Quantitative Impacts of Independent Research and Development, Foreign and Domestic Technology Transfer on Energy Consumption

O.A Olanrewaju
Quality and Operations Department, Faculty of Engineering and the Built Environment
University of Johannesburg, South Africa
dlp4all@yahoo.co.uk

C. Mbohwa
Quality and Operations Department, Faculty of Engineering and the Built Environment
University of Johannesburg, South Africa
cmbohwa@uj.ac.za

Abstract

Energy continues to play a significant role in human lives. Among the indicators that have a major part to play in the consumption of energy is intensity factor. Considering the influence of intensity on energy consumption; its reduction will go a long way in promoting the sustenance of energy supply both locally and internationally. Many activities have been investigated upon that can assist in its reduction. These activities include research and development (R&D), introduction of foreign technology and domestic technology transfer driven activities. This study aims to evaluate these activities with the focus on minimizing energy consumption. A designed integrated model (artificial neural network and data envelopment analysis) that can be used in this regard is established. With South Africa as a case study, the model identified much concentration on foreign technology transfer as a means of energy reduction.

Keywords
Integrated model; R&D; foreign technology transfer; domestic technology transfer.

1. Introduction
Energy continues to play a significant role in human lives. For this reason, the world is taking the responsibility to map out a decisive process on improving infrastructures needed to obtain the required energy for efficient supply and to attain the economic output growth. Energy remains significant because of the energy and economic development interdependence. The dynamics of energy and economy present unique challenges to the present and future generations. Among the indicators that have a major part to play in the consumption of energy is intensity factor. Considering the influence of intensity on energy consumption; its reduction will go a long way in promoting the sustenance of energy supply both locally and internationally. Technology transfers, both foreign and domestic with Research and Development (R&D) are activities that can rise to the world energy challenges in the regard of its reduction. These activities (independent activities) will help achieve the phenomenon of intensity reduction. The main goal of investments in R&D, innovation, and new technologies is to have an improvement in energy usage and reduction of carbon emitted as it maintains or enhances countries and sectors economic performance (Lanzi, 2013).

Technology transfer refers to the management of process used to convey technology from a developer to a user, as defined by (Lulu et al., 1996). Some energy technologies that could contribute to achieving a much lower carbon intensity of the energy sector are still expensive (Lanzi, 2013) and yet to find their ways to the market. Results would be more easily achievable if there are transfers of these technologies. After the first oil shock, emphasis leaned towards R&D (Soriano and Mulatero, 2011). R&D activities are the engine of technological development (Garrone and Grilli, 2010, Olanrewaju and Jimoh, 2014). These activities have in part directed towards developing energy efficient technology (Olanrewaju and Jimoh, 2014, Henriksson et al., 2012).

Technology has always been a key element of industrialization and catch-up in developing countries (Fu et al., 2011). As much as R&D activity is the motor of technological development (Sagar and Zwaan, 2006), technology transfers are crucial to seeing the effects of various R&Ds. In choosing improved technologies, firms engage into in-house R&D or bring in technologies from dealers in developed countries (Hagedoorn, 1993). It is important to assess quantitatively the importance of technology transfers (both domestic and foreign) and R&D activities that can result in the reduction of intensity on energy consumed. The quantitative assessment of these activities on the use of energy can benefit the nation, especially the department of energy by way of decision-support and emission/consumption reduction. This paper's objective focuses on analyzing the efficiency and influence of technology transfers and R&D by using artificial neural network (ANN) and data envelopment analysis (DEA) on South Africa's consumption of energy. On the initial stage, ANN was used to effectively predict the baseline of the energy consumed. On the second stage, DEA was employed to evaluate the comparative significance of the independent parameters against baseline value, also known to be sensitivity analysis. Under the investigation of this study, it will provide information as to what activity needs to be given extra attention to assist in mitigating the energy crisis. To establish policies that lead to the safety of the environment, sensitivity analyses on these various activities will be employed to establish the most significant activity in the reduction of energy intensity.

