Prediction of Residential Sector Energy Consumption: Artificial Neural Network Application

O.A Olanrewaju[1] and C. Mbohwa[2]

[1,2] Industrial and Operations Department, Faculty of Engineering and the Built Environment
University of Johannesburg, South Africa

dlp4all@yahoo.co.uk[1], cmbohwa@uj.ac.za [2]

Abstract

In order to analyze the way residential sector energy is consumed putting into consideration certain factors, this study predicted the United States residential sector energy consumption from 1984 to 2010. The factors having impact on the way energy is consumed were assessed using the connection weight approach while the energy is being predicted. Artificial Neural Network was successfully applied in the prediction with a correlation coefficient of 0.97903. It was observed that the median household income was the most important factor in the consumption of residential sector energy consumption with a percentage of 93% followed by household size and cost of residential natural gas with 90% and 56.5% respectively while resident population was the least important factor followed by cost of residential heating oil, gross domestic product and cost of electricity in percentages of -76%, -51%, -30.5%, and 18% respectively.

Keywords: Artificial Neural Network; Residential sector energy; connection weight; analyze; predict

Introduction

Energy consumed in the residential sector has a very complex as well as inter-related characteristics (Belaid, 2016). The residential sector has a large portion of consumed energy globally, and for that, remains a target for consumption of energy efforts (Swan and Ugursal, 2009). Everyday activities require accessibility and use of energy serving as pre-requisite for fundamental needs (Sovacool et al., 2014).The level of energy consumed by a building in any country is very specific to the country's economic and social indicators in the likes of country's income and the stage of urbanization (IEA, 2010). Residential sector records 16 – 50% of total energy consumption in nearly all countries (Saidur et al., 2007). This gives rise to increase in emitted GHGs (Ahmed et al., 2015). (Belaid, 2016) identified residential building sector as one of the most cost-effective sectors that can greatly cut down the amount of energy consumed and also mitigate greenhouse gas (GHG) emissions in France. This statement however is true across the globe.

The amount of energy consumed domestically depends on country, weather and building type. As much as these factors are the same, variation in consumption still occurs by virtue of pattern of occupancy and inhabitant's lifestyle (Ellsworth-Krebs et al., 2015). Determining the inputs of those factors responsible for the residential energy consumed can serve as a guide to decisions made by policy makers. Among the countries, the developed tend to consume more as compared to developing (IEA, 2010). However, the urban settlements of the developed countries tend to consume less energy per capita as compared to their rural counterparts. Reason for this can be attributed to district heating in higher-density areas, low transportation-related energy use, among other factors. On the other hand, the reverse is the case with developing countries (IEA, 2010).

A residential sector is expected to give comfort. In giving this, energy plays a major role to its realization. This study focuses on predicting accurately energy consumed in a residential sector as well as give level of importance to the factors resulting in the energy consumed. A general technique when it comes to prediction is the regression analysis. With the wide acceptance of this technique, it falls short when non-linear relationship is considered. Relationship between energy consumed and the factors responsible for the consumption of energy are mostly non-linear which

978-1-5090-3924-1/17/$31.00 ©2017 IEEE

nullifies the regression technique. Among the proven techniques to assess a non-linear relationship is the Artificial Neural Network (ANN). ANN in particular has gained a lot of recognition when it comes to the study of energy. Models adopted for residential energy consumption consider various parameter sets (Gruber et al., 2014). Many studies have confirmed the uniqueness of ANN in energy prediction. Among those studies are (Gajic et al., 2016, Moon and Jung, 2016a, Chiteka and Enweremadu, 2016, Moon and Jung, 2016b, Deb et al., 2016, Azadeh et al., 2008, Aydinalp et al., 2002)

(Gajic et al., 2016) used ANN in the estimation of the extent as well as the fluctuation effect for the production of steel of an electric arc furnace, putting into consideration, the electrical energy consumed. The network was structured into 5-5-1 architecture, with 5 inputs, 5 hidden layers and one output. The inputs were the steel composition – carbon, chromium, nickel, silicon and iron, whereas the output was the electrical energy consumed. In their study, ANN had a good prediction with coefficient of determination of 0.91. The study concluded that among the components, carbon had the highest effect on the energy consumed.

