend Analysis and Linear Regression

Kone and Buke [26] employed regression analyses to forecast energy-related CO_2 emissions. Trend analysis approach was used for its modelling. To this aim first, trends in CO_2 emissions for the top-25 countries and the world total CO_2 emissions during 1971 to 2007 were identified. These data were regressed for against the year using a least squares technique. On developing the regression analyses, the regression analyses with R_2 values less than 0.94 showing insignificant influence in statistical tests have been discarded. Statistically significant trends were indicated in eleven countries namely, India, South Korea, Islamic Republic of Iran, Mexico, Australia, Indonesia, Saudi Arabia, Brazil, South Africa, Taiwan, Turkey and the world total. Therefore those eleven countries and world total CO_2 emissions were projected. The CO_2 emissions for eleven countries and world total CO_2 emissions correlation versus the year (Y) was obtained from modelling with the fit coefficients and R_2 values for each fitting. All the regression analysis has been carried out using EViews 5.0 package. The results obtained from the analyses showed that the models for those countries can be used for CO_2 emission projections into the future planning. The calculated results for CO_2 emissions from fitted curves had been compared with the projected CO_2 emissions given in International Energy Outlook 2009 of U.S. Department of Energy calculated from ''high economic growth case scenario'', ''reference case scenario'' and ''low economic growth case scenario'' respectively. Agreements between calculated results and the projected CO_2 emissions from different scenarios were in the acceptable range.

2.8 Fuel Analysis and Direct Measurement

Jakhrani *et al*., [27] had carried out a fuel analysis to estimate the amount of carbon footprints emitted from diesel generators in terms of CO_2. A constant load demand of with six hours of operation of a diesel generator per day was selected for this analysis. The researchers believed that the best way to calculate the CO_2 emissions was based on the amount of fuel consumption by diesel generator. The fuel consumption rate and carbon footprints in terms of CO_2 were determined. According to the researchers, the best way to calculate the carbon dioxide emissions is based on the amount of fuel consumption by diesel generator. The consumption of one litre diesel emits around 2.7 kg of CO_2. Carbon footprints can also be expressed in kg carbon rather than kg carbon dioxide. It can be converted from kg carbon to kg carbon dioxide by multiplying with a factor. The rated power capacity of diesel generators was changed for comparative results. The reported ranges of emission factor from diesel generators were found in literature from 2.4 to 3.5 kgCO_2/litre of diesel fuel consumption. Therefore, the emission factor of 3.0kgCO_2/litre was considered for this study. However, the influence of various emission factors and rated power capacities of diesel generator on emission of carbon footprints were also determined. It was discovered that emission of carbon footprints increased by five folds as emission factor was increased. Similarly, the increment of a single rated power diesel generator at a constant emission factor had increased the carbon footprint emissions. It was revealed that the efficiency of diesel generator is inversely proportional to its rated power, fuel consumption rate and CO_2 emissions.

Kahforoushan *et al.,* [28] used a fuel analysis as well as direct measurements to estimate CO_2 emission factors for main combustion sources including gas turbines, boilers, and gas flares in an Iranian oil and gas processing plant. The researchers believed that CO_2 emission factors varied significantly with the quality of fuels and operation conditions. Besides, the fuel analysis method was based on mass balance principle. The selected plant processed both sour gas with high H2S content and sweet gas separately. The main combustion sources in the plant were gas turbines, boilers, and flares. To analyse flared gases, some samples from all types of flares in the plant were taken and analysed by Chrompack CP9000 model gas chromatography. To consider any change in fuel composition, fuel analysis was performed monthly over a six-month period and average values of data were considered as average composition of fuel. For CO_2 emission measurement in gas turbines and boilers, a LANCOM III model flue gas analyser was used. This analyser used an infrared sensor in order to measure CO_2 concentration measurement with accuracy of 0.5% Vol. Considering the similarity of sources, a random sample device was selected from each kind of combustion source. Ten tests at five different times during six months were performed for sources. In conclusion, the gas turbine CO_2 emission factors estimated in this study had good agreement with the values reported by Environmental Protection Agency (EPA) and Canadian Association of Petroleum Producers (CAPP). Nevertheless, it seemed that published emission factors were not the preferred approach, because these emission factors were developed using the average of all available data. So, fuel-specific analyses based on direct measured CO_2 emission factors were more reliable than published average emission factors.

