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Modeling Supply of Energy by Fuzzy and Neural Network Algorithms

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ABSTRACT

Background: Energy is one of the most important inputs for production; also energy is necessary goods for household. So, supply of energy is very important for policy makers. **Objective:** The aim of this paper is modelling and forecasting supply of new energies with fuzzy and neural network algorithms. We applied two methods of fuzzy and neural networks for modelling supply of new energies. We have used the data of supply of new energies of New Zealand during 1960-2010. We have used Mean Square Error (MSE) and Root Mean Square Error (RMSE) for selection the best model based on forecasting accuracy. **Results:** Results indicate that ANFIS model has more forecasting accuracy than FL model in forecasting energy supply. **Conclusion**: therefore, we can use the Neural Network Algorithms for forecasting supply energies for making secure supply energy for an economy.

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INTRODUCTION

Energy supply is intimately tied in with development in the broad sense [Sims and *et al* (2007)]. At present, the one billion people living in developed (OECD) countries consume around half of the 470 EJ current annual global primary energy use (IEA, 2006b), whereas the one billion poorest people in developing countries consume only around 4%, mainly in the form of traditional biomass used inefficiently for cooking and heating Sims and *et al* (2007). The United Nations has set Millennium Development Goals to eradicate poverty, raise living standards and encourage sustainable economic and social development (UN, 2000) Sims and *et al* (2007). Economic policies aimed at sustainable development can bring a variety of co-benefits including utilizing new energy technologies and improved access to adequate and affordable modern energy services Sims and *et al* (2007).

Persaud and Kumar (2001) presented useful insights into the complexities of projecting oil and gas supply, developed an analytical framework which explains the approach used by natural resources Canada (NRCan) in preparing oil and gas supply forecasts, solved the oil and gas supply model (OGSM) and gave the projections of oil and natural gas supply and demand to the year 2020 Persaud and Kumar (2001).

Price and Sharp (1986) described a study of the application of ten forecasting methods to a single time series: that of peak electricity demand in England and Wales Price and Sharp (1986). The performance measure used, however, is not one of the usual forecast ones, e.g., MSE or MAPS, but a managerial one in that the impact of different forecast methods on the profitability of the Central Electricity Generating Board for England and Wales is assessed using a financial simulation model Price and Sharp (1986). As well as examing the effects of forecast method on profitability the effects of two other factors, namely the use of a temperature corrected data series and the impact of log transformation of the data is considered. All these effects are both statistically and practically significant. The results are then examined from a different standpoint: specifically the extent to which the financial impacts of alternative forecast methods can be explained using a number of conventional forecast accuracy measures Price and Sharp (1986). This question is of major importance in applications since accuracy is one of the few easily measured characteristics of a potential forecasting method. It is concluded that much, though not all, of the results can be explained by accuracy considerations Price and Sharp (1986).

Calantone (1994) has discussed the importance of incorporating dynamic relationships between technological changes and both cost and volume of reserves in supply cost functions, and also provided an illustration of the influence of these factors using Western Canada gas supply Calantone (1994). It is argued that such a function offers a more accurate representation of the true long-term supply cost function, and is therefore more appropriate for planning than fixed technology models. Caution in the use of such forecasts is advised for

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two reasons Calantone (1994). First, there is considerable uncertainty associated with the technological change parameters and second, the quantity of the dynamically evolving (and strictly time-dependent) reserves must not be confused with reserves that are defined at a point in time Calantone (1994).

Soldo (2012) presented a state-of-the-art survey of forecasting natural gas consumption. He provided analysis and synthesis of published research in this area from beginning to the end of 2010, insights on applied area, used data, models and tools to achieve usable results, in order to be helpful base for future researchers Soldo (2012).

