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Chapter 5

Assessing the Possible Potential in Energy Consumption and Greenhouse Gas Emission: Application of a Proven Hybrid Method

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Additional information is available at the end of the chapter

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Abstract

Energy evaluation together with greenhouse gas mitigation goes a long way in sustaining the growth and economy of a nation. Various evaluation methods have been adopted by researchers, academia and various country wise energy department ministries to achieve this aim. The most effective method is the hybrid evaluation method. This takes into consideration strength of a particular method to overcome the weakness of another method. This chapter focuses on a recently proven integrated method on energy and greenhouse gas studies—integrated IDA-ANN-DEA (index decomposition analysis—artificial neural network—data envelopment analysis). Case studies were exemplified using this approach in evaluating possible energy potential that could be saved in the manufacturing industries in Canada and South Africa as well as a particular food and beverage industry. Another case study focused on the amount of possible greenhouse gas that could be mitigated in the Canadian industry. The hybrid model proved very useful in its analysis.

Keywords: energy, evaluation, greenhouse gas, mitigation, hybrid method, IDA-ANN-DEA

Overview

Energy's involvement in the growth of the economy is very crucial. The role it plays, as well as greenhouse gas, has led to various questions leading to various practices and trends in research and development (R&D). One of the leading objectives of R&D in the energy sector is to find how best to conserve energy. To achieve this objective, research trends in energy use, energy potentials, policy formulations as well as investment patterns and technology choices have been ongoing.

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1. Introduction

A huge amount of potential exists which is yet to be tapped for energy efficiency in all sectors that improves the economy [1]. From [2] definition 'evaluation is a careful retrospective assessment of merit, worth, and value of administration, output and outcome of governmental interventions, which is intended to play a role in future, practical situations'. Various tools are used to identify opportunities that lie in energy efficiencies as well as energy-saving potentials. Energy evaluation goes a long way by affording users where improvement is needed. On the other hand, it also saves money on a long-term basis. During energy evaluation, lots can be achieved from revelation of the way energy is consumed, waste identification to efficient use of energy. Not only is energy efficiency being introduced when energy use is successfully evaluated but also during greenhouse gas evaluation, as it is well known that the struggle against environmental pollution has been for a decade plus [3].

Efficient energy use continues to be a significant topic both nationally and internationally when policies are discussed. It remained one of the fundamental areas for sustainable growth environmentally and economically [4, 5]. The evaluation of energy efficiency in various countries has been significant to each of the countries. Various quantitative methods have gained popularity with various researchers and scholars in this regard [6]. Not too long was an agreement made by the European Union (EU) that at least a saving of 27% of energy should be realized between 2020 and 2030 when compared with the business-as-usual and various policy objectives [5, 7]. Among the methods employed is the economic analysis that considers engineering assumptions and benchmark factors as well as methodological techniques [6]. Other methods are the hybrid models. Models have been agreed by the scientific world to be a scientific standard tool applied to various indicative factors on a comprehensive note [6].

The consumption of energy mostly gives room for pervasive externalities, ranging from local to global emissions which do not reflect in costs of energy supply as well as the preparation efforts [8]. Most recently, the issue of GHG emissions has attracted serious attention that it has given rise to global research in the climate change arena [9]. With unmitigated GHGs, there will be continuous adverse effects in the global environment [10]. The reduction of GHG is known to be the key mitigation process in combating climate change [11]. However, knowing the amount of possible emission that would be reduced goes a long way. Addressing climate change issues as well as establishing targets of GHGs that need reduction from industrialized/developed countries was recognized during the conference of parties (COP) which took place in Kyoto, Japan, in 1997 [12]. Subsequent COPs after that continued to recognize this need to address climate change issues.

Studies have confirmed that both commercial and domestic buildings constitute up to 33% of the GHGs emitted in the global village [13]. Emission of GHGs has proved to be a key threat that can lead the world human civilization's collapse in the present century [14]. It is crucial to reduce the amount of GHGs that are being emitted to the atmosphere [15]. Modelling has gained upperhand in supporting most decisions made which can help develop and introduce fresh management practices to see to the reduction of GHGs [16]. From 1990 to 2010, the global economic growth grew to 88% [17], leading to 45% energy-related CO_2 emission increase [18]. As informed by the study of Ref. [19], 'One of the most important issues in the policy debate is

the role to be played by developing countries for reducing GHG emissions, and particularly CO_2 emissions side by side with developed countries'. A very practical and rigorous effort will always be needed in mitigating climate change [20].

Appropriate methodologies do help in implementing appropriate mitigation approaches in the areas of GHGs as well as conservation techniques in the areas of energy consumption. An integrated approach has been advocated for solving the energy/greenhouse gas problems [12]. The objective of this chapter is to understand the application of a particular hybrid methodology (IDA-ANN-DEA) in the assessment of energy-saving potential and GHG mitigation potential. The continuous increase in the amount of energy consumed and the GHGs emitted necessitated the development of this hybrid model.

2. Hybrid methods

Most recent methods adopted to evaluating energy studies are the optimization models. These optimization models can be grouped into three algorithms according to Ref. [21]; these are evolutionary, derivative-free search and the hybrid algorithms. Evolutionary methods include genetic algorithms (GAs) and its improved states like non-dominated sorting genetic algorithm II (NSGA-II) among the rest, particle swarm optimization (PSO) and other evolutionary methods [22]. Derivative-free search are the direct search methods [23] like Hooke-Jeeves, coordinate search and mesh adaptive search, among others. The hybrid is an integration of various methods [22]. One of the combined methods often times serves to offset the bias of the other. Taking nothing from the other two methods, they are very unique and efficient in their own way when it comes to evaluating energy use; however, this study focuses on the hybrid method which combines the strength of each model into a single capacity. Among the hybrid studies relevant to energy evaluation are the studies of Refs. [24–27].