Very few empirical studies have been carried out on energy R&D and technology transfers on the consumption of energy. Domestic technology depends on various parameters like the technological know-hows of the home country, investment proprietorship, the part engaged by the governments in attaining foreign technology accessibility, including local efforts in the promotion of the learning process that comes from such technologies, amongst other important parameters (Audretsch and Feldman, 1996). Watanabe in one of his studies analyzed the contributing factors to energy reduction in Japan. From his study, the reduced unit of energy is 44% and this is attributed to the swap in technology for energy and the last contribution was due to R&D intensity (47.5%) as well as the price increase in energy (8.5%) (Watanabe, 1993). More than a decade ago, a research conducted in the U.S (DOE, 1995) quoted a hand-full of successes of energy research development and demonstration. An agreement exists within the economist society about R&D having a payback which is higher than many other investments (Worrell et al., 2001).

The existence of both theoretical arguments and observed evidences have verified indigenous and foreign technologies to be complementary (Fu et al., 2011, Herrerias et al., 2015). A framework was developed and tested empirically to highlight allowance management capability and organizational capability as key drivers of interaction which increases the success of technology transfer. The framework is based on a fuzzy set qualitative comparative analysis (fsQCA) as an original diagnostic approach to conducting configurational analyses (Leisching et al., 2014). The results of their study underscored the need to focus on interactions between inter organizational transfer partners as key to successful transfer of technology.

The organization of the remainder of the paper is as follows: presentation of the data for this study is in section 2. Section 3 describes the method employed is developed that is studied on the South African data. Section 4 presents the results and finally, conclusion is presented in section 5.

2. Data

Table 1 shows the data gathered from 2005/06 to 2011/12 for this study. The missing data were calculated based on the trend and relationships of the gathered data. The following regression equations were used to calculate the missing data for energy from 2010/11 to 2011/12, for domestic technology transfer from 2007/08 to 2011/12 and foreign technology transfer from 2005/06 to 2009/10, where DTT represents domestic technology transfer and FTT represents foreign technology transfer, t in the equations below represents coded years:

$$Energy = 9032914.855 - 285974.94t \tag{1}$$

$$DTT = 1434214.5 + 16316119t \tag{2}$$

$$FTT = 172228571.43 + 34796428.57t \tag{3}$$

Table 1. Acquired and calculated values

Year	**Energy (Joules)**	**DTT (Rands)**	**FTT (Rands)**	**R&D (Rands)**
2005/06	7949201	119672000	33042857	712712000
2006/07	7742673	124677000	67839286	922202000
2007/08	7538066	148279286	102635714	1074767000
2008/09	6874635	164595405	137432143	1700671000
2009/10	6683347	180911524	172228571	947554000
2010/11	6459140	197227643	196300000	898173000
2011/12	6173165	213543762	285000000	949880000

3. Methodology

This study aims at employing a combined framework of ANN-DEA to analyze and assess energy consumption considering independent research and development, introduction of foreign technology and domestic technology transfer driven activities. The schematic framework of the proposed methodology is given in Figure 1. This report will develop concepts and methods meant for practical applications. The approach adopted by the study is the integration of artificial neural network (ANN) and data envelopment analysis (DEA) into a single model. This methodology combines modeling, which is at the core of an energy-management technique, with a wider interpretation of independent research and development, introduction of foreign technology and domestic technology transfer driven activities which contribute to energy/emission mitigation.