2.9 Travel Survey Information

Mathez *et al.,* [29] conducted a travel survey in order to estimate CO_2 emissions generated by individuals commuting to McGill's downtown campus. Mode split, travel distance, age, gender and job category were uncovered by a 2011 travel survey that we conducted across the University, from which daily individual GHG emissions were estimate. A large-scale online survey was conducted through the month of March, 2011. The target population of the survey included McGill students, staff, and faculty, with the goal of capturing representative data for all types of statuses/job categories. Emission factors for GHGs were generated for each travel mode in grams of CO_2eq per kilometre per passenger depending on speed and vehicle type. The survey revealed lower emissions in the Fall, mostly due to an increase in active transportation. Suburban commuters showed the most stable emissions over the two seasons due to their lower predisposition to switch transport mode. Faculty and staff were found to be responsible for significantly higher per person emissions than students. Transit emissions were lowest but emissions from park-and-ride trips were much higher indicating that savings in emissions achieved by taking transit can be quickly offset when driving (especially single occupancy vehicle) becomes part of the trip chain.

2.10 Multiple Linear Regression and EPA's NONROAD

Hajji and Lewis [30] developed a tool by combining the multiple linear regressions (MLR) approach with the EPA's NONROAD model that can be used to estimate the production rate, activity duration, total fuel use, and total pollutants emissions from earthwork activities. The excavator data was selected to build the productivity model, and emission factors of all type of pollutants from NONROAD model were used to estimate the total fuel use and emissions. The MLR was used to estimate model for the productivity rate. Since the model was proven accurate and precise, the result of this research was good to be used as a benchmark for estimating the fuel use and emissions from a certain type of heavy duty diesel (HDD) equipment performing earthwork activities. The productivity rate from this model was used with fuel use rate and emission factors from EPA's NONROAD model to estimate the total fuel use and total emissions of NOx, PM, HC, CO, and CO_2 from excavator. Based on the methodology presented in this paper, the results revealed several trends related to fuel use and emissions of the excavator. To compare the results from the model with the actual fuel use and emissions from in-use excavators, the field data were collected by using portable emissions measurement system (PEMS). Results indicated that the excavator productivity model had high precision and accuracy, low bias, with trench depth and bucket size were in the model, it can explained 92% variability of productivity rate data, and can be used as the basis for estimating the fuel quantities that will be required and the total expected pollutant emissions for the project

2.11 Panel Data

Du *et al.*, [31] estimated the driving forces, emission trends and reduction potential of China's CO_2 emissions based on a provincial panel data set covering the years 1995 to 2009. A series of static and dynamic panel data models were estimated, and then an optimal forecasting model selected by out-of-sample criteria was used to forecast the emission trend and reduction potential up to 2020. Estimation of CO_2 emissions was done for 29 provinces of China. Estimation was from both fossil fuel burning and cement production. Furthermore, for the burning of fossil fuel, coal, coke, petroleum (further divided into gasoline, kerosene, diesel and fuel oil) and natural gas were considered. The estimation results showed that economic development, technology progress and industry structure are the most important factors affecting China's CO_2 emissions, while the impacts of energy consumption structure, trade openness and urbanization level were negligible. The inverted U-shaped relationship between per capita CO_2 emissions and economic development level was not strongly supported by the estimation results. The impact of capital adjustment speed was significant. Scenario simulations further showed that per capita and aggregate CO_2 emissions of China will increase continuously up to 2020 under any of the three scenarios developed in this study, but the reduction potential was large.

2.12 Logistic Function

Meng and Niu [32] used the logistic function to simulate the S-shaped curve and to improve the goodness of fit CO_2 emissions from fossil fuel combustion in China. In this study, the values of CO_2 emissions from the following industries were included: agriculture, forestry, animal husbandry, fishery, and water conservancy; industry; construction; transport, storage and post; wholesale and retail trades, hotels, and catering services; others from 1999 to 2008. Parametric estimation methods of the logistic equation were investigated and further adopted to model the curve of CO_2 emission from fossil fuel combustion. Three algorithms were provided to estimate its parameters where three equations were derived and the equation with optimum goodness of fit was selected. Considering the different emission characteristics of different industries, the three algorithms estimated the parameters of CO_2 emission in each industry separately. The most suitable parameters for each industry were selected based on the criterion of MAPE. With the combined simulation values of the selected models, the estimate of total CO_2 emission from fossil fuel combustion was obtained. The empirical analysis of China shows that the method was better than the linear model in terms of goodness of fit and simulation risk.

2.13 Carbon dynamic model and IPCC Cement Model

Liu *et al*., [33] employed the carbon dynamic model and IPCC cement model to estimate the amount of carbon emitted by energy and cement, and used CO2FIX model to predict the forest carbon sinks in Beijing, Tianjin and Hebei Province from 2009 to 2050. Gross domestic product and capital stock in this research were all converted to fixed price of 2000. Besides that, energy data for 1980 to 2008 also had been considered. Then, they analysed the influential factors and the contribution of forest carbon sinks to carbon emissions reduction. They calculated the amount of net carbon emission of these three provinces in two parts. The first part was calculating the carbon emissions from different carbon sources. The second part was calculating the forest carbon sinks which mainly combine the model of CO2FIX to estimate the carbon sinks of the Beijing, Tianjin and Hebei province, and it can offset a part of carbon emissions. Since they needed to estimate economic growth and energy consumption, they used the optimal economic growth rate model that had been proposed by Yongbin Zhu and Zheng Wang which contains energy intensity. The main conclusions were as follows: taking forest carbon sinks into account, the carbon emissions of the three regions all show increase firstly, then, decrease, and the forest carbon sinks have no significant effect on carbon emissions reduction; the peak years of carbon emissions of Beijing and Tianjin were very close, which were 2029 and 2030 respectively, however, the peak year of Hebei Province was 2039; the forest carbon sinks was decreasing in Beijing and Tianjin, the opposite situation occurred in Hebei province as well

