Assessing the Energy Efficiency of Industrial Sector: Artificial Intelligence Approach

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Abstract

This paper uses Index Decomposition Analysis (IDA) and Artificial Neural Network (ANN) to investigate the efficient use of energy consumption in the Canadian industrial sector between 1990 and 2000. First, the IDA using the energy consumption indicator decomposed the indicator into activity, structural and intensity effects. ANN was later employed to calculate the overall energy efficiency after predicting the energy consumption using the decomposed effects as input variables to the neural network.

Keywords
IDA, ANN, energy efficiency.

1. Introduction
Today, saving energy is not the reason for reducing the energy consumption of any organization. Rather, there are two key factors that should be taken into account. First, additional profits can be created by improving energy efficiency. Second, saving energy has a significant impact on environment, since improved energy efficiency is one of the quickest and most cost effective responses to the threat of global warming [1]. Energy consumption in the industrial sector is influenced by three indictors namely activity, structural and efficiency changes. Energy is a basic need for different purposes in industrial facilities around the world. Energy efficiency in the industrial sector began to be considered as one of the main functions in the 1970s. Since then, the world has trimmed its energy budget by utilizing higher efficiencies, while still growing economically, and has realized the importance of protecting the environment [2]. There is need for a technique to understand how energy can be efficiently used.This study makes the energy efficiency analysis a decision problem which can be addressed with the aid of index decomposition analysis (IDA) and artificial neural network (ANN). The use of index decomposition analysis to understand the activity growth, structure and efficiency changes factors that influence energy consumption originates from index numbers used to study the contributions of price and quantity levels to changes in aggregate commodity consumption. The use of IDA which evaluates energy consumption patterns and understands the driving factors leading to changes in energy consumption in order to analyze historical and forecast future demand has gained great value for researchers who want to decompose aggregate indicators.

Artificial neural network (ANN) was used to capture the relationship between energy consumption and its driving factors so as to make accurate forecasting of the energy consumption, considering the factors that led to the changes in energy consumption as the input factors. Apart from capturing the relationship, it has also been employed to determine the efficiency. In a study by [3], various index decomposition analysis methods were compared and concluded that the LMDI method is the preferred method. LMDI has been the preferred method [3-6] amongst the other decomposition methods because of the following reasons: its consistency in aggregation; its perfect decomposition; its adaptability; its ease of use and result interpretation; it has a solid theoretical foundation; and

there is no unexplained residual term. This method is considered “robust”. The change of industrial carbon emissions from 36 industrial sectors in China over the period 1998-2005 was analyzed based on time series decomposition of the LMDI [7]. The results 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 total increased industrial carbon dioxide emissions. The overwhelming contributors to the change of China’s industrial sectors’ carbon emissions in that period were the industrial activity and energy intensity; the impact of emission coefficients of heat and electricity, fuel shift and structural shift was relatively small. Ref. [8] used LMDI decomposition analysis to assess the impact of the production, structure and energy efficiency effects to changes in sub-sectoral manufacturing energy to selected sub-sectors of the Greek manufacturing sector from 1985 to 2002 for electricity, fossil fuels and total energy use. Another study that deals with the decomposition analysis of energy-related carbon dioxide emissions in Greece was carried out by [9] from 1990 to 2002. The Arithmetic Mean Divisia Index (AMDI) and LMDI techniques were applied 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 biggest contributor to the rise in carbon dioxide emissions is the income effect; on contrary, the energy intensity effect is mainly responsible for the decrease in carbon dioxide emissions. Ref. [10] 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 show that GDP growth is by far the biggest contributor to global emissions followed by an increasing population, while decreasing energy intensity was and still is the most important factor to reduce emissions.