3.1 ANN

Models developed from actual data is a basic issue in many areas, such as analysis of statistical data, processing of signals, control, forecasting, and intelligence computation (Amina et al., 2012). Many improvements have been made in exploiting intelligent systems, some inspired by biological neural networks, fuzzy systems and integration of them (Hayati and Shirvany, 2007). Nonetheless, artificial neural networks (ANN) have obtained the widest application indisputably, referenced along with the most potent computational mechanisms ever built (Hsu and Chen, 2003). In this study, modeling will be used to explore the implications of the various activities in a quantitative framework. ANNs are composed of attributes that lead to perfect solutions in applications where we need to learn a linear or non-linear mapping (Azadeh et al., 2010). ANN will be used to capture the relationship between the various activities and energy consumed so as to make accurate forecasting of the energy consumption baseline. The ANN methodology allows unswerving forecasts which subsequently permits for planning and conducts necessary procedures to attain definite objectives (Kljajic et al., 2012).

The various activities responsible for the energy consumption serve as input to ANN, whose equation is given by

$$y_j = f(\sum_i w_{ij} x_{ij}) \quad (4)$$

with yj representing the output of node j, f(.) represents transfer function, wij represents connection weight between node j and node i in the lower layer and Xi the input signal from the node i in the lower layer. Substituting the activities as input values and the output value into equation (1) becomes

$$U_{tot} = f(\sum_i w_{ij} \{A_{ij}, B_{ij}, C_{ij}\}) \quad (5)$$

Where Aij represents independent research and development, Bij represents foreign technology transfer and Cij represents domestic technology transfer.

Minimizing the average sum of errors between the energy consumed (output to the neural network) and the target energy consumed (predicted output) is the aim. Thus,

$$mse = \frac{1}{Q} \sum_{K=1}^{Q} [U_{tot} t(k) - U_{tot} a(k)]^2 \quad (6)$$

Where $U_{tot}t$ is the predicted output and $U_{tot}a$, the observed output.

3.2 DEA

DEA is a known mathematical procedure that uses a linear programming technique to assess the efficiencies of decision-making units (DMUs). DEA is a nonparametric method that results in a single measure of efficiency for each unit relative to its peers. It is a recognized robust tool used for appraising organizations' performance (El-Mashaleh et al., 2010). DEA is an extension of Farrell's (1957) knowledge of linking the computation of technical efficiency with production frontiers. The first DEA model was developed by Charnes Cooper and Rhodes (1978) (CCR). The CCR model is a fractional programming model, which measures the relative technical efficiency of a DMU by calculating the ratio of weighted sum of its outputs to the weighted sum of its inputs (Kabnurkar, 2001).

DEA is based on a linear programming that produces a single measure of efficiency using both the observed and predicted energy consumption as variables for this study. DEA is a powerful data analytic tool that is widely used by researchers and practitioners alike to assess relative performance of Decision Making Units (DMUs). The period in question will be the DMU for this study. This study makes use of the input-oriented Charnes-Cooper-Rhodes (CCR) model of DEA. The input model aims to minimize inputs while satisfying at least the given output (Liu et al., 2010). The mathematical form for the CCR model is shown below (William et al., 2007):

$$\text{Max} \quad \frac{\sum_{r=1}^{s} y_{ro}u_r}{\sum_{i=1}^{m} x_{io}v_i}$$

$$\text{Such that} \quad \frac{\sum_{r=1}^{s} y_{ro}u_r}{\sum_{i=1}^{m} x_{io}v_i} \le 1, \; j = 1 \ldots n \qquad (7)$$

$$v_i \ge 0, i = 1,\ldots,m;$$

$$u_r \ge 0, r = 1,\ldots,s.$$

Where the yro, r=1,…,s represent outputs and the xio, i=1,…,m represent inputs for each of j=1,…n DMUs and j=0 identifies the DMUj to be evaluated. ur is the output weight while vi is the input weight. From the DEA equation; substituting $U_{tot}(t)$ as the output variable and $U(\mathrm{i})$ as the input variable gives