2.14 Dispersion Model – GIS Aided

Yousefi-Sahzabi *et al*., [34] used dispersion model in order to develop prediction modelling of CO_2 dispersion in the surrounding atmosphere from a planned 50 MWe geothermal power plant prior to its production. The dispersion model was described as a set of mathematical equations that attempt to simulate (model) the transport, diffusion, chemical transformation, physical interactions, and removal of pollutants in the atmosphere. The dispersion type for gases and their average removal rate depends on the meteorological conditions such as wind direction, wind speed, precipitation, atmospheric stability, and surface roughness and topography. After optimization of the dispersion model, applying Geographic Information System (GIS) for quality visualization of the model outputs was the second step. GIS capabilities were used for quality visualization of the model outputs and presenting an accurate numerical copy of the study area in the northwest (NW) Sabalan geothermal field. It is located in the northwest Iran. For this study the results of the evaluations also indicated that all the predicted concentration of CO_2 was within the standard level criteria and no further analysis was necessary. Therefore like in many other geothermal energy projects, CO_2 emission is not expected to have any environmental impact on the study area apart from those associated with its accumulation in the atmosphere. However a comparison between the amounts of CO_2 emissions from geothermal power plants and conventional fossil fuel power plants revealed the significant differences between them and confirms geothermal energy as a clean energy sources for environmental impact reduction and climate change mitigation. The results by the prediction model showed that the natural transfer of CO_2 will be from the power plant toward east and northeast and CO_2 concentration trends after the power plant utilization will be similar to the background conditions with minor changes.

2.15 Pinch Analysis

Jia *et al*., [35] presented graphical and algebraic carbon emissions pinch analysis method for regional CO_2 emissions forecasting and decision-making based on pinch analysis. Pinch analysis approach is a preliminary energy planning tool which is demonstrated with a case study. A case study of chemical industrial park was presented to illustrate the proposed method. According to its location and the existing industry distribution, this park will be rebuilt and expended in order to realize the transition of industrial ecology. It was mainly divided into four parts as follows: ecological restoration and pollution control region (Region 1), ecological supporting region (Region 2), ecological industry expansion region (Region 3) and ecological industry transition region (Region 4). Based on the overall regional planning, regional energy allocation scheme will be changed with the limited CO_2 emissions. The data for a chemical industrial park was collected. Using cumulative CO_2 emissions- cumulative energy composite curves, energy demand and CO_2 emissions were targeted. In conclusion, the proposed energy planning scheme has a 29.7% reduction of CO_2 emissions.

2.16 "Top-Down" Method

Wei and Zhao [36] presented the development of the CO_2 emission inventory of Wanzhou shipping in Chongqing municipality, China by using "top-down" method. The method contained two main parameters, which were fuel consumption and emission factors. According to the researchers, there were two typical approaches in developing a ship emissions inventory: "bottom-up" and "top-down". When "bottom-up" method is used, ships are classified by their type, size, engine type, engine load, engine power and fuel consumption, each group of ship is matched with special emission factor and fuel consumption factor. The "bottom-up" method is better when accurate, transparent and stable data are available. Even though the "bottom-up" method seems more accurate when precise activity data is available, the emissions inventory shows more transparent and comparable if we use "top-down" method, when basic activity data, such as information on engine, ship category and operation hours, are lacked. Hence, this paper had chosen the 'top-down" method. The researchers also used the recommendation from The Revised 1996 IPCC Guidelines for National Greenhouse Gas Inventories that emissions from navigation be estimated by multiplying the amount of fuel consumed by an appropriate emissions factor. The results showed that CO_2 emissions of Wanzhou shipping were fluctuating with little change. At the same time, passenger and cargo turnover of Wanzhou shipping increased rapidly from 2003 to 2008, it implied the reduction of CO_2

emission per unit turnover volume in recent years. Based on the development plan of Wanzhou shipping, the researchers forecasted the CO_2 emission in 2011, 2015, 2020 under the two situations (baseline scenario and new policy scenario). There was an effective emission reduction under new policy scenario, compared with the baseline scenario where it can reduce CO_2 emissions only in 2020.