Numerous advances have been made in developing intelligent systems, some inspired by biological neural networks, fuzzy systems and combination of them [11]. However, artificial neural networks (ANN) have received the most extensive application undoubtedly, cited among the most powerful computational tools ever developed [12]. In general, ANN applications in engineering have received wide acceptance [13-15]. The popularity and acceptance of this technique stems from ANNs features that are particularly attractive for data analysis [13]. These features include handling of fragmented and noisy data, generalization capability over new data, ability to effectively incorporate a large number of input parameters, and its capability of modelling linear and non-linear systems. ANNs have become a useful tool in the energy studies. For example, [16] developed ANN model for office buildings with day-lighting for subtropical climates. To forecast regional load in Taiwan [12] and green house gases in Turkey [17]. Analyzing and predicting wind power generation [18], prediction of net energy consumption in Turkey [19] and the forecasting of daily electric load profiles of a suburban area [20] are among the ANN studies conducted. To understand how energy can be efficiently utilized, it is important to first understand the factors leading to the consumption of energy. Due to this fact, index decomposition was employed. Employing ANN would help predict based on the decomposed factors which later leads to the best way energy can be efficiently used. In this paper, for the assessment of energy efficiency analysis, LMDI decomposed the energy consumption into changes in activity growth, structure and efficiency changes. ANN incorporates all variation sources; the measured energy consumption, activity growth, structure and efficiency changes of the Canadian industrial sector into evaluation by considering them as inputs and output indicators. Furthermore, ANN was used to determine the energy efficiency of the industrial sector.

2. Case Study

In this paper, we analyze 15 aggregated sectors between 1990 and 2000 of the Canadian industrial sector. Data used (table 1) was from [21]. The productions are all given by the gross domestic product (GDP) output expressed in 1986 U.S $.

3. Proposed Model

This study includes an integrated approach based on LMDI and ANN for total energy efficiency assessment and optimization of energy consumption in the Canadian industrial sector. Figure 1 presents schematic view of the general proposed model. The general proposed model can be summarized as follows:

I. An IDA based on LMDI was performed to assess the respective contribution of activity, structural and intensity effect on the 15 industrial sectors.
II. Energy consumption, activity, structural and intensity effects are selected as ANN inputs and output indicators. Energy consumption indicator is the output and activity, structural and intensity indicators are the input indicators.
III. The predicted results of the energy consumption are determined using ANN.

IV. Efficiency for the energy consumption is proposed for each year for the Canadian industrial sectors using ANN.

Table 1: Statistical Data for the 15 aggregated sectors of the Canadian industrial sector between 1990 and 2000

	1990		1991		1992		1993		1994		1995	
	Energy	GDP	Energy	GDP	Energy	GDP	Energy	GDP	Energy	GDP	Energy	GDP
average	101512.5	3383.2	104056.1	3288.87	104866.3	3282.13	106659.3	3368.4	114296.3	3478.4	122001.3	3506.13
standard deviation	209833.7	2820.53	217035	2785.33	220305.2	2851.31	221969.9	2922.89	238459.5	2988.35	250185.5	2998.05
min	1238	399	1123	315	1186	308	1336	315	1394	330	1023	325
max	753644	9422	764345	9643	768176	9793	768042	9832	860165	10173	900336	10228

	1996		1997		1998		1999		2000	
	Energy	GDP	Energy	GDP	Energy	GDP	Energy	GDP	Energy	GDP
average	121683	3571.33	122428.2	3688	120761	3754.53	125066.5	3862.4	124487	3970
standard deviation	241101	3083.49	242737.3	3087.6	239744	3121.9	254538.5	3215.13	250021	3298.62
min	1159	287	1238	285	1236	261	1204	235	1167	192
max	851217	10560	856159	10434	840058	10779	899419	10943	891116	11216

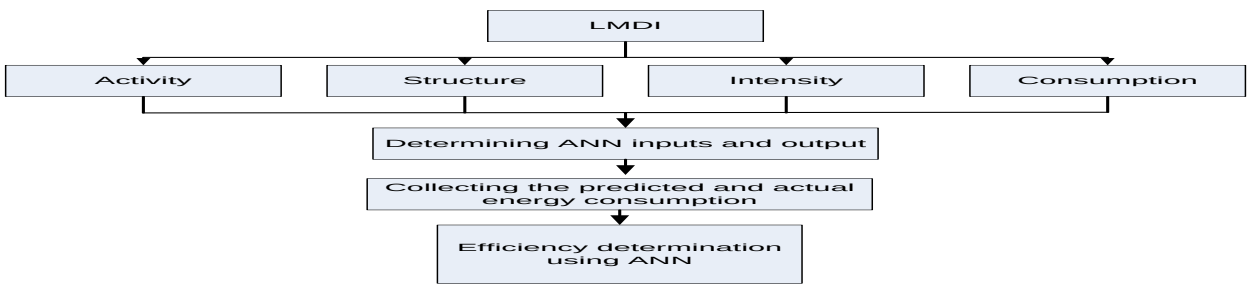

Figure 1: Schematic view of the general proposed model.