In the paper of Singhal and Swarup (2011), Electricity price forecasting in deregulated open power markets using neural networks is presented. Forecasting electricity price is a challenging task for on-line trading and e-commerce. Bidding competition is one of the main transaction approaches after deregulation Singhal and Swarup (2011). Forecasting the hourly market-clearing prices (MCP) in daily power markets is the most essential task and basis for any decision making in order to maximize the benefits. Artificial neural networks are found to be most suitable tool as they can map the complex interdependencies between electricity price, historical load and other factors Singhal and Swarup (2011). The neural network approach is used to predict the market behaviors based on the historical prices, quantities and other information to forecast the future prices and quantities. The basic idea is to use history and other estimated factors in the future to “fit” and “extrapolate” the prices and quantities Singhal and Swarup (2011). A neural network method to forecast the market-clearing prices (MCPs) for day-ahead energy markets is developed Singhal and Swarup (2011). The structure of the neural network is a three-layer back propagation (BP) network. The price forecasting results using the neural network model shows that the electricity price in the deregulated markets is dependent strongly on the trend in load demand and clearing price Singhal and Swarup (2011).

In the paper of Chae and *et al* (1995), The energy supply optimization model MESSAGE-III is improved to evaluate the role of nuclear energy system in Korean long-term energy supply strategy Chae and *et al* (1995). Emphasis is placed on the potential contribution of nuclear energy in case of environmental constraints and energy resource limitation. The time horizon is 1993–2040. A program to forecast useful energy demand is developed, and optimization is performed from the overall energy system to the nuclear energy system [Chae and *et al* (1995)]. Reactor and fuel cycle strategy and the expanded utilization options for nuclear energy system are suggested [Chae and *et al* (1995)]. FBRs, HTGRs and thorium fuel cycle would play key roles in the long run. The most important factors for nuclear energy in Korean energy supply strategy would be the availability of fossil fuels, CO2 reduction regulation, and the supply capability of nuclear energy Chae and *et al* (1995).

In the paper of Tang and *et al* (2012), a novel hybrid ensemble learning paradigm integrating ensemble empirical mode decomposition (EEMD) and least squares support vector regression (LSSVR) is proposed for nuclear energy consumption forecasting, based on the principle of “decomposition and ensemble” Tang and *et al* (2012). This hybrid ensemble learning paradigm is formulated specifically to address difficulties in modeling nuclear energy consumption, which has inherently high volatility, complexity and irregularity Tang and *et al* (2012). In the proposed hybrid ensemble learning paradigm, EEMD, as a competitive decomposition method, is first applied to decompose original data of nuclear energy consumption (i.e. a difficult task) into a number of independent intrinsic mode functions (IMFs) of original data (i.e. some relatively easy subtasks) Tang and *et al* (2012). Then LSSVR, as a powerful forecasting tool, is implemented to predict all extracted IMFs independently. Finally, these predicted IMFs are aggregated into an ensemble result as final prediction, using another LSSVR. For illustration and verification purposes, the proposed learning paradigm is used to predict nuclear energy consumption in China Tang and *et al* (2012). Their empirical results demonstrated that the novel hybrid ensemble learning paradigm can outperform some other popular forecasting models in both level prediction and directional forecasting, indicating that it is a promising tool to predict complex time series with high volatility and irregularity Tang and *et al* (2012).

Murphy (1989) described the Intermediate Future Forecasting System (IFFS), which is the model used to forecast integrated energy markets by the U.S. Energy Information Administration. The model contained representations of supply and demand for all of the major fuels consumed in the United States, and is a partial equilibrium model containing a large number of equations and inequalities. He discussed methods for solving the models, as well as the convergence properties of the solution procedure. He also presented issues associated with managing large models.

Also, there are many studies about energy that some recent studies are: Vladislavleva and *et al* (2013), Rudberg, Waldemarsson, &Lidestam (2013), Iverson and *et al* (2013), Chen and *et al* (2013), Xu & Qian (2013) and Zhao and *et al* (2013).

The aim of this paper is modeling supply of new energies with fuzzy and neural network algorithms. This paper is organized by four sections, the next section is devoted to research method, section 3 shows empirical results and final section is devoted to conclusion.