2.17 Measuring Means, Statistical Method and Mathematical Model

Wu and Zhang [37] used one-by-one calculation method to sum the carbon emissions in Jinan City, China. According to the researchers, there were three main estimation methods of carbon emissions from energy consumption. The first method was measuring mean of emissions; the second was statistical method that estimated carbon emissions through gathering statistics date of fuel consumption, emission characteristics and proliferation. The third was mathematical model method. According to the summation method, the researchers calculated the carbon emissions from energy consumption every year in Jinan from 1990 to 2008. Variable chosen were carbon emissions from final energy consumption, carbon emissions from final energy consumption plus parts of loss of energy conversion (input-output). Carbon emissions from total energy consumption also were used in the study. This study used final energy consumption (excluding heating and electricity) plus energy consumption for the production of heat and electricity to calculate energy consumption of carbon emissions, ignoring the energy loss of transport, transmission and distribution. Then the total carbon emissions, carbon emissions per capita, carbon emission intensity and sub-sectors carbon emissions were compared respectively. In conclusion, carbon emissions from energy consumption were bigger than economic weight and the proportion of the total population in Jinan. Meanwhile, carbon emissions per person in Jinan was high but carbon productivity was low and carbon emissions intensity continues to decline in Jinan

2.17Adaptive Neuro-Fuzzy Intelligent System

Rodrigues *et al*., [38] proposed a Neuro-Fuzzy Intelligent System – ANFIS (Adaptive Network based Fuzzy Inference System) for the annual forecast of greenhouse gases emissions (GHG) into the atmosphere. The purpose of this work was to apply a Neuro-Fuzzy System for annual GHG forecasting based on existing emissions data including the last 37 years in Brazil. Such emissions concern tCO_2 (tons of carbon dioxide) resulting from fossil fuels consumption for energetic purposes, as well as those related to changes in the use of land, obtained from deforestation indexes. Economical and population growth index had been considered too. The system modelling took into account the definition of the input parameters for the forecasting of the GHG measured in terms of tons of CO_2. Three input variables had been used to estimate the total CO_2 one year ahead emissions. The results indicated the Neural-Fuzzy System produces consistent estimates validated by actual test data.

2.18 Statistical Methods

Saimolov *et al*., [39] had carried out a statistical method of estimation and medium-term forecasting of greenhouse gas emission in Russia. Estimation of the annual anthropogenic GHG emission and its prognostic estimation for the period from 1 to 3 years under Russian conditions were considered in this work. The emission estimated for the period between 1998 and 2004 based on the regression model using as GDP predictors and some sectorial indicators, and prognostic series for the period beyond 2004also computed by using the regression model. In conclusion, availability of quite significant and stable statistical relationships between GHG emission and several indicators of the country economy allowed operational estimation and forecasting of GHG emission in the economy of the Russian Federation with a lead time out to several years. It was possible to estimate and predict both the total emission of all GHG in terms of the CO_2-equivalent and individual GHG emission in different economy sectors. Both macroeconomic and branch indicators of economy development can be used as predictors, when building regression models for forecasting.

2.19 Non-energy Use Emission Accounting Tables Model

Martin *et al*., [40] presented a simple bottom–up model by developing a simplified version of the detailed Non-energy Use Emission Accounting Tables model (NEAT-SIMP) for estimating non-energy use of fossil fuels and resulting CO_2 emissions. They applied this model for the year 2000: (1) to the world as a whole, (2) to the aggregate of Annex I countries and non-Annex I countries, and (3) to the ten non-Annex I countries with the highest consumption of fossil fuels for non-energy purposes. The researchers found that worldwide non-energy use was equivalent to 1,670 ± 120 Mt (megatonnes) CO_2 and leads to 700 ± 90 Mt CO_2 emissions. Around 75% of non-energy use emissions were related to industrial processes. The remainder was attributed to the emission source categories of solvent and other product use, agriculture, and waste. Annex I countries account for 51% and non-Annex I countries for 49% of worldwide non-energy use emissions. Among non-Annex I countries, China was by far the largest emitter of non-energy use emissions. Despite existing model uncertainties, they recommended NEAT-SIMP to inventory experts for preparing correct and complete non-energy use emission estimates for any country in the world.

2.20 Scenario Analysis

Wang *et al*., [41] used three designed scenarios: high-emission, medium-emission and low-emission scenarios to forecast energy-related CO_2 emission of China in future. It had done based on the projection of primary energy demand of China. In order to analyse the factors impacting energy-related CO_2 emissions, five indicators (primary energy consumption intensity, proportion of coal in primary energy consumption, energy-related CO_2 emission intensity, GDP per capita and urbanization level) were extracted based on what mentioned above, to make Pearson correlation analysis according to the historical data of more than 50 countries. Correlation analysis showed that there exist remarkable correlation between energy-related CO_2 emission intensity and primary energy consumption intensity. Finally they found that according to the forecasted results, average annual growth rate of energy-related CO_2 emissions under high, medium and low emission scenarios in 2005 to 2025 were 3.5%, 2.7% and 2.5% respectively. Energy-related CO_2 emission intensity was still higher than that of developed countries, but decreased respectively compared with that of 2005. Average annual growth rate of energy-related CO_2 emissions per capita was lower than historical level of 1990 to 2005, energy-related CO_2 emissions and per capita in 2025 were still far below the current level of developed countries.