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

$$\text{Such that} \quad \frac{\sum_{r=1}^{s} U_{tot}(t)_{ro}u_r}{\sum_{i=1}^{m} U(\mathrm{i})_{io}v_i} \le 1, \; j = 1 \ldots n \qquad (8)$$

$$v_i \ge 0, i = 1,\ldots,m;$$

$$u_r \ge 0, r = 1,\ldots,s.$$

Transforming into an ordinary linear programming problem, thus; **μ**r = β **μ**r , vi = β vi is obtained with the same optimum value as equation (8)

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

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

$$-\sum_{i=1}^{m} U(\mathrm{i})_{ij} + \sum_{r=1}^{s} \mu_r U_{tot}(t)_{rj} \le 0, \; j = 1,\ldots n, \qquad (9)$$

$v_i \geq 0, i = 1,..m,$

$\mu_r \geq 0, r = 1,...s.$

Equation (9) has a dual form that can be written as

Min η_o

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

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

$\lambda_j \geq 0, \ j = 1,...,n$ (10)

Equations (9) and (10) will allow the accountability of each of the independent activities (inputs) while keeping the expected energy to be consumed at the baseline level. For sensitivity analysis, measure-specific DEA model was used. A way of testing the robustness of DEA results is conducting the analysis by omitting an input or output and then studying the results (Tyagi et al., 2009). The equation that governs it is as follows:

$\min \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$

Subject to

CRS $\quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}; i \in I;$

$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}; i \notin I;$

$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0}; r = 1, .., s$

$\lambda_j \geq 0 \quad j = 1,2, \dots n.$ (11)

where I represent the sets of specific inputs respectively. For this study, the constant returns to scale (CRS) approach was employed. For more on CRS, interested readers are referred to (William et al., 2006). The inputs will be omitted one after the other.

4. Results

4.1 ANN Analysis

MATLAB R2014a (8.3.0.532) was employed in carrying out the neural network analyses. Comparison of the performance of different cross-validated networks, from 1 to 10 hidden neurons, the best network performance was established and selected. The predicted energy consumption is very close to the actual energy consumption with minimal error as observed by visual inspection (Figure 2). It was a network creation of three input neurons (R&D activity, foreign technology transfer and domestic technology transfer), five hidden neurons and a single output neuron (energy consumption). Figure 3 depicts the network structure. In the analysis, network parameters of learning rate and momentum were set to 0.3 and 0.2, accordingly. Variable learning rate with momentum (trainlm) as network's training function, sigmoid and linear activation functions for the layers were employed. For the prediction, 2005/06, 2007/08, 2009/10 and 2011/12 were used for training, 2006/07 and 2009/10 for testing, whereas 2008/09 is used for validation. Table 2 shows the results of the predicted and target values with the errors.

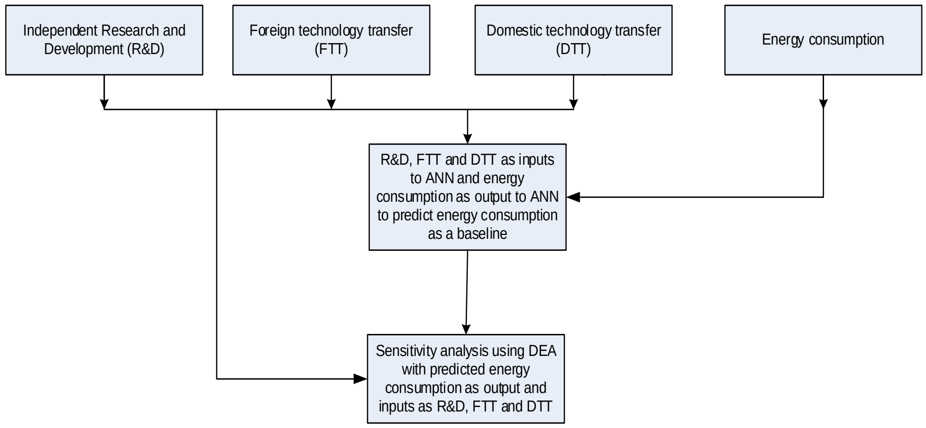

Figure 1. Schematic framework of the proposed study.