From the study of Ref. [26], they showed how the hybrid of GA with simulated annealing (SA) optimized successfully a thermal building. The technique was employed under various climate conditions. The results generated from the approach were much more reliable when compared to employing either GA or SA alone. In another study of analysing energy performance of a building [25], it compared two different hybrid methods. These are hybrid covariance matrix adaptation evolution strategy algorithm and hybrid differential evolution (CMA-ES/HDE) and the second is PSO/HJ. In their study, CMA-ES/HDE performed successfully on complex objective functions whereas PSO/HJ identified the objective functions optimally. In comparison of these hybrid models, CMA-ES/HDE performed better with less parameters, however, PSO/HJ performed better when problem dimension increased. However, this study focuses on the IDA-ANN-DEA hybrid method.

3. IDA-ANN-DEA

This chapter employed the hybrid index decomposition analysis (IDA), artificial neural network (ANN) and data envelopment analysis (DEA) as an evaluation model to determine the way energy is consumed and how greenhouse gas could be mitigated through identification of

waste and how best to use/mitigate energy/greenhouse gas efficiently. This will best identify the possible potentials that could be saved and how much greenhouse gas is possibly awaiting mitigation. From the structure of the hybrid model in **Figure 1**, regression analysis played a vital role in verifying and validating ANN in this hybrid approach. The mathematics behind this model will be elaborated.

The structure of the framework presented below indicates independent inputs depending on the amount of inputs; however, for this study, input activity, structure, intensity and energy mix (for greenhouse gas) are the most common inputs responsible for energy consumption and greenhouse gas, and the output in this situation is always the energy consumed/greenhouse gas emitted. As the structural framework shows, the output is being decomposed through logarithmic mean Divisia index (LMDI) to the various independent variables. LMDI is one of the most used IDA. The energy consumption/greenhouse gas is predicted to decide the reference energy consumed/greenhouse gas emitted by employing the input factors to the ANN. Through validation of the reference energy outcome, this allows the DEA to execute its sensitivity analysis using both the actual and predicted energy/greenhouse gas to decide how much possible energy/greenhouse gas potential could be saved/yet to be mitigated (**Figure 2**).

The steps to applying the model are given below:

(I) LMDI based on IDA performs the operation for the assessment of the various GHG and energy consumption drivers.

(II) Total inputs and outputs are selected for the ANN prediction process.

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

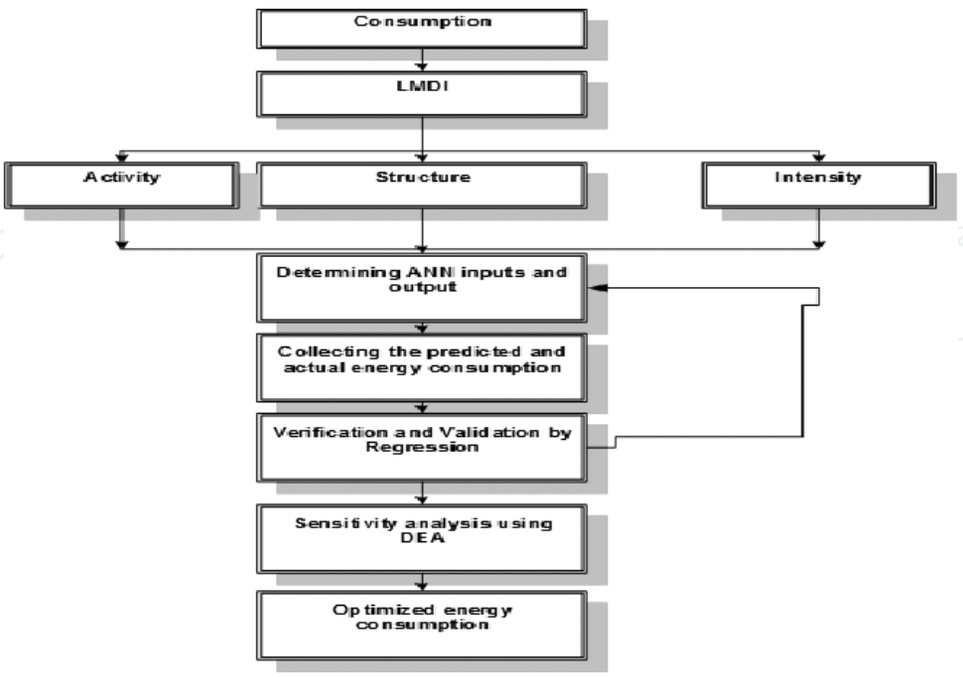


Figure 1. Hybrid structure for energy potential analysis.

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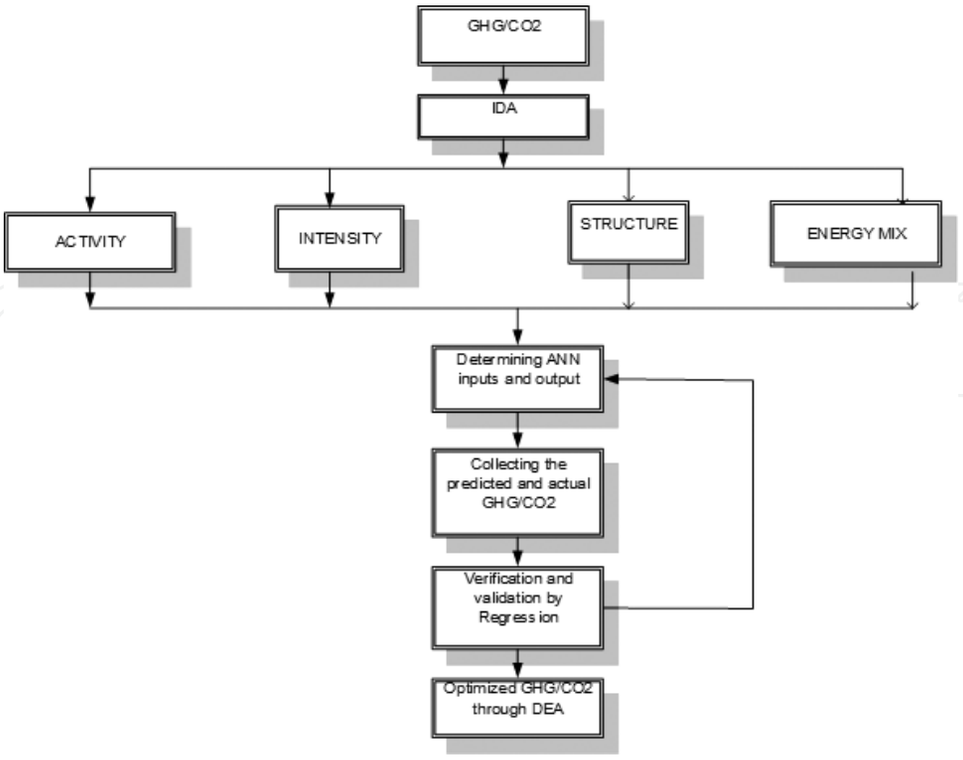


Figure 2. Hybrid structure for greenhouse gas potential analysis.