2. Research Method:

We have used two methods of fuzzy and neural networks for modeling supply of new energies as following:

2.1. Fuzzy Logic:

Fuzzy Logic (FL) is a problem-solving control system methodology that lends itself to implementation in systems ranging from simple, small, embedded micro-controllers to large, networked, multi-channel PC or workstation-based data acquisition and control systems Kaehler (1998). FL provides a simple way to arrive at a definite conclusion based upon vague, ambiguous, imprecise, noisy, or missing input information. FL's approach to control problems mimics how a person would make decisions, only much faster Kaehler (1998). FL incorporates a simple, rule-based IF X AND Y THEN Z approach to a solving control problem rather than attempting to model a system mathematically. The FL model is empirically-based, relying on an operator's experience rather than their technical understanding of the system Kaehler (1998). FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them Kaehler (1998). FL was conceived as a better method for sorting and handling data but has proven to be a excellent choice for many control system applications since it mimics human control logic. It can be built into anything from small, hand-held products to large computerized process control systems. It uses an imprecise but very descriptive language to deal with input data more like a human operator. It is very robust and forgiving of operator and data input and often works when first implemented with little or no tuning Kaehler (1998).

How is FL Used?

1) Define the control objectives and criteria: What am I trying to control? What do I have to do to control the system? What kind of response do I need? What are the possible (probable) system failure modes? Kaehler (1998).

2) Determine the input and output relationships and choose a minimum number of variables for input to the FL engine (typically error and rate-of-change-of-error). Kaehler (1998).

3) Using the rule-based structure of FL, break the control problem down into a series of IF X AND Y THEN Z rules that define the desired system output response for given system input conditions. The number and complexity of rules depends on the number of input parameters that are to be processed and the number fuzzy variables associated with each parameter. If possible, use at least one variable and its time derivative. Although it is possible to use a single, instantaneous error parameter without knowing its rate of change, this cripples the system's ability to minimize overshoot for a step inputs. Kaehler (1998).

4) Create FL membership functions that define the meaning (values) of Input/Output terms used in the rules. Kaehler (1998).

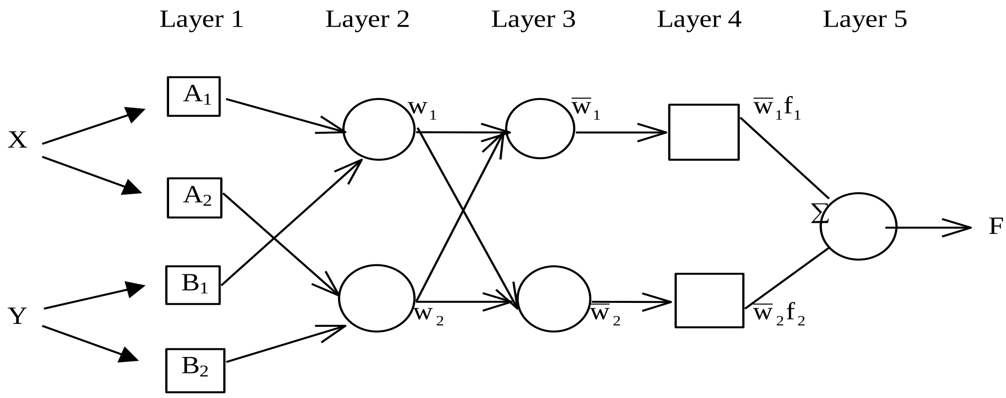
5) Create the necessary pre- and post-processing FL routines if implementing in S/W, otherwise program the rules into the FL H/W engine. Kaehler (1998).

6) Test the system, evaluate the results, tune the rules and membership functions, and retest until satisfactory results are obtained. Kaehler (1998).

2.2. Neural Networks:

ANFIS is an *adaptive network*. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It’s called adaptive because some, or all, of the nodes have parameters which affect the output of the node Jang, J.S. (1993).

The ANFIS architecture is shown below. The circular nodes represent nodes that are fixed whereas the square nodes are nodes that have parameters to be learnt Jang, J.S. (1993).