2.21 Statistical Data, Remote Sensing and GIS-based approach

Dang *et al*., [42] had carried out an investigation of estimating CO_2 emissions in Beijing city by using socio-economical statistical data, remote sensing and GIS-based approach. The main variables included transport, cement production, human respiration, carbon assimilation of green space and cropland. The vehicle density was determined by combining the remote sensing images from Google-Earth with road map and statistical data. The human respiration was estimated from census data and allocated to different districts. In order to estimate the impact of land use/land cover change on carbon absorption, the researcher first extracted the green space and cropland from Landsat TM data in 1992 and 2005 by using maximum likelihood method. The annual carbon assimilation of green space and cropland was estimated finally according to the carbon flux observation in green space, where mathematical equations were used by the researchers. However, simulated results for cropland gained by using Biome-BGC model. The results showed that the vehicles and industry contributed most in Beijing city. The total CO_2 emission had increased from 1992 to 2005. The increased of green space can partly compensate the decrease of cropland caused by urbanization at a certain extent.

2.22 Mathematical Model

Li and Wang [43] developed a simulation model on a synthesis of substrate combined Contois function with kinetics and the mass balance to predict ammonia and carbon dioxide emissions in simulated food waste composting processes. The objective of their study was to develop a mathematical model for the carbon dioxide and ammonia diversion from the thermophilic composting of food waste, considering biochemical, energy and mass balance. To verify the developed model, a series of composting experiments were undertaken. In this study, the simulated food waste mixture included potatoes, rice, carrot, leaves, pork meat, soybean, and seed soil. The materials were minced into pieces of less than 5 mm in diameter using a food processor and mixed well before the composting reactions. When the simulated food waste mixture was added into the reactor, the original sample was taken immediately and the composting reaction was assumed to start, and the reaction time was remarked as zero simultaneously. Oxygen, pH, water content, total carbon and the population of microorganisms in the exhaust gas was measured during the composting process. The Runge-Kutta algorithm is employed to numerically solve the model, since it is difficult to get analytical solutions. The model was implemented in MATLAB. The model shows better agreement with experimental result for soluble substrate concentration (S), in which the average relative error was 7.09%, and the average relative error of NH3-N concentration was 17.00%. But the ammonia loss rate of the model is not in accordance with the experiment and needs to be further improved.

2.23 Multiple Linear Regression and IPCC Method

Say and Yucel [44] developed a model that estimated the total energy consumption (TEC) based on GNP and country population (CP) by using multiple linear regression analysis in Turkey. TEC was predicted based on 6.7% annual increase in GNP, which was targeted in the last development plan. The annual data for the years from 1970 to 2002 were used in the analysis. Then, the relationship between the energy consumption and the total CO_2 (TCO_2) was modelled by using simple regression analysis. The linear regression analysis was performed in SPSS software. Also, the TCO_2 was calculated from intergovernmental panel on climate change (IPCC) method and the two results were compared. In the IPCC method, the TCO_2 was calculated by using the FC data and the properties of the fuel used in the energy production. When the predicted TCO_2 values obtained from the two methods were compared, it was seen that the values predicted by IPCC method were noticeably higher. Even though, IPCC is accepted worldwide for the calculation of the greenhouse emissions is the IPCC method, but in Turkey, the prediction of these values seen to be higher than the actual ones due to political and economical reasons.

2.24 Multiple Linear Regression and Neural Networks

Ionescu and Candau [45] performed multiple linear regression (MLR) to predict CO_2 and NO_2 released in the process of reheating furnace in the iron and steel industry. Furthermore, they also built artificial neural network (NN) for the same purposes. It focused on the development of a correlation method in the case of a real installation of the French iron and steel industry. RMSE values were calculated to find the accuracy of the modelling. It appeared that CO_2 can be satisfactorily estimated by a linear regression. Meanwhile the NO_2 appeared to have problem with this model. Hence, NO_2 emission modelling required a non-linear model. After that, neural network modelling was carried out for CO_2 and NO_2 emission. For CO_2, the results obtained by MLR were already comparable to the measurement error. In order to improve CO_2 estimation, a NN model was tested; the NN architecture that gave the best results for NO_2 was employed. Results showed that the difference from MLR to NN corresponds to a part of non-linearity in the CO_2 variation. The researchers had discussed that in the condition, the NN modelling can be considered a reliable correlation method as well for NO_2 and for CO_2. Moreover, in the case of CO_2, a simple linear model gave less efficient results than the neural networks (5.6%), but was still comparable to the measurement error