(IV) DEA sub-model is applied to determine the efficient computation for CO_2 emission/energy consumption that can be obtained.

The equations governing the analysis of energy consumption and greenhouse gas potentials towards the hybrid models are given below:

E_i: sector's aggregated energy consumed

E: aggregated energy consumed $\left(E = \sum_i E_i\right)$

Q_i: sector's production value

Q: aggregated production value $\left(Q = \sum_i Q_i\right)$

S_i: sector's production share $\left(S_i = \frac{Q_i}{Q}\right)$

I_i: sector's intensity of energy consumed $\left(I_i = \frac{E_i}{Q_i}\right)$ and $\left(w_i = \frac{(E_i^T - E_i^0)/(\ln E_i^T - \ln E_i^0)}{(E^T - E^0)/(\ln E^T - \ln E^0)}\right)$

D_{act} denotes activity, D_{str} denotes structure and D_{int} denotes intensity.

$$D_{\text{act}} = \exp\left[\sum_i w_i \ln\left[\frac{Q_i^T}{Q_i^0}\right]\right] \tag{1}$$

$$D_{\text{str}} = \exp\left[\sum\nolimits_i w_i \ln\left[\frac{S_i^T}{S_i^0}\right]\right] \tag{2}$$

$$D_{\text{int}} = \exp\left[\sum\nolimits_i w_i \ln\left[\frac{I_i^T}{I_i^0}\right]\right] \tag{3}$$

$$U_{\text{tot}} = D_{\text{act}} + D_{\text{str}} + D_{\text{int}} \tag{4}$$

For greenhouse gas potential analysis, the following applies:

C: total CO_2 emission

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

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

$M_{ij} = E_{ij}/E_j$: the fuel-mix variable

Q_i: value of production in sector i

Q: total value of production $\left(Q = \sum\nolimits_i Q_i\right)$

S_i: production share of sector $i\left(S_i = \frac{Q_i}{Q}\right)$

I_i: intensity of energy consumption in sector $\left(I_i = \frac{E_i}{Q_i}\right)$

$$C = \sum_{ij} Q \frac{Q_i}{Q} \frac{E_i}{Q_i} \frac{E_{ij}}{E_i} \frac{C_{ij}}{E_{ij}} = \sum_{ij} Q S_i I_i M_{ij} \tag{5}$$

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

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

$$D_{\text{act}} = \exp\left(\sum\nolimits_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{Q^T}{Q^0}\right)\right) \tag{7}$$

$$D_{\text{str}} = \exp\left(\sum\nolimits_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{S_i^T}{S_i^0}\right)\right) \tag{8}$$

$$D_{\text{int}} = \exp\left(\sum\nolimits_{ij} \frac{(c_{ij}^T - c_{ij}^0)/(\ln c_{ij}^T - \ln c_{ij}^0)}{(c^T - c^0)/(\ln c^T - \ln c^0)} \ln\left(\frac{I^T}{I^0}\right)\right) \tag{9}$$

$$D_{\text{mix}} = \exp\left(\sum_{ij} \frac{(c_{ij}^{T} - c_{ij}^{0})/(\ln c_{ij}^{T} - \ln c_{ij}^{0})}{(c^{T} - c^{0})/(\ln c^{T} - \ln c^{0})} \ln\left(\frac{M_{ij}^{T}}{M_{ij}^{0}}\right)\right) \tag{10}$$

$$D_{\text{tot}} = D_{\text{act}} D_{\text{str}} D_{\text{int}} D_{\text{mix}} \tag{11}$$

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

$$y_j = f\left(\sum_i w_{ij} x_{ij}\right) \tag{12}$$

Substituting the outcomes of Eqs. (1)–(3) (from energy consumption) and Eqs. (7)–(10) separately as input values and Eqs. (10) and (11) separately as the output value into Eq. (12), it becomes

$$U_{\text{tot}} = f\left(\sum_i w_{ij}\left\{D_{\text{act}(ij)}, D_{\text{str}(ij)}, D_{\text{int}(ij)}, D_{\text{mix}(ij),}\right\}\right) \tag{13}$$

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

$$mse = \frac{1}{Q}\sum_{K=1}^{Q} [U_{\text{tot}} t(k) - U_{\text{tot}} a(k)]^2 \tag{14}$$

Where $U_{\text{tot}}t$ is the predicted energy consumed/total CO_2 and $U_{\text{tot}}a$ is the actual energy consumed/decomposed total CO_2.