(Moon and Jung, 2016a) developed ANN in predicting the optimal start moment of a setback temperature. The setback temperature was predicted because of its usefulness as a potential method for the reduction of heating and cooling in residential consumption of energy. The study considered indoor air temperature, indoor air temperature changes from the indoor air temperature of the preceding control cycle, outdoor air temperature, outdoor air temperature change from one hour earlier and temperature difference from the setback temperature. In designing the optimal structure, 3 inputs were finally selected among the 5 inputs, these are the indoor air temperature, outdoor air temperature and the temperature difference from setback temperature, giving an architectural structure of 3-4-1.

In the prediction of global horizontal solar irradiance in Zimbabwe, (Chiteka and Enweremadu, 2016) adopted ANN for their study. The study considered both geographic and meteorological data as inputs. geographic data are the altitude, latitude and longitude while meteorological data are humidity, pressure, clearness index and average temperature. A good statistical result of 99.89% was achieved as the coefficient of determination, considering the result as very good. From statistical analyses, clearness of index contributed more to the performance with 19% next to temperature and humidity with 18% and 17%.

For improved thermal comfort as well as energy efficiency in domestic buildings, (Moon and Jung, 2016b) developed a thermal control algorithm employing ANN. Two predictive and adaptive ANN were developed. One of the models was for prediction of cooling the energy consumed when the building is not occupied at various setback temperatures. The second predicted time to restore present indoor temperature to the actual set-point temperature. The first model considered nine inputs while the second considered three inputs. The models showed their uniqueness in improving temperature and energy efficiency of a building.

An institutional buildings cooling energy in Singapore was predicted diurnally with the use of ANN (Deb et al., 2016). Three different buildings were used as case studies. ANN successfully trained and predicted the following day's energy use. The study considered three climatic conditions in air temperature, humidity and solar radiation. The input used for the study were 5 previous days' energy measured. The architecture of the ANN was 5-20-1, with 0.9794 as coefficient of determination. (Deb et al., 2016) addressed the possibility of predicting many days in succession without a change in any of the variables used in the models.

(Azadeh et al., 2008) successfully used ANN to predict electricity consumed by energy-intensive manufacturing industries on a long-term basis in 2008. When compared to regression analysis, statistically from MAPE error, it was clear that ANN was the better model. In a study to estimate the energy consumed by appliance, lighting and space cooling in a residential sector conducted by (Aydinalp et al., 2002), ANN was designed and employed. The study was compared to an engineering model which fell short to the ANN model. The coefficient of correlation was lower compared to the ANN. The next section focuses on the data and methodology followed by result and conclusion.

Data and Methodology

Data

Data for this study was from the study of (Kiralashaki and Reisel, 2013) from 1984 – 2010. The combination of residential population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil were defined as the inputs while the residential sector energy consumption was the output. The difference between present study and (Kiralashaki and Reisel, 2013) study is that all variables were considered in one model for this study whereas (Kiralashaki and Reisel, 2013) only considered few of the variables differently in three different ANN models. Table 1 below shows the data used for this study.

Table 1: Data for United States Residential energy consumption and its independent variables from 1984 – 2010 (Kiralashaki and Reisel, 2013).