3.1 LMDI

LMDI, the preferred IDA like other IDA methods can adopt either multiplicative or additive mathematical form in a time-series or base year method. Difference between the time-series and base year method can be found in Granel's dissertation [21] and [22]. For our study, the time-series multiplicative mathematical form was adopted. The multiplicative decomposition form decomposes the relative growth of an indicator I into determinant effects [23]

$$\frac{I^t}{I^{t-1}} = Determinant\ effect\ X\ Determinant\ effect\ X\ Determinant\ effect\ X\ Residual \quad (1)$$

The residual term for LMDI decomposition is always unity. Where energy consumption is the indicator for this study, equation (1) can be rewritten as

$$\frac{E^t}{E^{t-1}} = D_{tot} = D_{act} \cdot D_{str} \cdot D_{int} \quad (2)$$

The LMDI (multiplicative) takes the following form

$$E = \sum_i E_i = \sum_i Q \frac{Q_i}{Q} \frac{E_i}{Q_i} = \sum_i Q\, S_i I_i \quad (3)$$

$$D_{act} = \exp\left[\sum_i w_i \ln\left[\frac{Q^T}{Q^o}\right]\right] \quad (4)$$

$$D_{str} = \exp\left[\sum_i w_i \ln\left[\frac{S_i^T}{S_i^o}\right]\right] \quad (5)$$

$$D_{int} = \exp\left[\sum_i w_i \ln\left[\frac{I_i^T}{I_i^0}\right]\right]; \quad (6)$$

Where

$$w_i = \frac{(E_i^T - E_i^0)/(lnE_i^T - lnE_i^O)}{(E^T - E^0)/(lnE^T - lnE^0)} \text{ is the weight.} \quad (7)$$

Table 1. The variables used for the decomposition analysis

E_i – Total energy consumption in sector i

E - Total energy consumption ($E = \sum_i E_i$)

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 ($I_i = \frac{E_i}{Q_i}$)

Where D_{tot} represents the total energy consumption, D_{act} the activity involved, D_{str} the structural change and D_{int} the change in intensity. The derivation of the above equations can be found in [24]

3.2 ANN

ANNs are well known massively parallel computing models which have exhibited excellent behavior in solving problems associated to engineering, economics, etc. The most commonly applied network is the multilayer perceptron with error backpropagation learning algorithm [25]. Further studies on the neural network methodology, we refer reader to the paper of [26] for detailed treatment.

3.2.1 Problem formulation

The objective function chosen for this problem is the mean square error (MSE) between the outputs from the neural network and the target value which is the energy consumption. As the inputs are applied to the network, the network output is compared to the target. The error is calculated as the difference between the target output and the neural network output. The goal is to minimize the average of the sum of these errors.

$$\text{mse} = \frac{1}{\text{Q}}\sum_{\text{k=1}}^{\text{Q}} e(\text{k})^2 = \frac{1}{\text{Q}}\sum_{\text{k=1}}^{\text{Q}} (\text{t(k)} - \text{a(k)})^2 \quad (8)$$