From the DEA, interested readers can refer to [28]; substituting $U_{\text{tot}}(t)$ as the output variable and $U_{\text{tot}}(a)$ as the input variable, it gives

$$\begin{aligned} &\text{Max} \frac{\sum_{r=1}^{s} U_{\text{tot}}(t)_{ro} u_r}{\sum_{i=1}^{m} U_{\text{tot}}(a)_{io} v_i} \\ &\text{such that} \frac{\sum_{r=1}^{s} U_{\text{tot}}(t)_{ro} u_r}{\sum_{i=1}^{m} U_{\text{tot}}(a)_{io} v_i} \leq 1, j \ldots n \\ &v_i \geq 0, i = 1, \ldots, m; \\ &u_r \geq 0, r = 1, \ldots, s. \end{aligned} \tag{15}$$

With $U_{\text{tot}}(t)_{ro}, r = 1, \ldots, s$ representing outputs and the $U_{\text{tot}}(a)_{io}, i = 1, \ldots, m,$ representing inputs for each of $j = 1, \ldots, n,$ DMUs and $j = 0$ identifies DMUj to be evaluated. μ_r is the output weight while v_i is the input weight. Eq. (15) is thus transformed into an ordinary linear programming problem; $\mu_r = \beta\mu_r$, $v_i = \beta v_i$ is obtained with the same optimum value as Eq. (15)

$$\begin{aligned}
&\text{Max } \phi = \sum_{r=1}^{s} \mu_r U_{\text{tot}}(t)_{ro} \\
&\text{such that } \sum_{i=1}^{m} v_i U_{\text{tot}}(a)_{io} = 1, \\
&-\sum_{i=1}^{m} U_{\text{tot}}(a)_{ij} + \sum_{r=1}^{s} \mu_r U_{\text{tot}}(t)_{rj} \leq 0, j = 1, \ldots, n, \\
&v_i \geq 0, i = 1, \ldots, m, \\
&\mu_r \geq 0, r = 1, \ldots, s.
\end{aligned} \tag{16}$$

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

$$\begin{aligned}
&\text{Min } \eta_o \\
&\text{such that } \sum_{j=1}^{n} U_{\text{tot}}(a)_{ij} \lambda_i \leq U_{\text{tot}}(a)_{io} \eta_o, i = 1, \ldots, m \\
&\sum_{j=1}^{n} U_{\text{tot}}(t)_{ij} \lambda_j \geq U_{\text{tot}}(t)_{ro}, r = 1, \ldots, s \\
&\lambda_j \geq 0, j = 1, \ldots, n
\end{aligned} \tag{17}$$

Eqs. (16) and (17) will allow the accountability for the potential energy consumption and CO_2 emission while keeping the expected energy consumed and CO_2 emission at the baseline level.

4. Examples of applications of IDA-ANN-DEA

Case study 1: Application of the hybrid methodology in assessing possible GHG potentials for mitigation in the Canadian Industry

Objective: To determine possible potential for mitigation from 1991 to 2035 [29].

The study extended the decomposed factors responsible for the GHG emission from years 1991 through 2000 to 2035 results using least square trend line approach. This case study considered CO_2 based on final energy consumed without the report of induced electricity production. The considered fuels are coal, coke, coke oven gas, petroleum coke, natural gas, heavy fuel oil, LPG/propane as well as waste fuels consumption. Only 52 sectors and subsectors together with mining and all manufacturing industries with the omission of oil and gas extraction, forestry and construction industries were included.

The average decomposition result is given in **Table 1**. From **Table 1**, it showed that activity had the highest amount. From the second step of the application, the selected inputs were used to predict the output using the ANN. The ANN gave a good prediction with 4-6-1 structure. The average ANN results are depicted on **Table 2**. The results obtained were only accepted after successful validation through the regression analysis. The overall coefficient of correlation was

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0.97 which proved to be a successful prediction. **Figure 3** shows the visual inspection to also validate the good prediction. Incorporating the ANN results into the DEA equation simulated gave the average efficient result in **Table 3**. The result singled out the year 1992 to be the best performing year that other years are to emulate. With the model implemented, it was discovered that 3.13% of GHG could be eliminated. The amount relates to the possible percentage potential of CO_2 that can be easily mitigated if the rest of the years were to emulate 1992 operations. **Figure 4** shows the graph for the amount of GHG that can be mitigated for each year considered in the study.

Year	Average CO_2	Average energy mix	Average intensity	Average structure	Average activity
1991-2035	0.959	0.994	0.915	0.886	1.202

Table 1. Average decomposition results.

Year	Average actual CO_2	Average predicted CO_2	Average error
1991-2035	0.959	0.96	0

Table 2. Average ANN results.

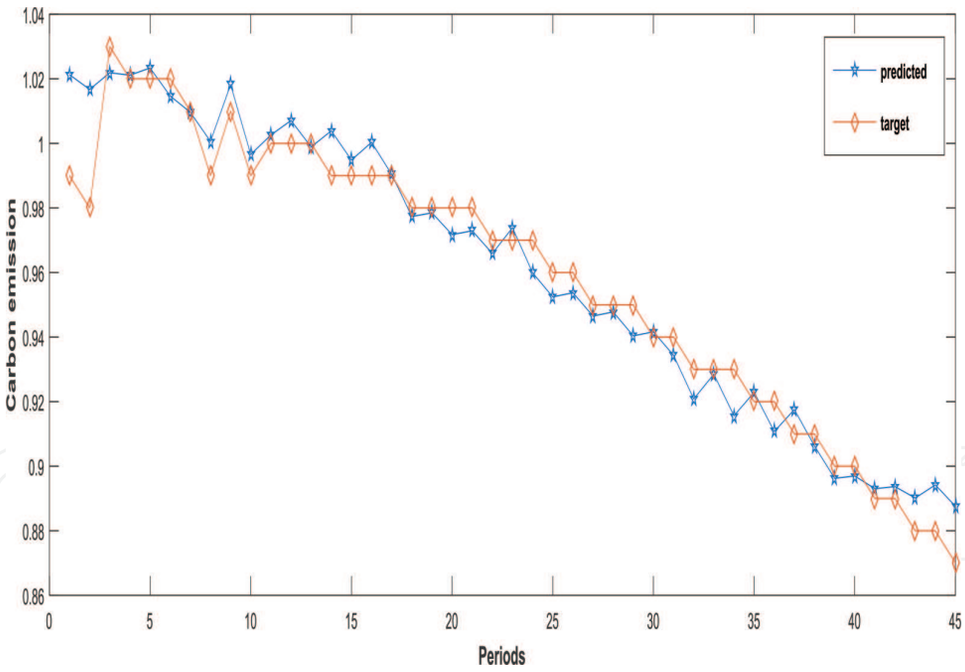


Figure 3. Visual inspection from the predicted and actual CO_2 emission [29].