2.25 Generated Coal Analyses

Sakulpitakphon *et al*., [46] used previously generated coal analyses from the University of Kentucky Center for Applied Energy Research (CAER) coal quality database to estimate the CO_2 emissions from maceral concentrates from Kentucky and Illinois high volatile bituminous coals. A large collection of well-characterized coals, were documented in the CAER's database. The data showed no correlation between CO_2 versus coal ranks and between CO_2 versus maceral content. Subsequently, eight sets of low-ash density-gradient centrifugation (DGC) maceral concentrates from five coal beds were examined, spanning in the high volatile rank range. Heating value was not determined on the concentrates, but instead was calculated using the Mott–Spooner formula. There was a good correlation between predicted CO_2 and maceral content for the individual iso-rank (based on vitrinite reflectance, analysed on whole (parent) coal) sets. In general, the predicted CO_2 increased from liptinite-rich through vitrinite-rich to inertinite-rich concentrates.

3.0 OBSERVATION

In this paper, 42 journal articles, which appeared in the period from 2003 to 2013, forecasting the CO_2 emissions using different methods were collected. The methods, their applications and emissions factors have been discussed in the previous section. Some observations, based on these journal articles were made in the following subsections.

3.1 The Most Popular Method

The first objective of this survey is to analyses the most popular method adopted in forecasting, predicting and estimating CO_2 emissions. As explained in the previous sections, the NN method was the most popular method. It accounted 14.29% from overall of the journal articles (see Figure 1).It was followed by GM, computer based simulation model, Tier 1 & 2 method based on IPCC model, optimal growth model, fuel analysis and others method(linear regression, trend analysis, travel survey information, multiple linear regression, panel data, logistic function, carbon dynamic and IPCC cement, dispersion, pinch analysis, "Top-down" method, measuring means, statistical method and mathematical model, ANFIS, non-energy use emission accounting tables model, scenario analysis, generated coal analyses).

NN and GM have attracted more attention mainly because of its robustness. The methods are actually types of artificial intelligence (AI) method, which the AIs are very well known as reliable methods to do forecasting, predicting as well as estimating. The NN is also well known with its variety of algorithms where in this paper, the RBFNN [8], back propagation, optimize layer-by-layer and RBFNN [6], conjugate gradient and LM algorithm [9] and so on were considered. Meanwhile, GM also well known as a superiority to conventional statistical method where it needs less data in any analysis rather than other methods which will make it easier to researchers. ANFIS which is a type of AI has been used by a researcher [38], in order to investigate the emissions.