The least mean square error (LMS) algorithm adjusts the weights and biases of the linear network so as to minimize the mean square error. The type of ANN used in this study is the Multilayer Perceptron (MLP) trained by the backpropagation algorithm, originally developed by [26]. Since the conception in the 1940s, different neural network models have been proposed, but the MLP is the most widely used [25]. The architecture of this network consists of three layers namely the input, hidden and output layer, with each layer having one or more neurons, in addition to bias neurons connected to the hidden and output layers. The computational procedure of the network is described below[12]:

$$\text{Y}_\text{j} = f(\textstyle\sum_\text{i} \text{w}_\text{ij}\text{X}_\text{ij}), \quad (9)$$

where Y_j is the output of node j, $f(.)$ the transfer function, w_ij the connection weight between node j and node i in the lower layer and X_i the input signal from the node i in the lower layer. The backpropagation is based on a steepest descent technique with a momentum weight (bias function) which calculates the weight change for a given neuron. It is expressed as follows [12, 27]: let $\Delta\text{w}_\text{ij}^\text{p}(\text{n})$ denote the synaptic weight connecting the output of neuron i to the input of neuron j in the pth layer at iteration n. The adjustment $\Delta\text{w}_\text{ij}^\text{p}(\text{n})$ to $\text{w}_\text{ij}^\text{p}(\text{n})$ is given by

$$\Delta\text{w}_\text{ij}^\text{p}(\text{n}) = -\eta(\text{n})\frac{\partial\text{E(n)}}{\partial\text{w}_\text{ij}^\text{p}}, \quad (10)$$

where η (n) is the learning rate parameter. By using the chain rule of differentiation, the weight of the network with the backpropagation learning rule is updated using the following formulae:

$$\Delta\text{w}_\text{ij}^\text{p}(\text{n}) = \eta(\text{n})\partial_\text{j}^\text{p}(\text{n})\,\text{X}_\text{i}^{\text{p}-1}(\text{n})\text{m(n)}\Delta\text{w}_\text{ij}^\text{p}(\text{n}-1), \quad (11)$$

$$\Delta\text{w}_\text{ij}^\text{p}(\text{n}+1) = \text{w}_\text{ij}^\text{p}(\text{n}) + \Delta\text{w}_\text{ij}^\text{p}(\text{n}), \quad (12)$$

where $\partial_\text{j}^\text{p}(\text{n})$ is the nth error signal at the jth neuron in the pth layer, $\text{X}_\text{i}^{\text{p}-1}(\text{n})$ is the output signal of neuron i at the layer below and m is the momentum factor.

3.3 ANN Measure of Efficiency

The efficiencies of each year of the Canadian industrial sector will be determined by using their predicted values obtained from the solution to the models. Their efficiencies can be obtained using the following equation:

$$E = \frac{Y}{Y^{Pre} + (\max)\,\mathrm{Er}} \tag{13}$$

where

Y is the observed energy consumption

Y^{Pre} is the predicted energy consumption by the solution to the model

$(\max)\,\mathrm{Er}$ is the maximum residual obtained.

4. Results

4.1 LMDI

The results of the decomposition analysis are provided in Table 2. It shows, among others, the increase in the energy consumption for the 15 Canadian industrial sectors from 1990 to 2000 which amounts to a total of 1.2264 PJ. All the underlying factors led to the increase in energy consumption for the period investigated. The activity effect is responsible for 1.1735 PJ (or 95%) of the total increase in energy consumption. Furthermore, structural changes and intensity changes also contributed to the increase in energy consumption, 84% and 83% respectively. See Table 2 below.

Table 2: Decomposition of Canada's 15 industrial sectors

Year	Energy consumption	Activity	Structural	Intensity
1990-1991	1.0251	0.9721	1.0229	1.0308
1991-1992	1.0077	0.9980	0.9993	1.0105
1992-1993	1.0171	1.0263	1.0219	0.9698
1993-1994	1.0716	1.0326	1.0022	1.0355
1994-1995	1.0674	1.0080	1.0037	1.0551
1995-1996	0.9974	1.0186	0.9939	0.9852
1996-1997	1.0061	1.0327	0.9933	0.9808
1997-1998	0.9864	1.0180	0.9805	0.9882
1998-1999	1.0357	1.0287	1.0156	0.9913
1999-2000	0.9954	1.0279	0.9978	0.9706
Total	1.2264	1.1735 95%	1.0307 84%	1.0140 83%

4.2 ANN and Efficiency

The data used by the network was from the result of the LMDI (Table 2). The number of hidden neurons was determined by comparing the performance of different cross-validated networks, with 1 – 15 hidden neurons, and chose the number that produced the greatest network performance. This resulted in a network with activity, structural and intensity indicators as input neurons, six hidden neurons and a single output neuron (energy consumption). Figure 2 shows the architecture of the network. In the analyses, network parameters of learning rate and momentum were set to 0.06 and 0.7, respectively. Variable learning rate with momentum (trainlm) as network's training function, with purelin and tansig as activation functions. Table 3 presents the results of the Artificial Neural Network. In the ranking and selection of the most efficient use of energy consumption under the case study, year 1993-1994 made the most efficient use of energy, following the ANN efficiency analysis.