Year	Average efficiency
1991-2035	0.969

Table 3. Average efficiency results.

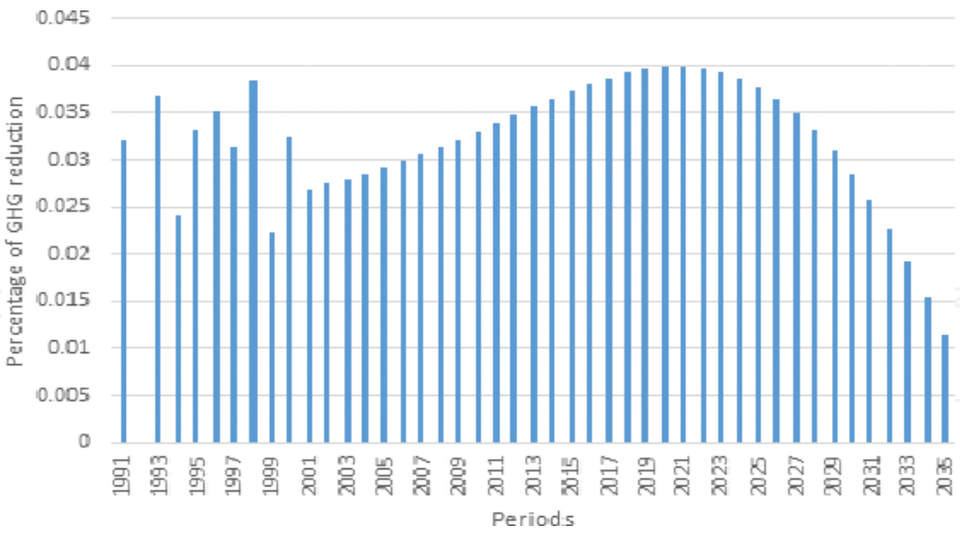


Figure 4. Amount of GHG potential that can be mitigated for the period of study [29].

Case study 2: Application of the hybrid methodology in assessing energy potential in a food and beverage industry in South Africa

Objective: To assess the effectiveness of energy management policies in a food and beverage industry [30].

Energy consumed in the production of two different products was analysed to determine how much energy potential to the food and beverage industry could have been saved between January 2010 and April 2012. The study employed both additive and multiplicative LMDI. The reason for the additive was to comprehend the way the various factors contributed to the amount of energy consumed while the multiplicative was for the integration into DEA as DEA was applicable for non-negativity results obtained from the multiplicative LMDI. **Table 4** shows the summary of the factors responsible for the energy consumed. During the period of study, it can be said that considering only the activity factor, total energy would decline by 11116.6 GJ, total structure by 83.58 GJ and intensity increased by 11644 GJ. This result in summary only indicated poor energy management.

Integrating the LMDI result into the ANN gave a good prediction with a structure of 3-5-1, three representing the activity, structure and intensity inputs, five representing the number of hidden neurons and one representing the energy consumption. **Figure 5** depicts the visual inspection of the prediction result. The regression also confirmed the successful prediction

	Possible energy (GJ)		
Period of study	**Activity**	**Structure**	**Intensity**
January 2011-April 2012	−11116.6419	−83.5841	11644

Table 4. Summary of factors responsible for energy consumed in a food and beverage industry.

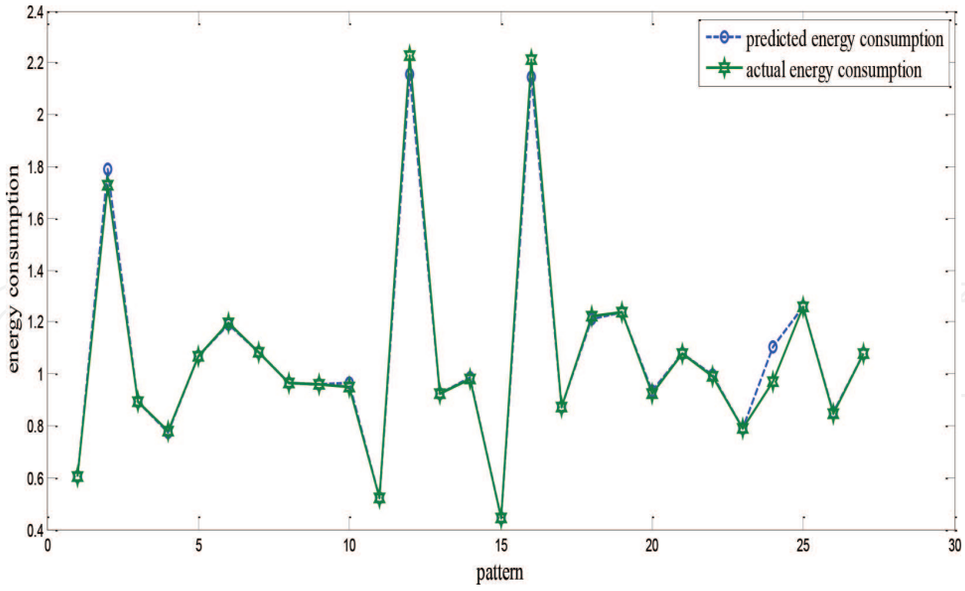


Figure 5. Visual inspection of actual and predicted energy consumption in the food and beverage industry [30].

with the coefficient of correlation result as 0.996. Integrating ANN result to the DEA equation singled out December 2011–January 2012 to be the most efficient month when energy was consumed. **Table 5** shows the average of all the efficiencies computed. If activities considered during this efficient month were to be considered throughout the period of study, the food and beverage industry would have saved 11% energy potential which is equivalent to 171, 533.78 GJ. **Figure 6** below shows the possible energy potential that could have been saved for each month.

Case study 3: Application of the hybrid methodology in assessing energy potential in the Canadian industry

Objective: To assess the energy efficiency through optimization of the responsible factors [31].

