Forecasting Net Energy Consumption of South Africa using Artificial Neural Network

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Abstract— This work proposes the use of Artificial Neural Network (ANN) as a new approach to determine the future level of energy consumption in South Africa. Particle Swarm Optimization (PSO) was used in order to train Artificial Neural Networks. The population size, the percentage losses, the Gross Domestic Product (GDP), the percentage growth forecasts, the expected Final Consumption Expenditure of Households (FCEH) as well as the relevant manufacturing and mining indexes are the "drivers" values used for the forecasts. Three growth scenarios have been considered for the forecasting namely low, moderate and high (less energy intensive) scenarios. These inputs values for the period of 2014 to 2050, from the Council for Scientific and Industrial Research (CSIR), were used to test data and validate the use of this new approach for the prediction of electricity demand. An estimate of the annual electricity demand forecasts per scenario was calculated. Besides the speed of the computation, the proposed ANN approach provides a relatively good prediction of the energy demand within acceptable errors. ANN was found to be flexible enough, as a modelling tool, showing a high degree of accuracy for the prediction of electricity demand. It is expected that this study will contribute meaningfully to the development of highly applicable productive planning for energy policies.

***Index Terms*— Artificial Neural Network, Energy demand, Forecasting.**

1 INTRODUCTION

Being able to predict the future demand of electricity constitutes part of the issues utilities companies, policy makers and private investors willing to invest in developing countries are facing. The use of efficient, reliable electricity demand predictor would improve significantly the infrastructure planning and the expansion of power transmission. Since any excess of power generated is not easily stored, an underestimation of the electricity demands results in shortage of supply or a power outage, on one side. This might have an effect on the economic growth and the productivity [1] [2]. On the other side, an overestimation of electricity demand requires extra investment in generation capacity which could ultimately result in high electricity cost since investments have to be recovered to maintain financial viability.

The challenge associated with forecasting includes a range of uncertainties namely the population growth, the technological development, the economic performance, the weather conditions and consumer tastes [3]. This challenge worsens in developing countries because of the lack of reliable data, the political influences and the volatility of historical electricity demand due to macroeconomic or political instability.

It appears that having accurate and reliable electricity demand forecasts for utilities together with investors and policy makers would be of great interest to many developing countries. There is a fair amount of electricity forecasting literature focusing on developing countries like Saudi Arabia, Brazil, Lebanon, South Africa and Egypt. Table I provides an overview of the studies conducted.

Table I. Summary of some studies on forecasting of Electricity Consumption

Author	Country	Sample	Forecast	Method
Abdel-Aal and Al-Garni [4]	Saudi Arabia	1987-1993	12 months	ARIMA
Sadownik and Barbosa [5]	Brazil	1990-1994	1 month	UCM
Saab et al. [6]	Lebanon	1970-1999	10 years	ARIMA
Inglesi [7]	South Africa	1980-2005	15 years	ECM
El-Shazly [8]	Egypt	1982-2010	2 years	ARDL / ECM

Notes.
ARIMA: Autoregressive integrated moving average model
ARDL: Autoregressive distributed lag model.
ECM: (Vector) error correction model.
UCM: Unobserved components model.

A methodology for forecasting annual electricity demand was developed by the Council for Scientific and Industrial Research (CSIR). The modelling approach adopted has been described in Ref. [9]. Details of the methodological aspects and the process used in the development of the methodology are available in Ref. [10].

This study has quantified different scenarios based on economic variables like the expected Gross Domestic Product (GDP), the expected Final Consumption Expenditure of Households (FCEH) and the manufacturing and mining indexes. The speculation on the uncertainties regarding the future electricity forecasts is related to the future values of these variables (drivers). In order to validate the methodology proposed in this paper, we have adopted similar values in this paper.

The purpose of this paper is to develop a model for forecasting energy consumption for the period of 2014-2050 in South Africa using Artificial Neural Network (ANN).