Year	Resident population (thousand)	Gross Domestic Product (billion dollars)	Household size (persons)	Median household income (2010 dollars)	Cost of residential electricity (dollars per million Btu)	Cost of residential natural gas (dollars per million Btu)	Cost of residential heating oil (dollars per gallon)	Residential Sector energy consumption estimates (billion Btu)
1984	235825	3930.9	2.69	44802	20.169	5.719	7.571	15959563
1985	237924	4217.5	2.67	45640	20.129	5.517	7.056	16041334
1986	240133	4460.1	2.66	47256	19.842	5.169	5.5	15975109
1987	242289	4736.4	2.64	47848	19.221	4.73	5.097	16262213
1988	244499	5100.4	2.62	48216	18.531	4.494	4.955	17132613
1989	246819	5482.1	2.63	49076	18.081	4.412	5.233	17785725
1990	249623	5800.5	2.63	48423	17.558	4.308	5.864	16945297
1991	252981	5992.1	2.62	47032	17.301	4.145	5.394	17420310
1992	256514	6342.3	2.66	46646	17.15	4.072	4.8	17355685
1993	259919	6667.4	2.67	46419	16.875	4.147	4.546	18217687
1994	263126	7085.2	2.65	46937	16.572	4.203	4.301	18112431
1995	266278	7414.7	2.65	48408	16.154	3.872	4.102	18518963
1996	269394	7838.5	2.64	49112	15.616	3.937	4.545	19504218
1997	272647	8332.4	2.62	50123	15.394	4.21	4.421	18964947
1998	275854	8793.5	2.61	51944	14.852	4.05	3.769	18954918
1999	279040	9353.5	2.6	53252	14.355	3.906	3.791	19556929
2000	282172	9951.5	2.58	53164	14.024	4.392	5.489	20424794
2001	285082	10286.2	2.58	52005	14.199	5.284	5.089	20042076
2002	287804	10642.3	2.57	51398	13.75	4.279	4.525	20810265
2003	290326	11142.1	2.57	51353	13.89	5.086	5.31	21109915
2004	293046	11867.8	2.57	51174	13.886	5.547	5.909	21092623
2005	295753	12638.4	2.57	51739	14.181	6.326	7.576	21626073
2006	298593	13398.9	2.56	52124	15.119	6.625	8.459	20698278
2007	301580	14061.8	2.56	52823	15.054	6.143	9.014	21565031
2008	304375	14369.1	2.57	50939	15.328	6.282	10.78	21596245
2009	307007	14119	2.59	50599	15.724	5.521	8.019	21063265
2010	309349	14660.4	2.58	49445	15.511	5.106	9.252	22153450

Methodology

The development of ANN came from the study of the human nervous system. They are composed of interconnected neurons, with each neuron linked to the other by synaptic weights. A general neural network model is built with an input, hidden and output layer. With each of the layer operating by a number of neurons (Ata, 2015). They are understudy the pattern of a situation, i.e., in the form of data and replicate it. They have gained recognition in the prediction and optimization area (Han et al., 2016). ANN techniques have become so relevant as an alternative to traditional techniques. They are very reliable in solving complex problems. They have been relevant in the areas of medicine, engineering, social sciences, to name a few. The categories of their application include forecasting and prediction control, identification and evaluation, prediction and efficiency (Ata, 2015).

ANN is equipped with a learning algorithm (Han et al., 2016). ANN have the ability to understand and learn the vital information within a vast information domain. They have also gained advantage over its competitors when it comes to speed, simplicity, capacity to model a multivariable problem in solving very complex relationships between variables. They are also able to extract the non-linearity in a relationship through data training (Kalogirou, 2003). ANN is not "model – driven" but "data – driven" (Chakraborty et al., 1992) and is regarded as a non-parametric regression technique/ model used to predict and classify problems (Chiteka and Enweremadu, 2016). ANN exhibits three fundamental properties – (1) assumptions are not required, (2) they extrapolate from previous data to make predictions and (3) the complexity of non-linear problems are no problems (Ata, 2015). The responsibility of the ANN is to have the weighted sum of inputs activated from the preceding layer of neurons together with a bias neuron in the below equation

$$y = f\left[\sum_{i=1}^{n} x_i w_i + b\right] \qquad \text{equation 1}$$

Where b represents the bias neuron, x_i - input and w_i - weight from the ith neuron from the preceding layer and f - activation function (Gajic et al., 2016). Frequently used activation functions are the sigmoid and linear. The most popular form of ANN is the backpropagation algorithm (Ata, 2015). This study employed the feedforward backward propagation algorithm. The ANN is trained so as to build an optimal network for estimation of the effect of the input factors on the energy consumed by the residential sector within the period under study. MATLAB R2015b software was employed to learn the ANN. The process continued until the minimum value of sum of squares for error (SSE) was reached. Other statistical measure that was observed in the evaluation of the performance of ANN is the coefficient of determination ((R^2) . The equations to this measure of performance is given below:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}(y_i^e - y_i^p)^2}{\sum_{i=1}^{n}(y_i^e - \overline{y}_i^e)^2}\right) \qquad \text{equation 2}$$