The consumption of energy within 15 aggregated sectors was successfully analysed by applying the hybrid methodology in the Canadian industry between 1990 and 2010. The industries included in the analysis were metal mining, non-metal mining, food industry, beverage industry, rubber products, plastic products, clothing industry, wood, furniture and fixtures, paper and allied products, printing public plus allied and primary metal. IDA decomposed the responsible factors to the energy consumed into activity, structure and intensity based on the provided data of production and energy consumption. **Table 6** shows the average of the decomposition results. The result clearly identified activity as the most important factor with intensity and structure having a close margin.

Period	Average efficiency
January 2010-April 2012	0.885

Table 5. Average efficiency result.

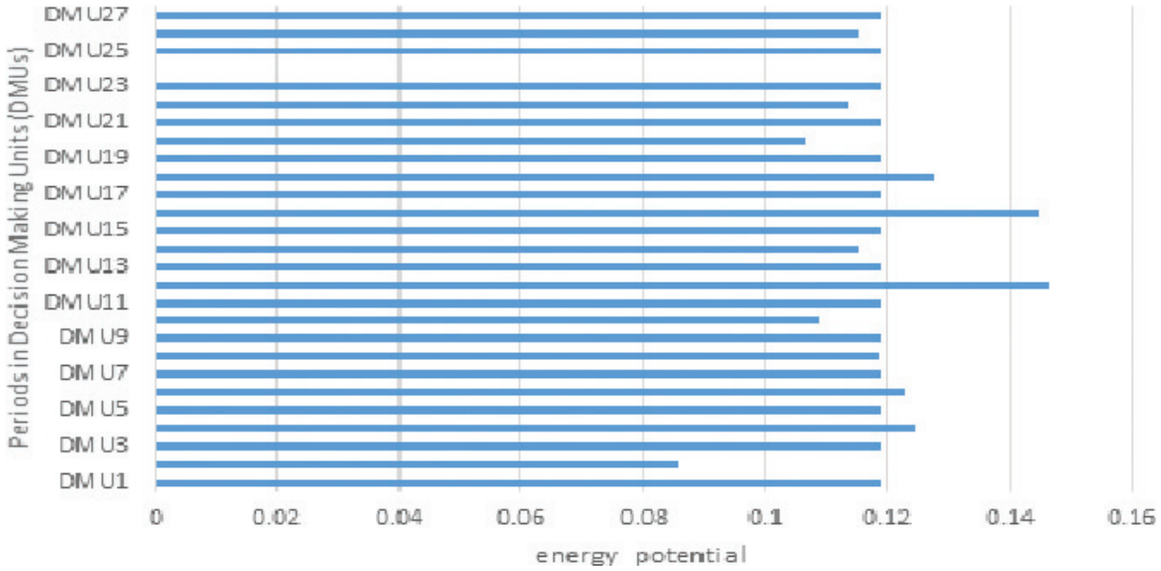


Figure 6. Possible energy potential [30].

Average energy consumption	Activity	Structure	Intensity
1.01856	1.01629	1.00086	1.00177

Table 6. Average decomposition result.

Integrating the outcomes of LMDI into the ANN equation gave an architectural structure of 3-6-1, where the 3 represents the decomposed inputs, 6 stands for hidden neurons and the 1 stands for the energy consumption as the output. **Table 7** shows the average ANN results while **Figure 7** shows the visual inspection result. The results validated the good prediction including the coefficient of correlation result which is 0.95. The integration of the ANN result to the DEA reported year 1994–1995 as the most efficient DMU, while year 1994–1995 was the least efficient of the DMUs. Comparing the efficient period to other periods in evaluating the amount of possible potential resulted into 0.47% of energy that could have been saved. **Table 8** shows the average efficiency obtained throughout the analysis and **Figure 8** shows the potential energy graph.

Case study 4: Application of the hybrid methodology in assessing energy potential in the South African industry

Objective: To assess the energy efficiency through optimization of the responsible factors [32].

The study successfully assessed the energy consumed in a cumulative of 11 sectors in the coal mining, other mining, basic iron and steel, non-metallic minerals, food, paper and paper

Year	Average actual energy consumption	Average predicted energy consumption	Average error
1990-2010	1.01856	1.0179	0.00066

Table 7. Average ANN results.

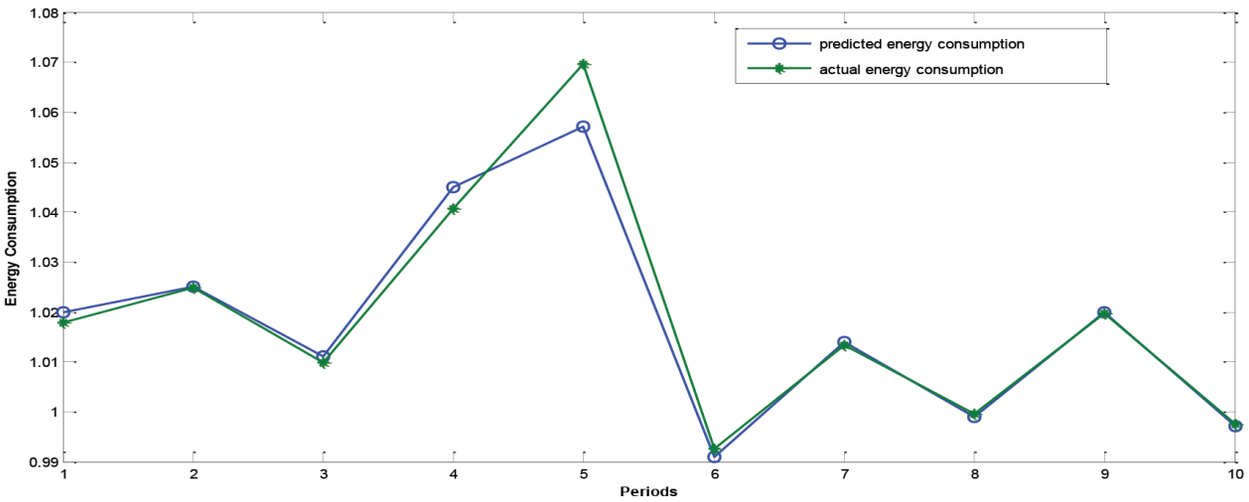


Figure 7. Visual inspection of actual and predicted energy consumption in the Canadian industry.