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ANN is defined as a computational-based, non-linear empirical model that has the ability to “learn” very complex behaviour of physical systems. As such, the ANN is considered as a black box that could predict the value of specific output variables when sufficient inputs information have been provided [11].

ANNs have been used in many field such as control, forecasting, optimization, pattern recognition, speech vision, classification, data compression etc. The ANN is made of neurons connected among themselves through weights (W) and biases (b). While this modelling technique is advantageous with regards to developing accurate mathematical model even when the phenomenon occurring during the process is not fully known, ANNs are incapable to extrapolate with accuracy [11]. A typical ANN model is shown in Fig. 1. The input layer receives the inputs. In between the input and output layers are the hidden layers. The propagation of inputs signals is done gradually in the forward direction in order to reach the output layers. There are activation function at each node, transmitted successively from previous layers.

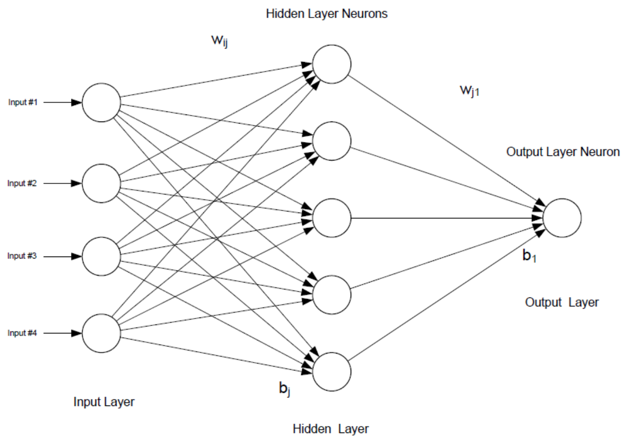

Fig. 1. Typical ANN architecture [12]

Upon the formation of the ANN network, the next step consist of training the network. The main purpose of the training is to find optimum values of the various weight (W) and biases (b) of the ANN. This training is an iterative process that uses nonlinear optimization algorithm. In this paper, the training of the network has been conducted through particle swarm optimization as described by Alam et al. [12]. Details about the particle swarm optimization can be found in Refs [13] and [14]. These details have not been discussed in this paper since there are beyond the scope of this work.

2 METHODOLOGY

In this section, the details of the historical datasets used to obtain the forecasts presented in this paper are given. The proposed artificial neutral network training approach using particle swarm optimization has been described.

2.1. Data on electricity consumption

In order to validate the approach proposed in this work, the data on “drivers” for electricity consumption were compiled from three different sources as indicated in Ref. [9]. This CSIR report [9] stipulates that the values reported were compiled in consultation with Eskom in order to ensure that indices are standardised according to the same year. Table II provides the details of the sources of the details used for the forecasting results reported in this paper.

Table II. Sources of data [9]

“Driver” data	Source
Gross Domestic Product (GDP)	Reserve Bank of South Africa
Final Consumption Expenditure of Households (FCEH)	Reserve Bank of South Africa
Index for Manufacturing production volumes	Statistics South Africa
Index for Mining production volumes	Statistics South Africa
Population	Statistics South Africa
Number of households and average household size	Statistics South Africa
Gold ore milled and gold ore treated	Chamber of Mines

The “driver” values used for the forecasts reported in this paper are given in the following six Tables. The populations and the loss percentage across all scenarios are provided in Table III. These values were considered irrespective of the scenario. The percentage GDP growth forecasts per scenario are given in Table IV. The FCEH % growth forecasts per scenario is given in Table V. The Manufacturing index forecasts per scenario are given in Table VI. The Forecasts for mining production index per scenario are given in Table VII. The Forecasts for gold ore treated per scenario are given in Table VIII.