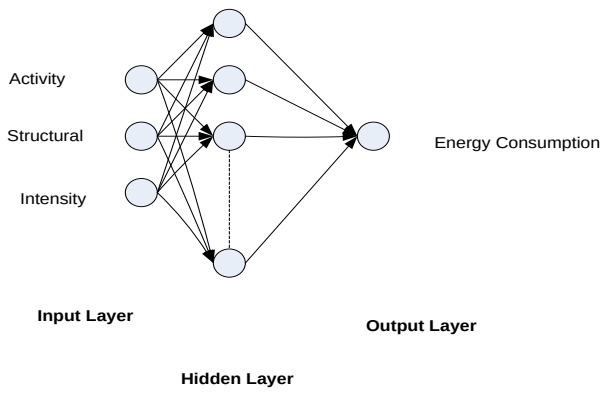

Figure 2. Architecture of the ANN

Table 3:Results from ANN

Years	Observed (PJ)	Predicted (PJ)	Observed-Predicted (PJ)	Efficiency	Ranking
1990-1991	1.0251	1.0255	-0.0004	0.993	5
1991-1992	1.0077	1.0070	0.0007	0.994	4
1992-1993	1.0171	1.0151	0.002	0.996	3
1993-1994	1.0716	1.0658	0.0058	1.000	1
1994-1995	1.0674	1.0646	0.0028	0.997	2
1995-1996	0.9974	0.9991	-0.0017	0.992	6
1996-1997	1.0061	1.0062	-0.0001	0.994	4
1997-1998	0.9864	0.9939	-0.0075	0.986	8
1998-1999	1.0357	1.0380	-0.0023	0.992	6
1999-2000	0.9954	0.9979	-0.0025	0.991	7

5. Conclusion

This paper has sought to investigate the efficiency of energy consumption in the Canadian industrial sector. This study made energy efficiency a decision problem and employed IDA and ANN to address the problem. From the decomposition result, activity effect was the most responsible factor to increase the energy consumption followed by the structural and intensity changes. Neural network was able to predict the energy consumption using the decomposed changes as input variables to the network. Following the efficiency analysis, year 1993-1994 was found to have employed the most efficient use of energy. It has been investigated in this study that forecasting is of dire need to the energy management level that needs to predict energy consumption for the ranking and selection of the most efficient year of energy usage.

References

1. Hepbasli, A. and N. Ozalp, *Development of energy efficiency and management implementation in the Turkish industrial sector.* Energy conversion and Management, 2003. 44: p. 231-249.
2. Abdelaziz, E.A., R. Saidur, and S. Mekhilef, *A review on energy saving strategies in industrial sector.* Renewable and Sustainable Energy Reviews, 2011. 15: p. 150-168.
3. Ang, B.W., *Decomposition Analysis for policymaking in energy: which is the preferred method?* Energy Policy, 2004. 32(9): p. 1131-1139.
4. Mendiluce, M., I. Perez-Arriaga, and C. Ocana, *Comparison of the evolution of energy intensity in Spain and in the EU 15. Why Spain different?* Energy Policy, 2010. 38(1): p. 639-645.
5. Ang, B.W. and F.L. Liu, *A new energy decomposition method: perfect in decomposition and consistent in aggregation.* Energy, 2001. 26: p. 537 - 548.
6. Ang, B.W. and F.Q. Zhang, *A survey of index decomposition analysis in energy and environmental studies.* Energy, 2000. 25(12): p. 1149-1176.
7. Liu, L.-C., G.W. Ying Fan, and Y.-M. Wei, *Using LMDI method to analyze the change of China's industrial CO2 emissions from final fuel use: An empirical analysis.* Energy Policy, 2007. 35: p. 5892-5900.