Period	Average efficiency
1990-2010	0.99529

Table 8. Average efficiency result.

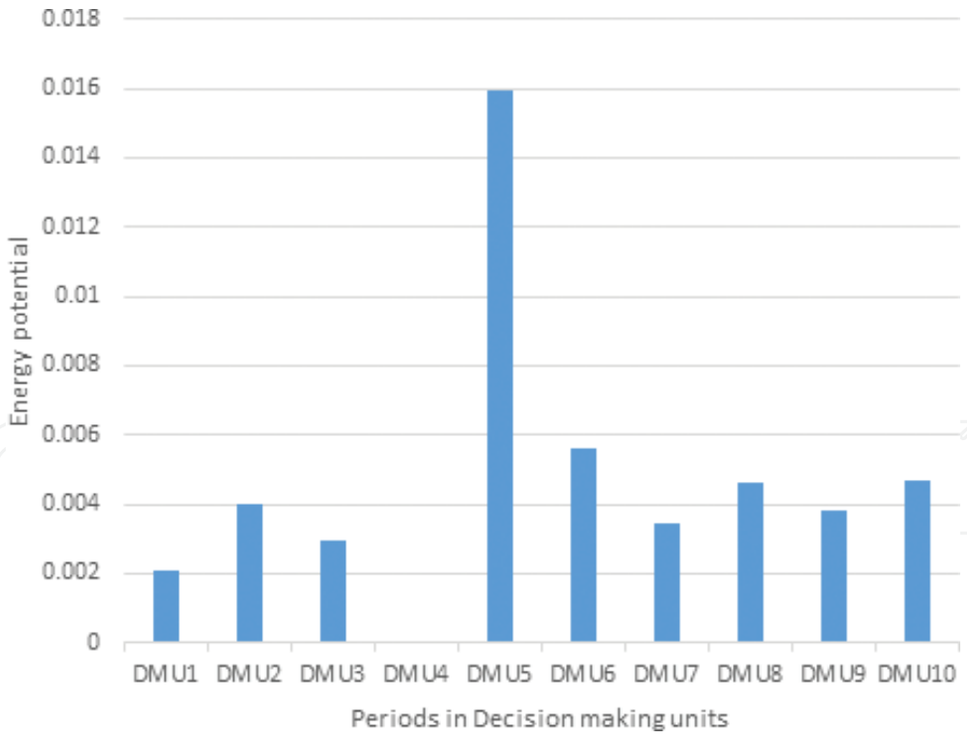


Figure 8. Possible energy potential.

products, gold and uranium ore mining, basic non-ferrous metals, basic chemicals, tobacco and other manufacturing items. These sectors are from the South African industrial sectors from 1971 to 2008. Most of the industries considered are high-energy intensive industries. The

application of LMDI proved activity to be the most consistent factor as compared to intensity and structural factors. Activity contributed 36.53% to the energy consumed while intensity and structure contributed an almost equal amount in 31.74 and 31.73 %, respectively. **Figure 9** depicts the decomposed effects of the energy consumed.

Integrating the result from LMDI to ANN gave a successful prediction with 3 inputs, 4 hidden neurons and 1 that stands for energy consumption as the output in a 3-4-1 architectural structure. Validation of the result gave a coefficient of correlation of 0.99 together with a visual inspection in **Figure 10**. The integration of ANN results into the DEA equation and confirmed period 1975–1976 as the most efficient DMU period. The average efficiency is 0.55 which indicates a very poor run of energy efficiency. **Table 9** shows the average efficiency achieved within the period of study. Emulating the practices within year 1975–1976 could save the cumulative of 11 sectors 44.9% of potential energy. Compared to a developed country like Canada [31], a developing country like South Africa still has a long way to go. **Figure 11** shows the possible energy potential that could have been saved per inefficient DMUs.

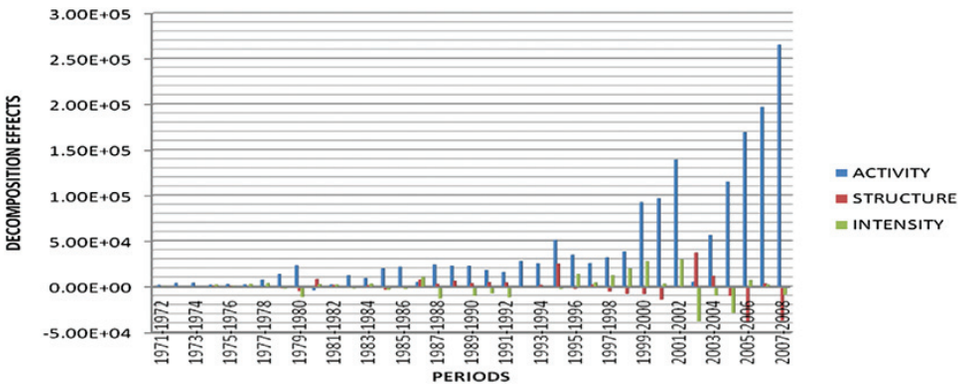


Figure 9. Decomposed effects to the energy consumed [32].