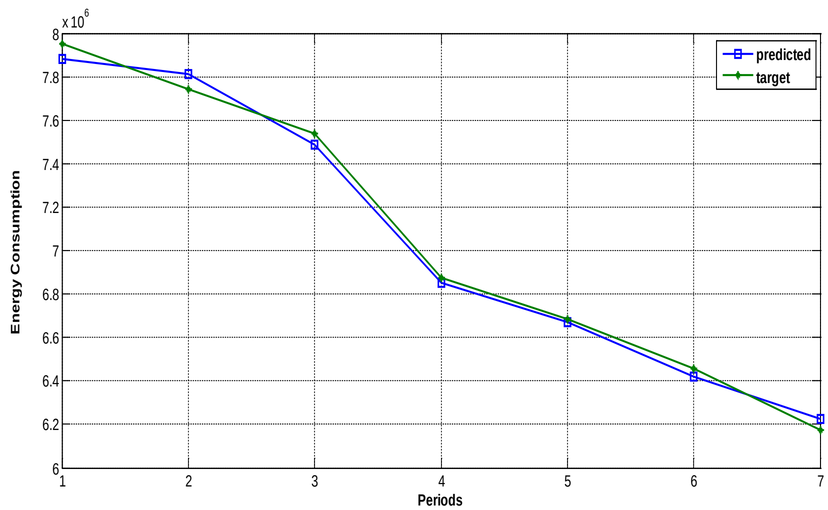

Figure 2. Visual inspection of the predicted and actual energy consumption.

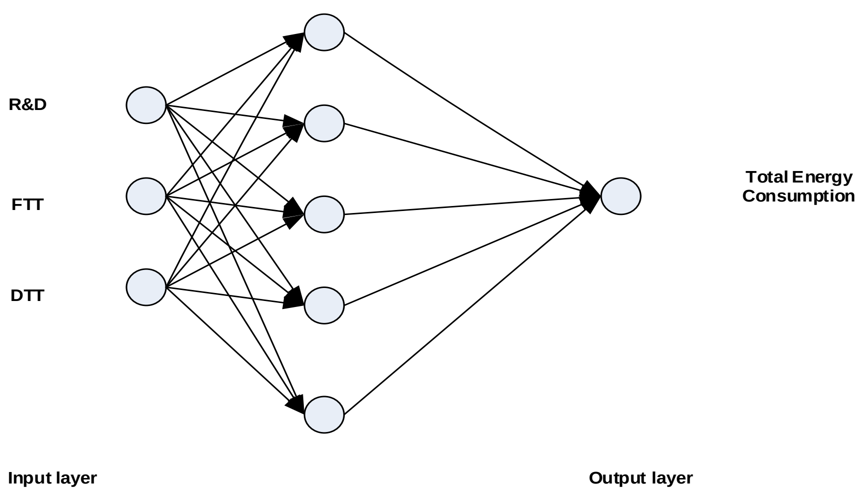

Figure 3. Artificial Neural network structure.

Table 2. Target and Predicted Energy consumption

Year	Target energy	Predicted energy	Error
2005/06	7949201	7882712.276	66488.72414
2006/07	7742673	7812663.978	-69990.978
2007/08	7538066	7486057.612	52008.38835
2008/09	6874635	6850639.024	23995.97627
2009/10	6683347	6671469.646	11877.35431
2010/11	6459140	6420814.312	38325.68845
2011/12	6173165	6223898.206	-50733.2057

4.2 DEA Analysis

DEAFrontier software package on Excel has been employed to carry out the DEA analysis. R&D, domestic and foreign technology transfers were selected as inputs, whereas the predicted energy consumption serving as the baseline was selected as the output data for the analysis. Each input was omitted one after the other with the output remaining constant throughout the analysis. Table 3 below shows the results of the omission of each input. Lowest mean (0.3393) and highest standard deviation (0.3183) is calculated for model 2, which indicates that South Africa has considered FTT as her most important factor to assist in the economic consumption of energy. The highest mean (0.6876) for model 1 indicates that South Africa combines FTT and R&D the more leaving out DTT in the reduction of energy consumption.