y_i^p represents the predicted energy consumption, y_i^e is the actual energy consumption, $\overline{y}_i^e$ is the average actual energy consumption and n is the number of periods. The training process adopted Levenberg-Marquardt for the training. The Levenberg-Marquardt is famous for solving non-linear least square problems (Chiteka and Enweremadu, 2016). The activation functions used for this study are Tansig for both between the input and hidden and between hidden and output layers. The equation is given below:

$$A = Tansig(x) = \frac{2}{1 + e^{-2x}} - 1 \qquad \text{equation 3}$$

With A representing the output, and x is the sum of inputs. In selecting the inputs according to the order of importance in having effect on the energy consumed, the connection weight approach of the ANN was employed. The connection weight approach is guided by the equation below:

$$significance(i) = \sum nx = 1(cw_{ih}(x) * cw_{ho}(x)) \quad \text{equation 4}$$

Significance (i) indicates the relative impact of each of the various inputs i; n is hidden nodes' number; x is the hidden node's index number; $cw_{ih}(x)$ represents connectivity weight between input factor i and hidden node x; $cw_{ho}(x)$ represents weight between hidden node x and the output node. Below is the flowchart of the ANN operation

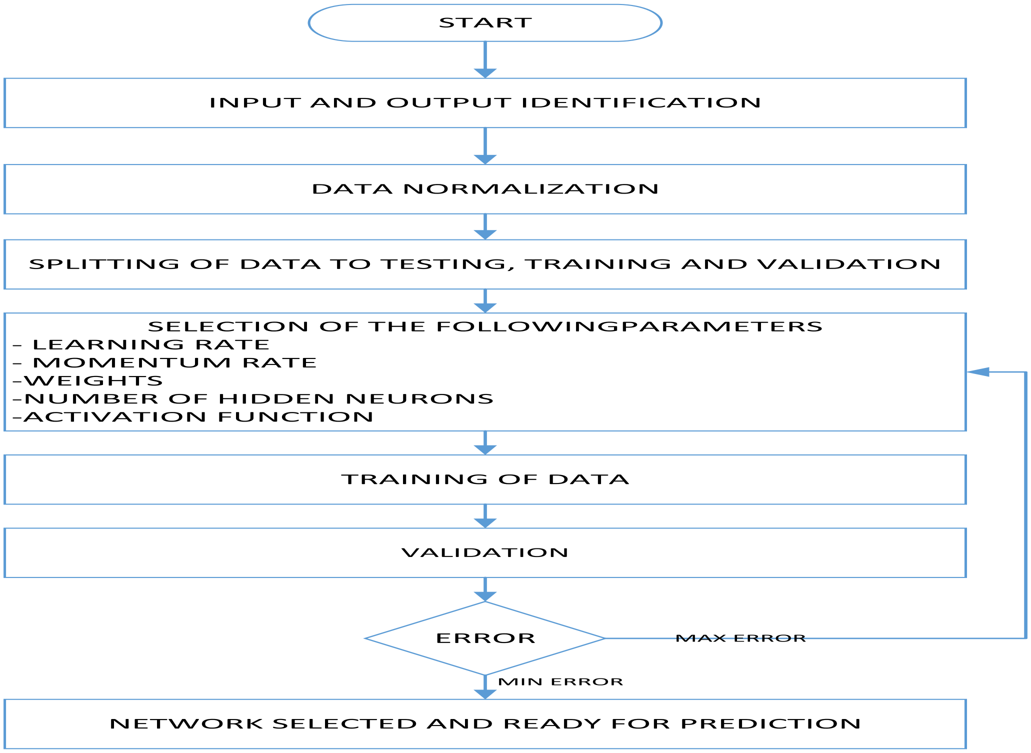

Figure 1: Flowchart of ANN Operation

Results