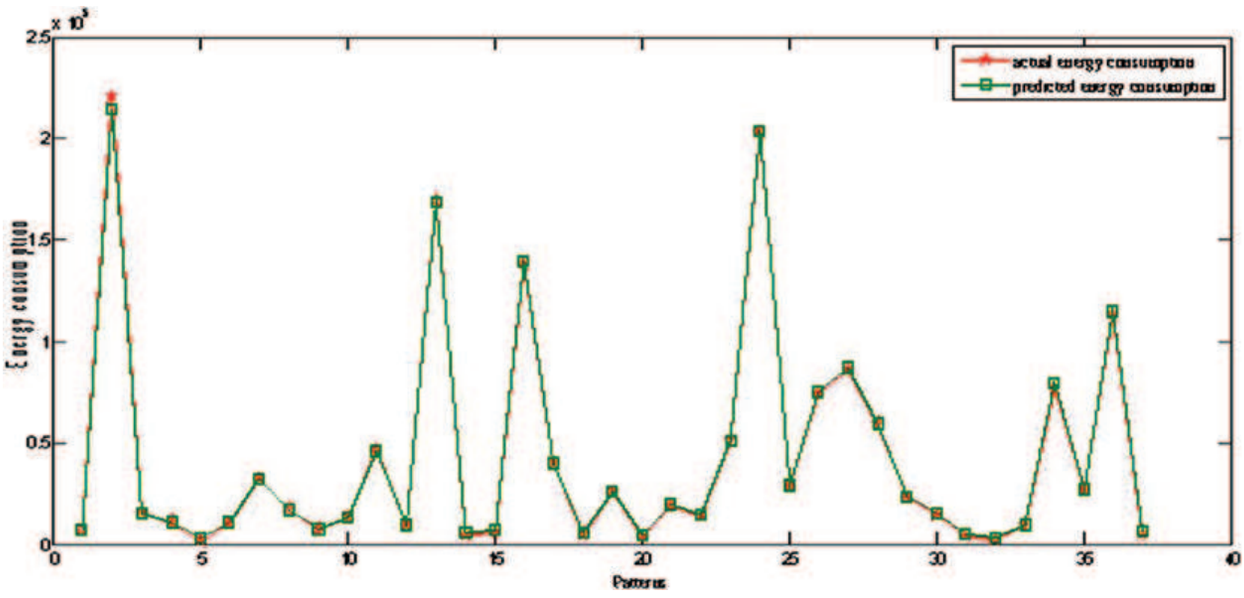


Figure 10. Visual inspection to the ANN prediction [32].

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Period	Average efficiency
1971-2008	0.55

Table 9. Average efficiency.

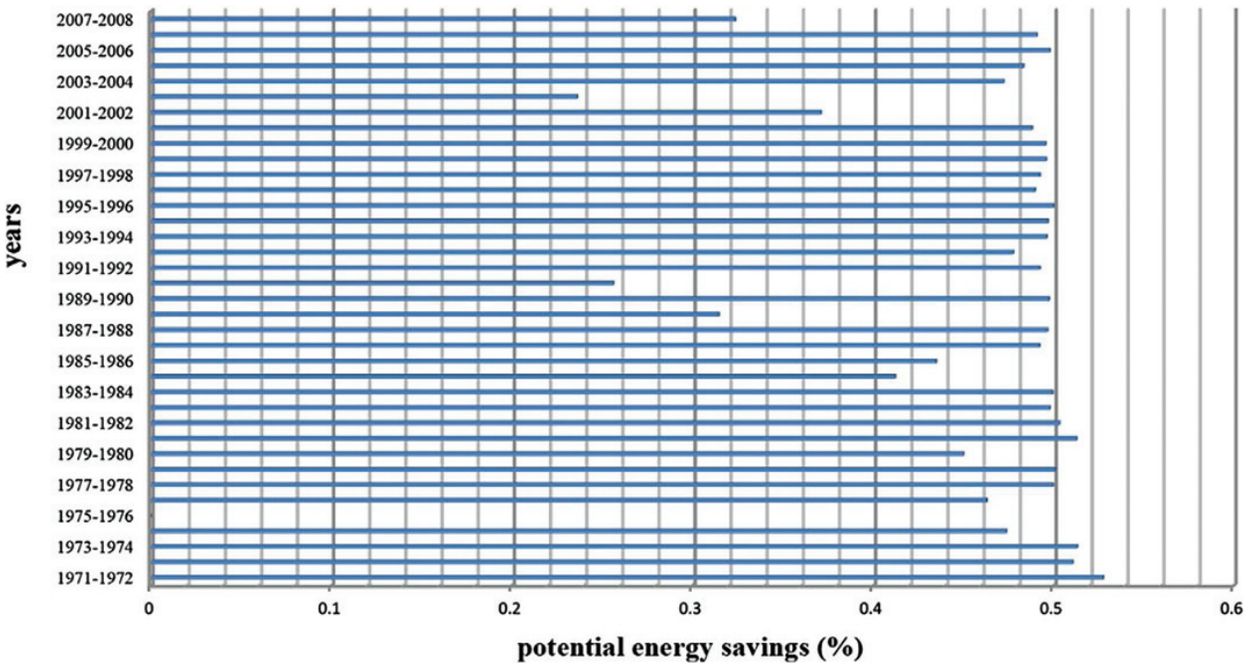


Figure 11. Possible energy-saving potential.

5. Conclusion

The hybrid method highlights the amount of energy that could be saved from the various case studies and possible greenhouse gas potential reductions observed in this chapter. Successful evaluation of energy use and mitigation of greenhouse gas with the hybrid method gives insight into how energy/greenhouse gas is being consumed and emitted in the industries of study, with similarity to other industries. Various hybrid methods exist to solving one problem or the other; this chapter however focused on a hybrid method with the advantage of offsetting the bias exhibited by one of the methods, with the strength of one method making up for the weakness of another method. This chapter expressed the various mathematics behind the models and their integration into a single model. The LMDI form of decomposition disintegrates both energy and greenhouse gas into the various factors that lead to the energy/greenhouse gas consumption/emission. The integration of the decomposed result must be a non-negative value for the hybrid model to be a success. Neural network has proved beyond reasonable doubt as a better prediction tool compared to traditional methods like regression analysis. However, regression analysis validated the perfection that neural network brings into the hybrid model. A proven benchmarking tool is the data envelopment analysis, which is the last method integrated into the hybrid model. It successfully identified the most efficient units and compared the efficient unit to the non-efficient to determine how best to make the non-efficient as efficient.

The hybrid model has energy, greenhouse gas, economy and environment combined to have a sustainable way of conserving energy/mitigating greenhouse gas and eliminating waste. From the case studies summarized, results proved energy planners can be easily assisted for a future green environment through the hybrid application. This can also assist in the formation of strategies and conservation schemes which can bring about relevant technology development as well as policies.

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