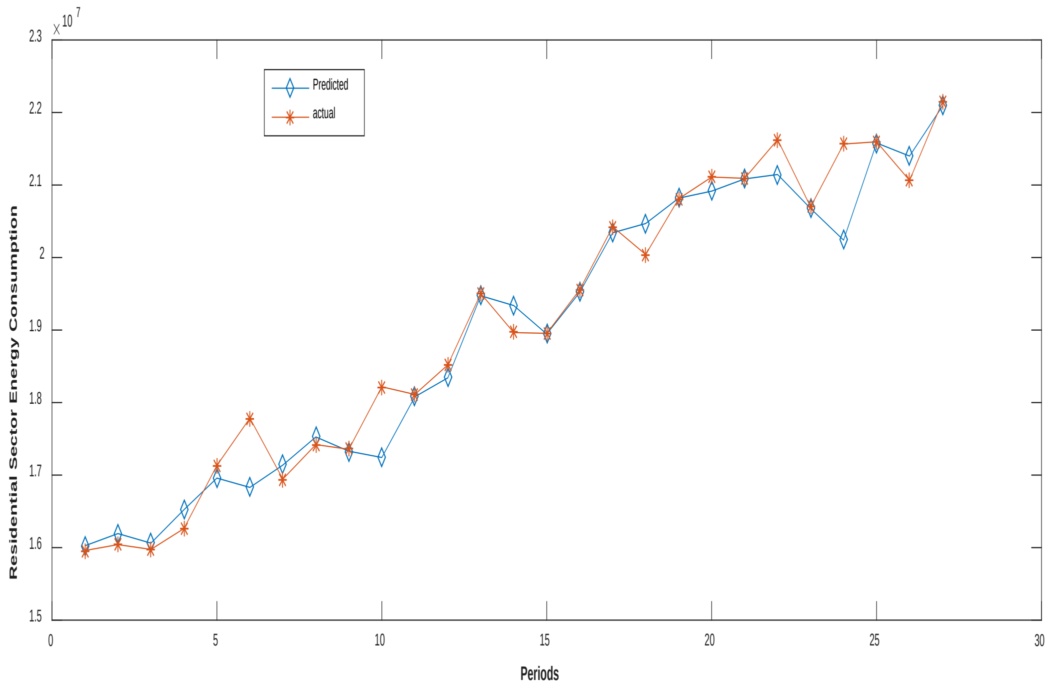

Figure 2. Visual Inspection of predicted and actual residential sector energy consumption.

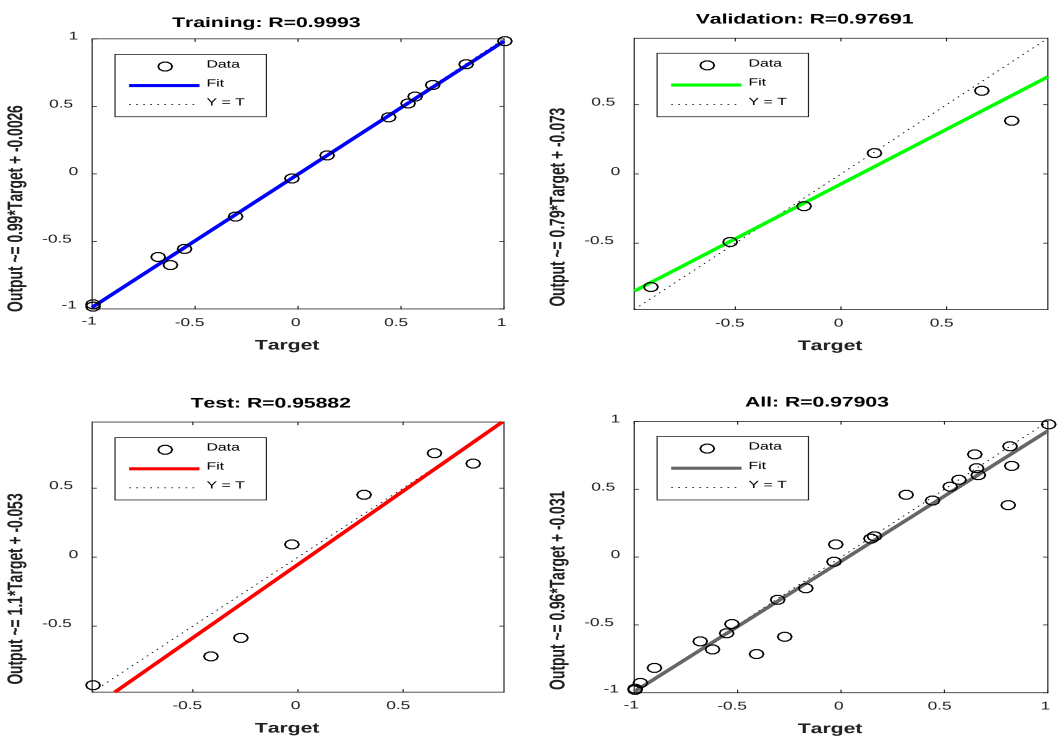

Figure 3. Regression Plots.