In attaining the objective of this study, the Residential sector was predicted using MATLAB 2015b software has told earlier. The neural network analysis was carried out with a 12-fold cross validation. As the performance of the different cross-validated networks were compared, with 1 – 12 hidden neurons, the number of hidden neurons with the most preferred performance and result was achieved and chosen. The data were divided into 52% training data, 26% testing data and 22% validation data. This created a network of seven input neurons (residential population, gross domestic product, household size, median household income, cost of residential electricity, cost of residential natural gas and cost of residential heating oil), five hidden neurons and a single output neuron (residential sector energy consumption). An architectural structure of 7 – 5 – 1. Figure 2 shows the relationship between actual and predicted residential sector energy consumption values obtained from the ANN model with a very good correlation coefficient of 0.97903. Figure 3 depicts the correlation results from every phase of the ANN. The analyses used network parameters of 0.05 learning rate and 0.7 momentum respectively. Variable learning rate with momentum (trainlm) as network's training function and sigmoid activation functions for the layers were employed.

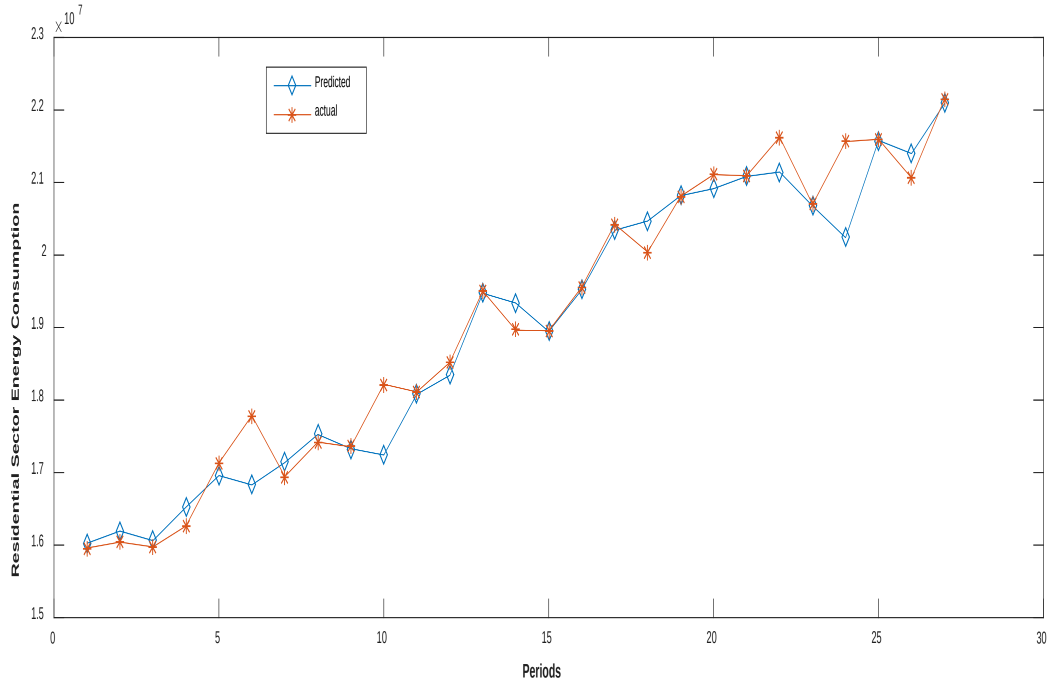

Figure 2: Visual Inspection of predicted and actual residential sector energy consumption.