Table 3. Sensitivity analyses result

DMU No.	DMU Name	Measure-Specific Efficiency (Model 1-without DTT)	Measure-Specific Efficiency (Model 2-without FTT)	Measure-Specific Efficiency (Model 3-without R&D)
1	2005/06	1	1	1
2	2006/07	0.93492	0.47442	0.75276
3	2007/08	0.76533	0.30529	0.62883
4	2008/09	0.62878	0.20793	0.36243
5	2009/10	0.55616	0.1613	0.63238
6	2010/11	0.49303	0.13678	0.64477
7	2011/12	0.4352	0.09004	0.58268

4.3 Validation with ANN

To validate the analysis carried out by DEA, the connection weight of ANN was used for validation. The connection weight approach adds the product of the weight of the connection from input neuron to the hidden neurons with the weight of the connection from the hidden neurons to the output neurons for all input parameters (Olden et al., 2004, Kemp et al., 2007). As the sum of the connection weights gets larger, the more the significance of the parameter linked to the input neuron. The comparative importance of the input factors is estimated along the following equation:

$$significance(i) = \sum nx = 1(cw_{ih}(x) * cw_{ho}(x)) \quad (12)$$

With significance (i) indicating the comparative significance of input i; n representing hidden nodes' number; x represents hidden node's index number; $cw_{ih}(x)$ signifies connectivity weight between input factor i and hidden node x; $cw_{ho}(x)$ signifies weight between hidden node x and the output node. Table 4 below is the application of the connection weight quantifying the input factors according to their level of significance. DEA sensitivity analyses was validated through the neural network connection weight (Table 4) ranking FTT as first factor concentrated upon the most in South Africa by 111%, next to R&D which is 21% and last is DTT which is (-) 32%.

Table 4. Connection weight approach analyzing the level of importance of the input factors

	Hidden 1	**Hidden 2**	**Hidden 3**	**Hidden 4**	**Hidden 5**
DTT	-0.3235	0.3417	0.4898	1.2086	0.1751
FTT	-0.0845	-1.6253	1.146	0.0239	1.3108
R&D	0.6381	-0.1962	0.0953	-0.1177	-0.1491
			x		
	-0.4642	1.0023	-0.4697	0.5243	-0.5615
			=		
DTT	0.1504922	0.3424	-0.23	0.6336	-0.0983
FTT	0.0393	-1.629	-0.5382	0.0125	-0.736
R&D	-0.2968	-0.1966	-0.0447	-0.0617	0.0837
			=		
			Level of Importance	**Percentage**	
		DTT	0.7981	-32%	
		FTT	-2.7389	111%	
		R&D	-0.5161	21%	

5. Conclusion

This paper introduces technology transfers and R&D activities as factors which are critical in deciding the optimal use of energy. These activities are quantified to show their level of importance on energy consumption reduction so that their significance can be taken seriously among the energy community. In order to have a clearer picture how these activities contribute to energy reduction, a designed model, integrating both artificial neural network and data envelopment analysis was established. In this regard, the artificial neural network was used to investigate and establish the baseline of the energy consumption based on the impacts of the various activities. Data envelopment analysis conducted a sensitivity analysis on the various inputs omitted one after the other. The result of the data envelopment analysis was validated with the connection weight approach of the artificial neural network. The South African case study gives a wider margin of how these activities contribute to energy reduction. It is very important that the country starts to concentrate on indigenous technologies and R&D activities so as to reduce the margin between them and the concentration on foreign technology transfer.