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An ANFIS architecture for a two rule Sugeno system
A Two Rule Sugeno ANFIS has rules of the form Jang, J.S. (1993):

$$If\ \ x\ is\ A_1\ and\ \ y\ is\ B_1\quad THEN\ \ f_1 = p_1 x + q_1 y + r_1$$

$$If\ \ x\ is\ A_2\ and\ \ y\ is\ B_2\quad THEN\ \ f_2 = p_2 x + q_2 y + r_2$$

For the training of the network, there is a forward pass and a backward pass. We now look at each layer in turn for the forward pass. The forward pass propagates the input vector through the network layer by layer. In the backward pass, the error is sent back through the network in a similar manner to backpropagation Jang, J.S. (1993).

Layer 1:
The output of each node is Jang, J. S. (1993):

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4$$

So, the $O_{1,i}(x)$ is essentially the membership grade for x and y.
The membership functions could be anything but for illustration purposes we will use the bell shaped function given by Jang, J. S. (1993):

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}}$$

where a_i, b_i, c_i are parameters to be learnt. These are the premise parameters.

Layer 2:
Every node in this layer is fixed. This is where the t-norm is used to 'AND' the membership grades - for example the product Jang, J. S. (1993):

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \qquad i = 1,2$$

Layer 3:
Layer 3 contains fixed nodes which calculate the ratio of the firing strengths of the rules Jang, J.S. (1993):

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}$$

Layer 4:
The nodes in this layer are adaptive and perform the consequent of the rules Jang, J. S. (1993):

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i)$$

The parameters in this layer (p_i, q_i, r_i) are to be determined and are referred to as the consequent parameters Jang, J.S. (1993).

Layer 5:
There is a single node here that computes the overall output Jang, J.S. (1993):

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

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This then is how, typically, the input vector is fed through the network layer by layer. We now consider how the ANFIS learns the premise and consequent parameters for the membership functions and the rules Jang, J.S. (1993).

2.3. Data:

We have used the data of supply of new energies of New Zealand during 1960-2010. The database is WDI 2012.

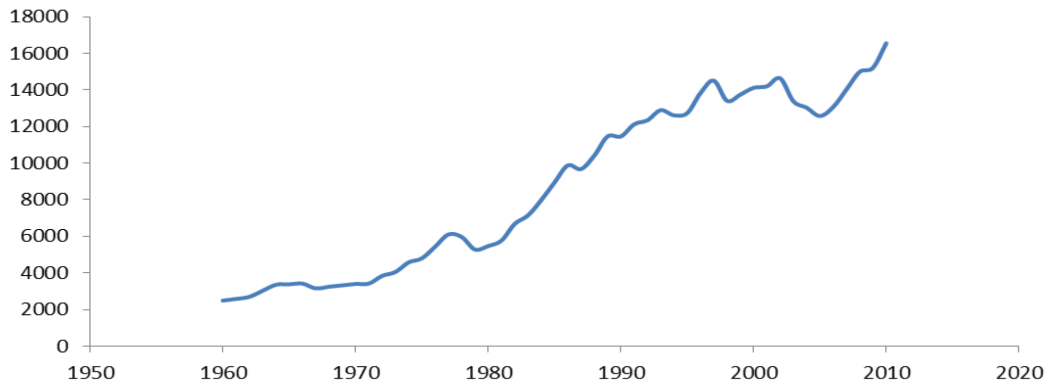

Fig. 1: The Series of Supply of New Energies.

Figure 1 indicates the series of supply of new energies of New Zealand during 1960-2010. The variable is Energy production (kt of oil equivalent).

Table 1: Descriptive Statistic of Data.

Mean	8753.336
Median	8950.167
Maximum	16555.14
Minimum	2486.816
Std. Dev.	4601.520
Skewness	0.024985
Kurtosis	1.390821
Jarque-Bera	5.507901
Probability Sum	0.063676 446420.1
Sum Sq. Dev.	1.06E+09
Observations	51

Table 1 indicates some statistic of the data. Mean is 8753.336, Median is 8950.167, Maximum is 16555.14, Minimum is 2486.816 and Standard Deviation is 4601.520.