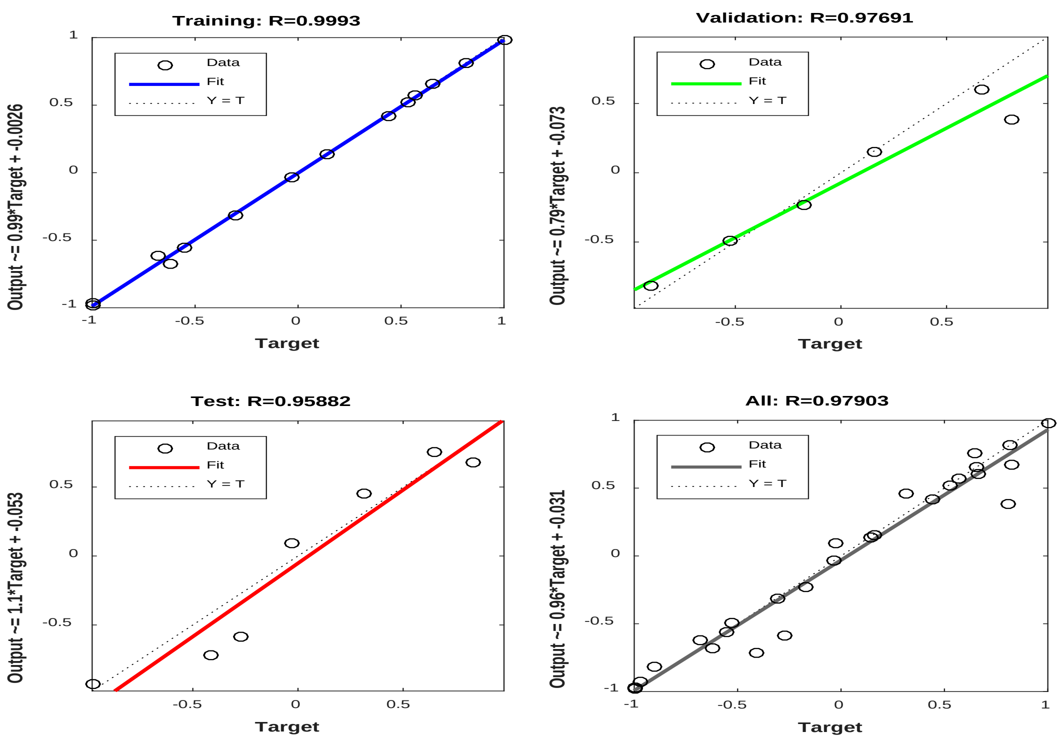

Figure 3: Regression Plots.

During simulation, some weights were generated for both the input and output data as explained by equation 1. These weights are known as the connection weights generated, as can be seen in their evaluation in Table 2. From Table 2, it can be said that median household income input was the most important factor when it comes to residential sector energy consumption next to household size input, with very high percentages of 93% and 90% respectively whereas resident population input was the least important factor next to cost of residential heating oil input.

Table 2: Connection weight results

Inputs	**Hidden 1**	**Hidden 2**	**Hidden 3**	**Hidden 4**	**Hidden 5**		
Resident population	0.0079	-1.0273	0.9186	1.547	-1.3797		-76%
Gross Domestic Product	0.2222	-0.7668	0.6595	1.0996	-0.3836		-30.50%
Household size	-2.2139	0.7037	0.2282	-0.3031	-0.2582		90%
Median household income	-1.1416	1.3351	-0.8756	1.0897	0.2223	=	93%
Cost of residential electricity	-0.3195	-0.7696	0.1301	0.4202	1.1895		18%
Cost of residential natural gas	-1.1201	0.6775	-0.5724	-0.8228	0.2618		56.50%
Cost of residential heating oil	1.2556	-0.467	2.702	-0.9218	-0.2186		-51%
			X				
	1.4047	-1.5368	-0.3181	-0.3549	-1.1023		

Conclusion

This study as compared to the study of (Kiralashaki and Reisel, 2013), used all the available inputs to predict accurately the amount of residential sector energy consumed in the United States. (Kiralashaki and Reisel, 2013) selected the inputs separately for three different ANN models, the first model considered GDP and cost of residential electricity, the second model considered GDP, median household income and cost of residential electricity while the third considered GDP, median household income, cost of residential electricity and cost of residential heating oil. From this present study, it can be said that all factors were able to predict the residential energy consumption successfully, however, the most important factors are the median household income followed by the household size, next to the cost of residential natural gas. From this present study carried out it can be said that the income received by household says a lot in the amount of energy consumed which was recognized in two models of the previous studies, however, household size as well as cost of residential natural gas were not selected as inputs in either of the three models. Based on the household income, it determines the type of household gadgets the family could afford as well as the energy efficient gadgets. The amount of individuals residing in a home based on their behavioral pattern will also affect how energy is being consumed, either efficiently or inefficiently. The United States residential sector case study gives a clearer view of how these factors do contribute to the energy consumed between 1984 and 2010. It is very important that the three key contributing factors identified in this study be attended to in ways that could assist in the conservation of energy consumed in the residential sectors.

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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.

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