References

Amina, M., Kodogiannis, V. S., Petrounias, I. P., Lygouras, J. N. & Nychas, G.-J. E. 2012. Identification of the Listeria monocytogenes survival in UHT whole milk utilising local linear wavelet neural networks. . *Expert system with Applications,* 39**,** 1435-1450.

Audretsch, D. & Feldman, M. 1996. R&D spillovers and the geography of innovation and production. *American Economic Reviews,* 86**,** 253-73.

Azadeh, A., Arab, R. & Behfard, S. 2010. An adaptive intelligent algorithm for forecasting long term gasoline demand estimation: The case of USA, Canada, Japan, Kuwait and Iran. *Expert Systems with Applications,* 37**,** 7427 - 7437.

DOE 1995. Energy R&D: Shaping our nations future in a competitive world. Task force on strategic Energy Research and Development. *In:* ENERGY, D. O. (ed.). Washington DC, USA.

El-Mashaleh, M., Rababeh, S. M. & Hydri, K. H. 2010. Utilizing data envelopment analysis to benchmark safety performance of construction contractors. . *International Journal of Project Management,* 28**,** 61-67.

Fu, X., Pietrobelli, C. & Soete, L. 2011. The role of foreign technology and indigenous innovation in the emerging economies: technological change and catching-up. *World Development,* 39**,** 1204-1212.

Garrone, P. & Grilli, L. 2010. Is there a relationship between public expenditures in energy R&D and carbon emissions per GDP? An empirical investigation. *Energy Policy,* 38**,** 5600-5613.

Hagedoorn, J. 1993. Understanding the rationale productivity differences among countries. *American Economic Reviews,* 60**,** 895-911.

Hayati, M. & Shirvany, Y. 2007. Artificial Neural Network Approach for Short Term Load Forecasting for Illam Region. *World Academy of Science, Engineering and Technology.*

Henriksson, E., Soderholm, P. & Warell, L. 2012. Industrial electricity demand and energy efficiency policy: The role of price changes and private R&D in the Swedish pulp and paper industry. *Energy Policy,* 47**,** 437-446.

Herrerias, M. J., Cuadros, A. & Luo, D. 2015. Foreign versus indigenous innovation and energy intensity: Further research across Chinese regions. *Applied Energy,* In Press.

Hsu, C.-C. & Chen, C.-Y. 2003. Regional load forecasting in Taiwan-applications of artificial neural networks. . *Energy conversion and Management,* 44**,** 1941-1949.

Kabnurkar, A. 2001. Mathematical Modeling for Data Envelopment Analysis with Fuzzy Restrictions on weights in Industrial and Systems Engineering. . Virginia: Virginia Polytechnic Institute and State University.

Kemp, S. J., Zaradic, P. & Hansen, F. 2007. An approach for determining relative input parameter importance and significance in artificial neural networks. *Ecological Modelling,* 204**,** 326-334.

Kljajic, M., Gvozdenac, D. & Vukmirovic, S. 2012. Use of Neural Networks for modeling and predicting boiler's operating performance. . *Energy***,** 1-8.

Lanzi, E. 2013. Impacts of innovation: Lessons from the empirical evidence. *Encyclopedia of Energy, Natural Resource and Environmental Economics***,** 82-88.

Leisching, A., Geigenmueller, A. & Lohmann, S. 2014. On the role of alliance management capability, organizational compatibility, and interaction quality in interorganizational technology transfer. *Journal of Business Research,* 67**,** 1049-1057.

Liu, C. H., Lin, S. J. & Lewis, C. 2010. Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. *Energy Policy,* 38**,** 1049-1058.

Lulu, M., Seyoun, G. & Swift, F. W. 1996. A decision model for technology transfer *Computers ind. Engng,* 31**,** 37-40.

Olanrewaju, O. A. & Jimoh, A.-G. A. 2014. Impacts of Independent Research and Development, Foreign Technology and Domestic Technology Transfer Driven Activities *In:* REITER, S. (ed.) *Energy Consumption - impacts of human activity, current and future challenges, environmental and socio-economic effects.* New York: Nova.