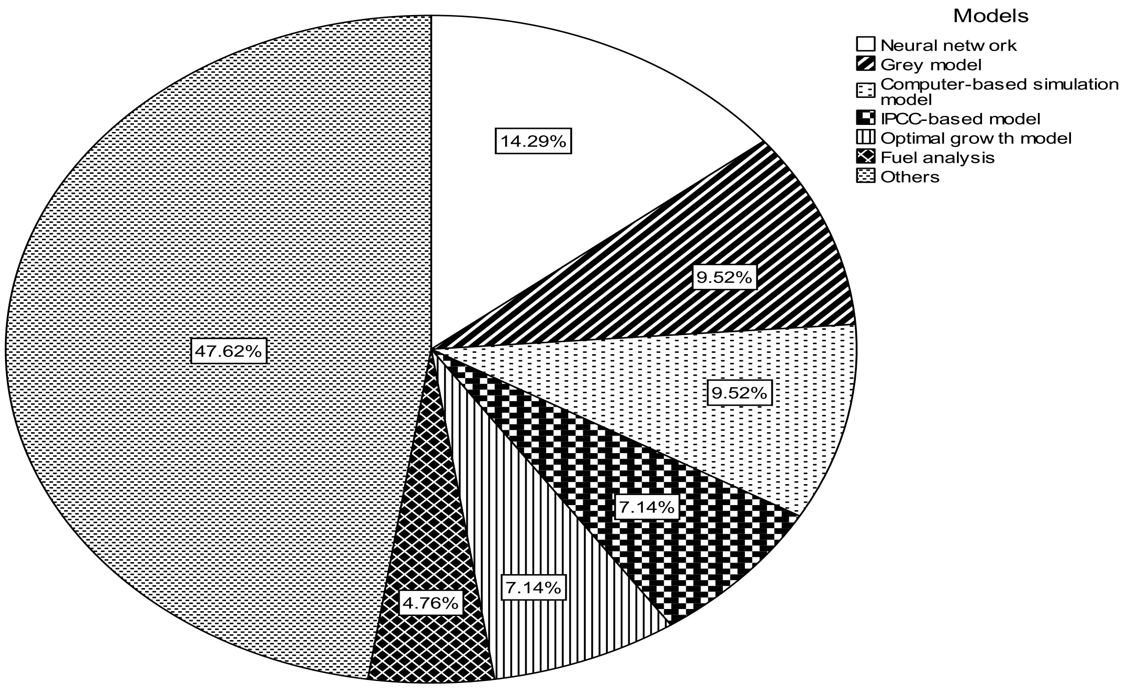


Figure 1 Percentage of articles and discussed model

Besides that, there are many others methods used in this area depending on various kind of factors investigated. For example, dispersion model with GIS aided used to predict CO_2 emissions from geothermal power plant and a computer based simulation model named MapReduce used to estimate on-road mobile fossil fuel combustion CO_2 emissions. Other than that, fuel analysis used to estimate CO_2 emissions from diesel generators and mathematical model was used to predict CO_2 emissions from food composition. Furthermore, generated coal analyses were used in order to estimate CO_2 emissions from two kinds of coal and so on.

3.2 The Most Popular Emission Factors

The second objective of this review is to discover the most popular emission factors considered by the researchers to produce a reliable and robust forecasting result. Many factors were considered and discussed in the Section 2. There are about forty different factors and each paper discussed at least one or more of the factors. The most popular factor is energy consumption by many sectors, followed by GDP, fuel combustion and many other emission factors especially from socio-economical factor or demographic factor.

Energy consumption accounted for 17 articles from the overall of journal articles. Many researchers had carried out investigations between CO_2 emissions and energy consumption in various forms as they believed that the energy consumed by various sectors will contribute to a significant effect on our environment. Besides that, GDP also has been a concern in this field. There are 11 articles which discussed about the emission factor. Most of the researchers and policy makers considered this factor as it can be a benchmark to development of one's country. Furthermore, the development of any country will increase the energy consumption of the country respectively. The third most popular is fuel combustion (9 articles) especially from fossil fuel. This is because fossil fuel combustions have been known to contribute a significant increase in greenhouse gases. However the fossil fuels are actually the main source of energy consumption in this world. Hence, researchers and policy makers always attracted to investigate the factor related with CO_2 emissions in order to find good solutions and make up effective environmental policy.

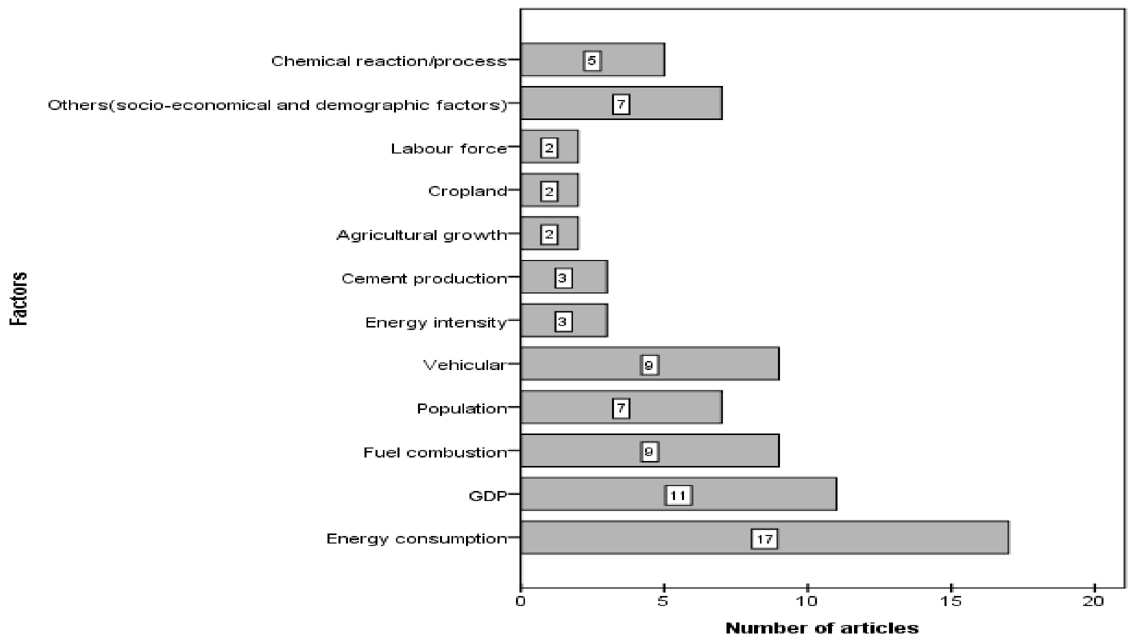


Figure 2 Number of articles and emissions factors

Other socio-economic and demographic factors that also been considered were population (7 articles), vehicular (9 articles), energy intensity (3 articles), cement production (3 articles), agricultural growth (2 articles), cropland (2 articles) and labour force(2 articles). Furthermore, there were other factors such as carbon intensity, human respiration, capital stock, oil trade movement, investment in fixed asset, export and climate change. Besides that, based on the observation, there were also another emission factors considered that were caused from chemical reaction, for example emissions from the process of food composition, emissions from geothermal power plant, reaction of chemical from a chemical park, emissions from the selected type of coal and also emissions from the process of reheating furnace in the iron and steel industry. Figure 2 depicts the number of articles which had discussed the emissions factors respectively