3. Empirical Results:

First of all, we have estimated Fuzzy model. The estimation results of energy supply by FL method indicate in Table 2.

Table 2: Forecasted energy supply by fuzzy method.

1961	2786.809
1962	3085.801
1963	3383.797
1964	3680.799
1965	3976.811
1966	4271.836
1967	4565.877
1968	4858.938
1969	5151.022
1970	5442.132
1971	5732.272
1972	6021.444
1973	6309.652
1974	6596.9
1975	6883.189

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1976	7168.524
1977	7452.908
1978	7736.344
1979	8018.834
1980	8300.383
1981	8580.993
1982	8860.668
1983	9139.41
1984	9417.223
1985	9694.109
1986	9970.073
1987	10245.12
1988	10519.24
1989	10792.46
1990	11064.76
1991	11336.15
1992	11606.64
1993	11876.23
1994	12144.91
1995	12412.71
1996	12679.61
1997	12945.62
1998	13210.74
1999	13474.98
2000	13738.34
2001	14000.82
2002	14262.42
2003	14523.15
2004	14783.02
2005	15042.01
2006	15300.15
2007	15557.42
2008	15813.83
2009	16069.4
2010	16324.1
2011	16577.96
2012	16830.97
2013	17083.14

Table 3 indicates the estimation results of energy supply by Neural Network Method.

Table 3: Forecasted energy supply by neural network method.

1961	2780.015
1962	3078.328
1963	3375.901
1964	3672.736
1965	3968.834
1966	4264.196
1967	4558.826
1968	4852.724
1969	5145.893
1970	5438.335
1971	5730.05
1972	6021.041
1973	6311.31
1974	6600.859
1975	6889.689
1976	7177.802
1977	7465.2
1978	7751.884
1979	8037.857
1980	8323.12
1981	8607.675
1982	8891.524
1983	9174.668
1984	9457.11
1985	9738.85
1986	10019.89
1987	10300.24
1988	10579.88
1989	10858.84

1990	11137.1
1991	11414.67
1992	11691.55
1993	11967.74
1994	12243.25
1995	12518.08
1996	12792.22
1997	13065.68
1998	13338.47
1999	13610.57
2000	13882
2001	14152.76
2002	14422.85
2003	14692.26
2004	14961.01
2005	15229.09
2006	15496.5
2007	15763.25
2008	16029.34
2009	16294.77
2010	16559.54
2011	16823.65
2012	17087.1
2013	17349.91

Figure 2 indicates forecasted series of energy supply by FL and Neural Network Method.

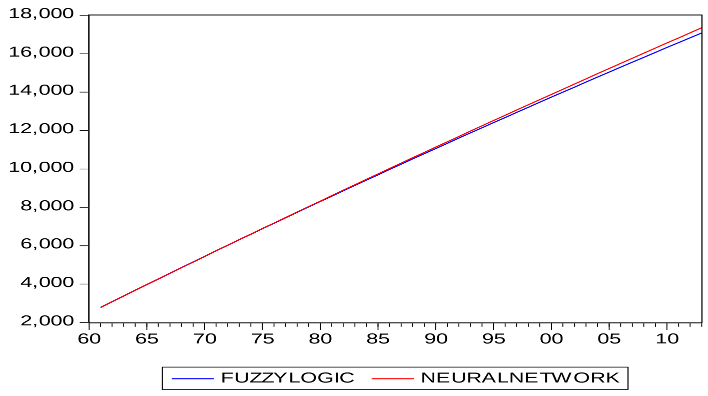

Fig. 2: Forecasted series of energy supply by FL and Neural Network Method.

We have used Mean Square Error (MSE) and Root Mean Square Error (RMSE) for selection the best model based on forecasting accuracy. MSE and RMSE calculated as following formula:

$$MSE = \frac{\sum(\hat{y}_t - y_t)^2}{n}$$

$$RMSE = \sqrt{\frac{\sum(\hat{y}_t - y_t)^2}{n}}$$

Based on above criteria, we have compared forecasting accuracy of the models. For do it, we have used 50 observations for assessment out of sample forecast.