Olden, J. D., Joy, M. K. & Death, R. G. 2004. An accurate comparison of methods for quantifying variable importance in artificial neural networks using simulated data. *Ecological Modelling,* 178**,** 389-397.

Sagar, A. D. & Zwaan, B. C. C. V. D. 2006. Technological innovation in the energy sector: R&D, deployment, and learning-by-doing. *Energy Policy,* 34**,** 2601-2608.

Soriano, F. H. & Mulatero, F. 2011. EU Research and Innovation (R&I) in renewable energies: The role of the Strategic Energy Technology Plan (SET-Plan). *Energy Policy* 39**,** 3582-3590.

Tyagi, P., Yadav, S. P. & Singh, S. P. 2009. Relative performance of academic departments using DEA with sensitivity analysis. *Evaluation and Program Planning,* 32**,** 168-177.

Watanabe, C. MITI's efforts to mitigate global warming by substituting technology for energy. IIASA's International Workshop on Assessment of Mitigation. Impacts and Adaptation to Climate Change, 1993 Vienna.

William, W. C., Jose, L. R. & Sirvent, I. 2007. Choosing weights from alternative optimal solutions of dual multiplier models in DEA. *European Journal of Operational Research,* 180**,** 443-458.

William, W. C., Lawrence, M. S. & Tone, K. 2006. Introduction to Data Envelopment Analysis and its uses with DEA-Solver Software and References. New York: Springer.

Worrell, E., Berkel, R. V., Fengqi, Z., Menje, C., Schaeffer, R. & Williams, R. O. 2001. Technology transfer of energy efficient technologies in industry: a review of trends and policy issues. *Energy Policy,* 29.

Biographies

Dr. Oludolapo Akanni Olanrewaju is currently a Post-doctoral student in Industrial Engineering and Operations Management at University of Johannesburg's (UJ) Faculty of Engineering and the Built Environment (FEBE). As an established researcher in the field of energy, his specializations include applications of Data Management and Analysis, Optimization, and Artificial Intelligence on energy systems with general research interests in energy and greenhouse gas potentials. Dr. Olanrewaju has presented at numerous conferences and published more than 20 papers in peer-reviewed journals and conferences, and 1 book chapter. He holds a BSc Honours in Electrical Engineering from the University of Ibadan in 2004. Upon graduating with his MSc in Industrial Engineering from the University of Ibadan in 2008, he was employed as an ad-hoc engineer by the same University he graduated from. He completed his doctoral studies at Tshwane University of Technology in South Africa.

Professor Charles Mbohwa is the Vice-Dean Postgraduate Studies, Research and Innovation at University of Johannesburg's (UJ) Faculty of Engineering and the Built Environment (FEBE). As an established researcher and professor in the field of sustainability engineering and energy, his specialisations include sustainable engineering, energy systems, life cycle assessment and bio-energy/fuel feasibility and sustainability with general research interests in renewable energies and sustainability issues. Professor Mbohwa has presented at numerous conferences and published more than 350 papers in peer-reviewed journals and conferences, 10 book chapters and three books. Upon graduating with his BSc Honours in Mechanical Engineering from the University of Zimbabwe in 1986, he was employed as a mechanical engineer by the National Railways of Zimbabwe. He holds a Masters in Operations Management and Manufacturing Systems from University of Nottingham and completed his doctoral studies at Tokyo Metropolitan Institute of Technology in Japan. Prof Mbohwa was a Fulbright Scholar visiting the Supply Chain and Logistics Institute at the School of Industrial and Systems Engineering, Georgia Institute of Technology, a Japan Foundation Fellow, is a Fellow of the Zimbabwean Institution of Engineers and is a registered mechanical engineer with the Engineering Council of Zimbabwe.