Table III. Populations and loss percentage across all scenarios

Year	Population (in millions)	Loss percentage across all scenarios
2014	53.48	9.0
2015	54.18	9.4
2016	54.83	9.9
2017	55.43	10.3
2018	56.04	10.7
2019	56.60	11.1
2020	57.11	11.5
2021	57.57	11.5
2022	58.03	11.5
2023	58.44	11.5
2024	58.85	11.5
2025	59.20	11.5
2026	59.55	11.5
2027	59.91	11.5
2028	60.21	11.5
2029	60.51	11.5
2030	60.81	11.5
2031	61.12	11.5
2032	61.42	11.5
2033	61.73	11.5
2034	62.04	11.5
2035	62.35	11.5
2036	62.66	11.5
2037	62.97	11.5
2038	63.29	11.5
2039	63.61	11.5
2040	63.92	11.5
2041	64.24	11.5
2042	64.56	11.5

2043	64.89	11.5
2044	65.21	11.5
2045	65.54	11.5
2046	65.87	11.5
2047	66.19	11.5
2048	66.53	11.5
2049	66.86	11.5
2050	67.19	11.5

Table IV. Percentage GDP growth forecasts per scenario

Year	Low	Moderate	High (less energy intensive)
2014	1.57	1.57	1.57
2015	1.40	2.20	2.50
2016	1.40	2.30	3.50
2017	1.80	2.70	4.00
2018	2.00	2.90	4.20
2019	2.00	3.00	4.50
2020	2.00	3.20	4.50
2021	2.20	3.50	4.50
2022	2.20	3.50	4.50
2023	2.20	3.60	4.50
2024	2.40	3.80	4.50
2025	2.40	3.80	4.50
2026	2.40	3.70	4.50
2027	2.40	3.70	4.30
2028	2.20	3.60	4.30
2029	2.20	3.60	4.30
2030	2.20	3.50	4.10
2031	2.20	3.50	4.10
2032	2.00	3.40	4.10
2033	2.00	3.30	4.00
2034	2.00	3.20	4.00
2035	2.00	3.20	3.80
2036	2.00	3.00	3.80
2037	1.80	3.00	3.80
2038	1.80	3.00	3.60
2039	1.80	3.00	3.60
2040	1.80	2.80	3.40
2041	1.80	2.80	3.40
2042	1.80	2.80	3.40
2043	1.80	2.80	3.20
2044	1.80	2.80	3.20
2045	1.80	2.50	3.20
2046	1.80	2.50	3.00
2047	1.80	2.50	3.00
2048	1.80	2.50	3.00
2049	1.80	2.50	3.00
2050	1.80	2.50	3.00

Table V. FCEH % growth forecasts per scenario

Year	Low	Moderate	High (less energy intensive)
2014	1.16	1.16	1.16
2015	1.25	1.84	2.50
2016	1.16	1.79	3.88
2017	1.54	2.21	4.13
2018	1.92	2.46	4.27
2019	1.97	2.54	4.55
2020	2.01	2.77	4.59
2021	2.05	3.28	4.58
2022	2.12	3.31	4.88
2023	2.05	3.40	4.78
2024	2.70	3.75	4.86
2025	2.71	3.82	4.87
2026	2.71	3.64	4.88
2027	2.71	3.74	4.65
2028	2.37	3.59	3.82
2029	2.35	3.70	4.67
2030	2.51	3.54	4.38
2031	2.51	3.57	4.41
2032	2.17	3.41	4.55
2033	2.15	3.33	4.39
2034	2.15	3.16	4.4
2035	2.15	3.29	4.09
2036	2.17	2.93	4.10
2037	1.83	3.06	4.12
2038	1.92	3.09	3.89
2039	2.26	3.58	3.05
2040	2.25	3.36	3.56
2041	2.30	3.45	3.55
2042	2.30	3.44	3.57
2043	2.30	3.43	3.41
2044	2.41	3.42	3.40
2045	2.40	2.89	3.40
2046	2.39	3.00	3.09
2047	2.43	2.99	3.11
2048	2.42	2.99	3.19
2049	2.41	2.98	3.19
2050	2.40	2.98	3.19