8. Salta, M., H. Polatidis, and D. Haralambopoulos, *Energy use in the Greek manufacturing sector: A methodological framework based on physical indicators with aggregation and decomposition analysis.* Energy, 2009. 34: p. 90-111.
9. Hatzigeorgiou, E., H. Polatidis, and D. Haralambopoulos, *CO2 emissions in Greece for 1990-2002: A decomposition analysis and comparison of results using Arithmetic Mean Divisia Index and Logarithmic Mean Divisia Index techniques.* Energy, 2008. 33: p. 492-499.
10. Bohm, D.C., *Assessment of Global Mitigation Progress: A Decomposition of CO2 Emissions for the World's Top Emitting Countries.* undated.
11. Hayati, M. and Y. Shirvany, *Artificial Neural Network Approach for Short Term Load Forecasting for Illam Region*. 2007, World Academy of Science, Engineering and Technology.
12. Hsu, C.-C. and C.-Y. Chen, *Regional load forecasting in Taiwan-applications of artificial neural networks.* Energy conversion and Management, 2003. 44: p. 1941-1949.
13. Al-Alawi, S., A. Al-Badi, and K. Ellithy, *An artificial neural network model for predicting gas pipeline induced voltage caused by power lines under fault conditions.* An artificial neural network model, 2003. 69.
14. Al-Alawi, S.M. and K.A. Ellithy, *"Tuning of SVC damping controllers over a wide range of load models using an artificial neural network.* International Journal of Electric Power and Energy Systems, 2000. 22(6): p. 405-20.
15. El-Sharkawi, M. and D. Niebur, *"Applications of artificial neural networks to power systems".* IEEE Intelligent Systems Applications of Power Systems, 1996. Working Group IEEE: p. 112-0.
16. Wong, S.L., K.K.W. Wan, and T.N.T. Lam, *Artificial neural networks for energy analysis of office buildings with daylighting.* Applied Energy, 2010. 87: p. 551-557.
17. Sozen, A., Z. Gulseven, and E. Arcaklioglu, *Forecasting based on sectoral energy consumption of GHGs in Turkey and mitigation policies.* Energy Policy, 2007. 35: p. 6491-6505.
18. Mabel, M.C. and E. Fernandez, *Analysis of wind power generation and prediction using ANN: A case study.* Renewable Energy, 2008. 33: p. 986-992.
19. Sozen, A. and E. Arcaklioglu, *Prediction of net energy consumption based on economic indicators (GNP and GDP) in Turkey.* Energy Policy, 2007. 35: p. 4981-4992.
20. M. Beccali, M.C., V. Lo Brano, and A. Marvuglia, *Forecasting daily urban electric load profiles using artificial neural networks.* Energy conversion and Management, 2004. 45: p. 2879-2900.
21. Granel, F., *A Comparison Analysis of Index Decomposition Methods*, in *Industrial and Systems Engineering*. 2003, National University of Singapore: Singapore.
22. Ma, C. and D.I. Stern, *China's Changing Energy Intensity Trend: A Decomposition Analysis.* Rensselaer Working Papers in Economics, 2006.
23. Hoekstra, R. and J.J.C.J.M.v.d. Bergh, *Comparing structural and index decomposition analysis.* Energy Economics, 2003. 25: p. 39-64.
24. Ang, B.W., *Index Decomposition Analysis Using LMDI: A Simple Guide*. 2008.
25. Mata, J., *Interpretation of concrete dam behaviour with artificial neural network and multiple linear regression models.* Engineering Structures, 2011. 33: p. 903-910.
26. Rumelhart, E., G.E. Hinton, and R.J. Williams, eds. *Learning Internal Representations by Error Propagation in Parallel Distributed Processing 1*. ed. J.L.M.a.t.P.R.G. D.E Rumelhart, Eds. 1986, MIT Press: Cambridge, MA. 318 - 362.
27. Huang, H., R. Hwang, and J. Hsieh, *A new artificial intelligent peak power load forecaster based on non-fixed neural networks.* Electric Power Energy Syst, 2002. 24: p. 245-50.