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		

4. 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.

Reference

ahmed, K., Pylsy, P. & Kurnitski, J. 2015. Monthly domestic hot water profiles for energy calculation in Finnish apartment buildings. *Energy and Buildings,* 97**,** 77-85.

Ata, R. 2015. Artificial neural networks applications in wind energy systems: a review. *Renewable and Sustainable Energy reviews*, 49**,** 534 - 562.

Aydinalp, M., Ugursal, V. I. & Fung, A. S. 2002. Modeling of the appliance, lighting, and space-cooling energy consumptions in the residential sector using neural networks. *Applied Energy,* 71**,** 87-110.

Azadeh, A., Ghaderi, S. F. & Sohrabkhani, S. 2008. Annual electricity consumption forecating by neural network in high energy consuming industrial sectors. *Energy Convers. Manag.,* 49**,** 2272-2278.

Belaid, F. 2016. Understanding the spectrum of domestic energy consumption: Empirical evidence from France. *Energy Policy,* 92**,** 220-233.

Chakraborty, K., Mehrotra, K., Mohan, C. K. & Ranka, S. 1992. Forecasting the behaviour of multivariate time series using neural networks. *Neural Netw. S.***,** 961-970.

Chiteka, K. & Enweremadu, C. C. 2016. Prediction of global horizontal solar irradiance in Zimbabwe using artificial neural networks. *Journal of Cleaner Production,* 135**,** 701-711.

Deb, C., Eang, L. S., Yang, J. & Santamouris, M. 2016. Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks. *Energy and Buildings,* 121**,** 284-297.

Ellsworth-Krebs, K., Reid, L. & Hunter, C. J. 2015. Home-ing in on domestic energy research: "House," "home," and the importance of ontology. *Energy Research and Social Science,* 6**,** 100-108.

Gajic, D., Savic-Gagic, I., Savic, I., Georgieva, O. & Gennaro, S. D. 2016. Modelling of electrical energy consumption in an electric arc furnace using artificial neural networks. *Energy,* 108**,** 132-139.

Gruber, J. K., Jahromizadeh, S., Prodanovic, M. & Rakocevic, V. 2014. Application-oriented modelling of domestic energy demand. *Electrical Power and Energy Sytems,* 61**,** 656-664.

Han, Y.-M., Geng, Z.-Q. & Zhu, Q.-X. 2016. Energy optimization and prediction of complex petrochemical industries using an improved artificial neural network approach integrating data envelopment analysis. *Energy Conversation and Management,* 124**,** 73-83.

IEA 2010. International Energy Agency: World Energy Outlook. Paris: IEA.

Kalogirou, S. A. 2003. Artificial intelligence for the modeling and control of combination processes: a review. *Prog. Energy Cobust. Sci.,* 29**,** 515-566.

Kiralashaki, A. & Reisel, J. R. 2013. Modeling of the energy demand of the residential sector in the United States using regression models and artificial neural networks. *Applied Energy,* 108**,** 271-280.

Moon, J. W. & Jung, S. K. 2016a. Algorithm for optimal application of the setback moment in the heating season using an artificial neural network model. *Energy and Buildings,* 127**,** 859-869.

Moon, J. W. & Jung, S. K. 2016b. Development of a thermal control algorithm using artificial neural network models for improved thermal comfort and energy efficiency in accommodation buildings. *Applied Thermal Engineering,* 103**,** 1135-1144.

Saidur, R., Masjuki, H. H. & Jamaluddin, M. Y. 2007. An application of energy and exergy analysis in residential sector of Malaysia. *Energy Policy,* 35**,** 1050-1063.

Sovacool, B. K., Sidortsov, R. V. & Jones, B. R. 2014. Energy Security, Equality and Justice. Routledge, London.

Swan, L. G. & Ugursal, V. I. 2009. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. *Renewable and Sustainable Energy reviews,* 13**,** 1819-1835.

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.