Table VI. Manufacturing index forecasts per scenario

Year	Low	Moderate	High (less energy intensive)
2014	106.4	106.4	106.4
2015	107.5	108.6	108.0
2016	108.6	111.3	110.2
2017	110.2	114.6	112.4
2018	111.9	118.3	115.2
2019	113.5	122.3	118.7
2020	115.2	126.7	122.2
2021	117.5	131.3	125.9
2022	119.9	136.3	129.7
2023	122.3	141.4	133.6
2024	124.1	146.8	137.3
2025	126.0	152.4	141.1
2026	127.9	158.2	145.1
2027	129.8	163.9	148.9
2028	131.7	169.8	152.7
2029	133.7	175.5	156.7
2030	135.3	181.5	160.8
2031	136.9	187.7	164.8
2032	138.6	194.1	168.4
2033	140.3	200.3	172.1
2034	141.9	206.7	175.9
2035	143.6	212.9	179.8
2036	145.4	219.3	183.7
2037	147.1	225.4	187.8
2038	148.6	231.7	191.5
2039	150.1	237.7	195.4
2040	151.6	243.5	199.3
2041	153.1	248.8	203.3
2042	154.6	254.3	207.3
2043	156.2	259.9	211.5
2044	157.4	265.6	215.7
2045	158.7	271.4	220.0
2046	159.9	276.9	224.4
2047	161.2	282.4	228.9
2048	162.5	288.1	233.0
2049	163.8	293.8	237.2
2050	165.1	299.7	241.5

Table VII. Forecasts for mining production index per scenario

Year	Low	Moderate	High (less energy intensive)
2014	102.7	102.7	102.7
2015	105.3	105.9	106.1
2016	108.1	109.4	109.7
2017	110.9	112.8	113.0
2018	113.7	116.2	116.4
2019	116.4	119.8	119.7
2020	119.0	123.5	123.1
2021	121.6	127.1	126.5
2022	124.2	130.8	129.8
2023	127.0	134.5	133.1
2024	129.5	138.3	136.5
2025	132.1	142.0	139.9
2026	134.7	145.7	143.2
2027	137.3	149.5	146.6
2028	139.9	153.3	149.8
2029	142.5	157.1	153.1
2030	145.2	160.9	156.2
2031	147.9	164.6	159.3
2032	150.6	168.2	162.1
2033	153.4	171.8	165.1
2034	156.2	175.5	167.9
2035	159.1	179.1	170.7
2036	161.9	182.7	173.4
2037	164.7	186.2	175.9
2038	167.6	189.5	178.4
2039	170.5	192.8	181.0
2040	173.4	196.1	183.5
2041	176.0	199.4	186.1
2042	178.6	202.8	188.5
2043	181.1	206.2	191.0
2044	183.6	209.7	193.5
2045	186.1	213.3	196.0
2046	188.6	216.7	198.6
2047	190.7	220.2	200.8
2048	192.8	223.8	203.1
2049	195.0	227.4	205.4
2050	197.2	231.1	207.8

Table VIII. Forecasts for gold ore treated (million metric tons) per scenario

Year	Low	Moderate	High (less energy intensive)
2014	41.6	41.6	41.6
2015	40.4	41.0	40.4
2016	39.2	40.4	39.2
2017	38.4	39.8	38.4
2018	37.6	39.4	37.6
2019	36.9	39.0	36.9
2020	36.1	38.6	36.1
2021	35.6	38.6	35.4
2022	35.0	38.6	34.7
2023	34.7	38.6	34.0
2024	34.3	38.6	33.3
2025	34.0	38.6	32.7
2026	33.8	38.6	32.0
2027	33.7	38.6	31.4
2028	33.5	38.6	30.7
2029	33.5	38.6	30.1
2030	33.5	38.6	29.5
2031	33.5	38.6	28.9
2032	33.5	38.6	28.6
2033	33.5	38.6	28.3
2034	33.5	38.6	28.1
2035	33.5	38.6	27.8
2036	33.5	38.6	27.5
2037	33.5	38.6	27.2
2038	33.5	38.6	27.0
2039	33.5	38.6	27.0
2040	33.5	38.6	27.0
2041	33.5	38.6	27.0
2042	33.5	38.6	27.0
2043	33.5	38.6	27.0
2044	33.5	38.6	27.0
2045	33.5	38.6	27.0
2046	33.5	38.6	27.0
2047	33.5	38.6	27.0
2048	33.5	38.6	27.0
2049	33.5	38.6	27.0
2050	33.5	38.6	27.0