4.0 FUTURE WORK

Based on the observations, there are many types of methods that have been used by researchers. However, the most appealing and able to catch researchers' attention is AI based- methods. NN and GM attracted numbers of researcher to apply it in this field. It is suggested that in order to build a more robust method, the AI methods could be improved or extended by integrating the methods with other new mathematical approaches such as interval type-2 fuzzy sets. This suggestion is based on the assumptions that the type-1 fuzzy set was successfully integrated with most of the AI methods. Recently, the development of the AI systems that include special toolkit, can be easily implemented by users even without great exposure of programming language. Type-2 fuzzy logic system is one of the new developments in AI system. The type-2 fuzzy logic system is an extension of type-1 fuzzy logic model. New exploration of the type-2 fuzzy logic system might include new algorithm to tune parameters in the model, additional membership functions such as Z-shape or S-shape function, or new proposal regarding method for type-reduction or defuzzification in designing type-2 fuzzy logic system. In addition, there are still lacks of researches that tend to test integrated model of type-2 fuzzy logic systems. Further research could be emphasized with an integration model such as type-2 fuzzy logic system and grey model. Implementation of the new emerging models may open a research direction for CO_2 emissions forecasting.

For the case of NN, however, one of the major drawback is the issue of number of data provided. The neural networks method required a training phase where a set of training data is used to develop the model. In order to build a robust model, the practitioners need to provide a large number of data to training phase. It can be seen that most of the authors provide the data for a period ten to twenty years only. For example, Radojevic *et al*., [4] simulated the NN model based on only eight years data (from 1999 to 2007). The other researchers also provide their data in the same range of period [5, 8]. Liu *et al*., [5] considered their data for a quite long period compared to the others. The data was for twenty-seven years (from 1980 to 2006). However the authors stated that the data was randomly divided: 60% of the data was used for training, 20% for cross validation and the rest were for testing phase. One of the normal issues regarding the division of data "is the data adequately enough for an optimum training phase and cross validation?" The issue of dividing data into training and testing is indeed an ending debate and still open for validation.

Further research for modelling CO_2 emissions could be further explored in an effort to find the most appropriate model for the forecasting. In line with development of computational intelligence domain, computer-based programming method may attract many researchers. However, the method that needs expertise in computer programming knowledge could hinder researchers into this venture especially those who has lack of computer-based programming knowledge. It also seems incomplete if the number of factors contributed towards CO_2 emissions left unattended for future research. The research may include number of unpopular factors such as deforestation, vegetation and climate change. These new factors normally exist in tandem with the current trend of industrialization. Combinations of multiple reliable factors and robust model could provide a promising alternative tool besides conventional statistical forecasting method.

5.0 CONCLUSION

The survey in this paper has been narrowed into several limitations. The authors are agreed to analyse the forecasting trend based on journals and conference proceedings that are collected from selected popular academic databases. There are many issues regarding to the CO_2 emissions worldwide. However, this paper only restricted its discussion on how the emissions were forecasted which is means to investigate what methods has been drawn the attention of researchers. Besides, the authors also were trying to evaluate what are the most influential factors contribute to CO_2 emissions. Additionally, the survey of the related literatures was carried out by choosing the literatures from 2003 to 2013. The ten years period were chosen as to make sure the methods in our findings are relatively relevant with our current development.

Based on our predetermined scope, first, it was discovered that numerous methods were used to forecast CO_2 emissions. They are capable of handling various kinds of emitter of CO_2 emissions. It is either to find the relationship between CO_2 emissions and the emissions factors or to find the most effective ways towards its reduction. The most prevalent method is the artificial intelligence of neural networks followed by grey model. Due to development of soft computing, artificial intelligence methods have attracted most of the researchers compared to conventional statistical method. It is a heavy task to the authors to classify the method based on individual methods or integrated methods since there are too many methods that were integrated and 'overlapped' with each other.

Second, it is observed that energy consumption is the most popular emission factor in CO_2 emissions investigation followed by gross domestic product (GDP), fuel combustion especially by fossil fuels and so on. This finding is consistent with the connotation that socio-economic factors are the main factors of the CO_2 emissions. Besides of the methods discussed, some recommendations were made based on the observations of the methods and the emission factors. This will definitely aids the researchers and policy makers in solving the environmental problem effectively.

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