2.2. Application of the Artificial Neural Network

To estimate the output value of the energy consumption, an ANN is trained and tested for its ability to generalize and interpolate. In order to train ANN using PSO, the following seven steps have been used [15]:

a. Collection of data;
b. Creation of the network;
c. Configuration of the network;
d. Initialization of the weights and biases;
e. Training of the network using PSO;
f. Validation of the network and
g. Utilization of the network.

There are three outputs neuron corresponding to each scenario. These outputs data (target data) were considered successively depending on the scenario. The values reported in Ref. [9] were used as shown in Table IX. The MATLAB codes used to train the ANN using PSO is available in Ref. [15].

Table IX. National electricity demand (GWh): CSIR recommended forecasts

Year	Low	Moderate	High (less energy intensive)
2014	233758	233758	232960
2015	236697	238080	236609
2016	239850	243070	242087
2017	243547	248694	247650
2018	247628	254859	253855
2019	251801	261430	260834
2020	256046	268576	268029
2021	259902	275428	274910
2022	263889	282669	282225
2023	267885	290203	289637
2024	272070	298301	297165
2025	276335	306669	304899
2026	280665	315114	312848
2027	285060	323691	320573
2028	289188	332340	327484

2029	293360	341108	335590
2030	297459	349934	343528
2031	301615	359008	351929
2032	305476	368140	360417
2033	309372	377162	368926
2034	313318	386208	377663
2035	317317	395331	386186
2036	321370	404242	394923
2037	325100	413196	403895
2038	328761	422375	412504
2039	332855	432104	419956
2040	337000	441394	428431
2041	341200	450679	437330
2042	345452	460169	446452
2043	349756	469867	455517
2044	354006	479779	464786
2045	358306	489102	474278
2046	362657	498374	483382
2047	367061	507833	492690
2048	371517	517484	502095
2049	376027	527331	511716
2050	380591	537379	521559

3 RESULTS AND DISCUSSIONS

The forecasts obtained for each of the three scenarios are provided in Table X. The values reported were used to validate the ability of the approach proposed in this paper to accurately predict the electricity demand.

Table X. National electricity demand (GWh): ANN forecasts

Year	Low	Moderate	High (less energy intensive)
2014	228140	235270	233620
2015	215690	232910	228790
2016	239390	250250	252260
2017	246970	246920	235370
2018	249090	252040	255370
2019	252820	256410	259000
2020	261290	269190	275740
2021	257730	279270	278780
2022	264730	287890	283780
2023	266520	290790	288200
2024	272930	297180	293760
2025	279380	305120	299540
2026	283430	312920	306080
2027	285620	321440	329510
2028	297710	331560	335370
2029	298260	338180	337430
2030	299770	349740	354270
2031	300120	356890	356100
2032	305190	369120	357680
2033	306890	380060	366010
2034	308660	390470	367240
2035	310890	395820	385060
2036	312950	406710	386330
2037	352390	412040	387680
2038	351960	415940	409730
2039	337030	428460	425800
2040	342260	443160	437770
2041	343470	455380	439810
2042	347550	462880	441560
2043	351400	470310	468870
2044	348770	477560	470900
2045	352620	477560	472970
2046	355920	500290	499530
2047	356640	508570	500470
2048	359360	519320	500570
2049	361780	527480	501270
2050	363940	537450	501930

A graphical representation of these results, showing the annual electricity demand per scenario, is shown in Fig. 2.

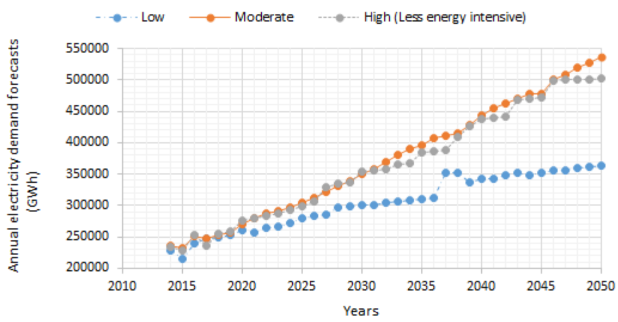

Fig. 2. Annual electricity demand per scenario using ANN

The comparison between the results recommended by CSIR and the results predicted using ANN has been done. Fig. 3, Fig. 4 and Fig. 5 show respectively the annual electricity demand forecast corresponding to low, moderate and high scenario. The average prediction error between ANN and CSIR outputs was calculated for each scenario. The deviations observed are reported in Fig. 6. It appears that the maximum deviation correspond to ±9% for the low scenario. A deviation below 5% and 3% were observed for the high and moderate scenario respectively. The performance of the proposed ANN in predicting the electricity demand was satisfactory due to the higher values of regression between the predicted and target (CSIR) outputs during training, testing and validation phases as shown in Fig. 7, Fig.8 and Fig. 9. These regression plots suggests that the responses obtained from ANN for any new inputs data within the range considered are reliable.

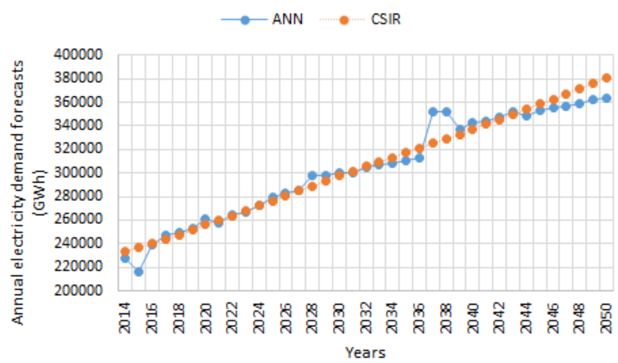

Fig. 3. Comparison between ANN and CSIR prediction: low scenario

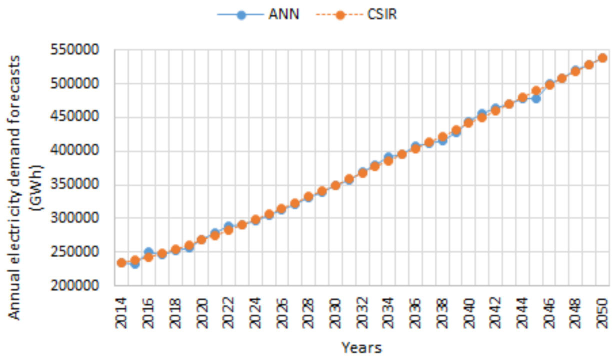

Fig. 4. Comparison between ANN and CSIR prediction: moderate scenario

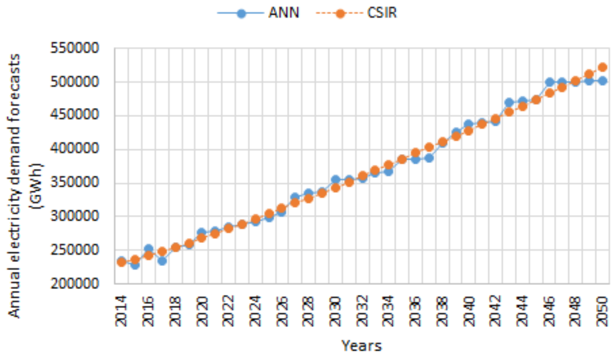

Fig. 5. Comparison between ANN and CSIR prediction: high scenario

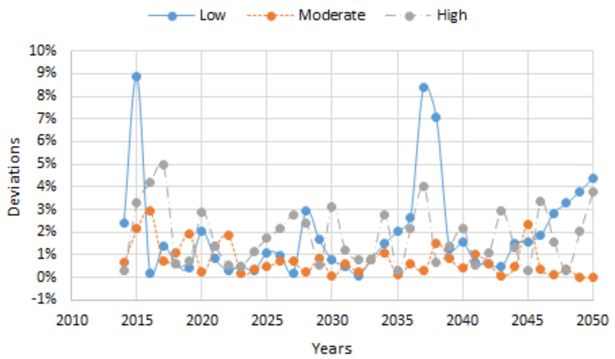

Fig. 6: Deviations in the estimations per scenario

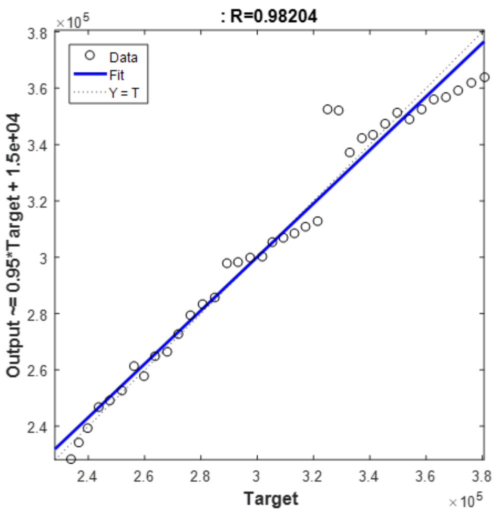

Fig. 7. Regression plots for training, testing and validation phases: low scenario

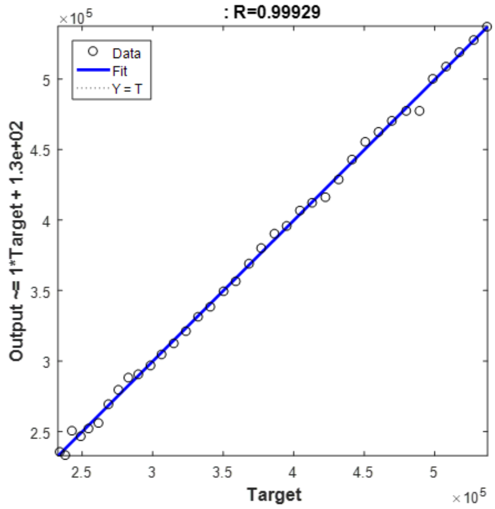

Fig. 8. Regression plots for training, testing and validation phases: moderate scenario

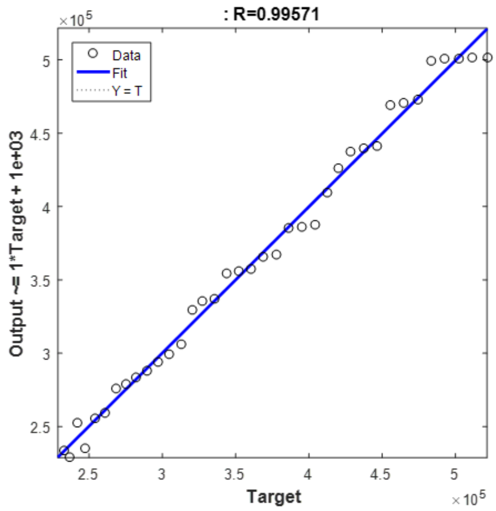

Fig. 9. Regression plots for training, testing and validation phases: high scenario

4 CONCLUSION

In this paper, Artificial Neural Network (ANN) has been used to model the electricity demand in South Africa. Particle swarm optimization (PSO) was used to train the ANN. This approach was implemented within the software MATLAB. The deviations between the predicted values using ANN and the recommended values by CSIR were well within 9%. This demonstrates the high accuracy of the ANN models and ability of the PSO to train ANNs. Most importantly, the flexibility of ANN technique makes it suitable for the determination of optimal solutions related to the future trends of electricity consumption. In addition, the high values of regressions models obtained suggest that the ANN is an effective tools for the prediction of electricity demand. This is necessary for the development of highly applicable and productive planning of energy policies.

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