Table 4: The Results of Assessment of the Models.

RMSE	*MSE*	Models
0.040082	0.001606	FL
0.00261	0.0000068	ANFIS

Resource: Calculations of Authors

Table 4 shows the results of assessment of the models based on MSE and RMSE criteria. Results indicate that ANFIS model has more forecasting accuracy than FL model in forecasting energy supply.

4. Conclusion:

Energy is one of the most important issues of the 21st century. Economic policies aimed at sustainable development can bring a variety of co-benefits including utilizing new energy technologies and improved access to adequate and affordable modern energy services Sims and *et al* (2007).

ANFIS is an *adaptive network*. An adaptive network is network of nodes and directional links. Associated with the network is a learning rule - for example back propagation. It's called adaptive because some, or all, of the nodes have parameters which affect the output of the node Jang, J.S. (1993).

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REFERENCES

Calantone, C., 1994. Forecasting long-term natural gas supply capability. Utilities Policy, 4(1): 77-82.

Chae, K.N., D.G. Lee, C.Y. Lim, B.W. Lee, 1995. The role of nuclear energy system for Korean long-term energy supply strategy. Progress in Nuclear Energy, 29: 71-78.

Chen, S., X. Li, S. Wang, J.L. Zhao, Z.H. Tang, 2013. PWM Design for Active Suspension without External Energy Supply Based on LQG Control. Applied Mechanics and Materials, 268: 1478-1481.

Iverson, Z., A. Achuthan, P. Marzocca, D. Aidun, 2013. Optimal design of hybrid renewable energy systems (HRES) using hydrogen storage technology for data center applications. Renewable Energy, 52: 79-87.

Jang, J.S., 1993. ANFIS: Adaptive-network-based fuzzy inference system. Systems, Man and Cybernetics, IEEE Transactions on, 23(3): 665-685.

Kaehler, S.D., 1998. Fuzzy Logic-An Introduction. available at www. seattle robotics. org/encoder/mar98/ fuz/fl_part1. html.

Murphy, F.H., J.J. Conti, S.H. Shaw, R. Sanders, 1988. Modeling and forecasting energy markets with the intermediate future forecasting system. Operations Research, 36(3): 406-420.

Persaud, A.J., U. Kumar, 2001. An eclectic approach in energy forecasting: a case of Natural Resources Canada's (NRCan's) oil and gas outlook. Energy policy, 29(4): 303-313.

Price, D.H.R., J.A. Sharp, 1986. A comparison of the performance of different univariate forecasting methods in a model of capacity acquisition in UK electricity supply. International Journal of Forecasting, 2(3): 333-348.

Rudberg, M., M. Waldemarsson, H. Lidestam, 2013. Strategic perspectives on energy management: A case study in the process industry. Applied Energy, 104: 487-496.

Sims, R.E.H., R.N. Schock, A. Adegbululgbe, J. Fenhann, I. Konstantinaviciute, W. Moomaw, H.B. Nimir, B. Schlamadinger, J. Torres-Martínez, C. Turner, Y. Uchiyama, S.J.V. Vuori, N. Wamukonya, X. Zhang, 2007. Energy supply. In Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change [B. Metz, O.R. Davidson, P.R. Bosch, R. Dave, L.A. Meyer (eds)], Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Singhal, D., K.S. Swarup, 2011. Electricity price forecasting using artificial neural networks. International Journal of Electrical Power & Energy Systems, 33(3): 550-555.

Soldo, B., 2012. Forecasting natural gas consumption. Applied Energy, 92: 26-37.

Tang, L., L. Yu, S. Wang, J. Li, S. Wang, 2012. A novel hybrid ensemble learning paradigm for nuclear energy consumption forecasting. Applied Energy.

Vladislavleva, E., T. Friedrich, F. Neumann, M. Wagner, 2013. Predicting the energy output of wind farms based on weather data: Important variables and their correlation. Renewable Energy, 50: 236-243.

Xu, Z.Q., K.G. Qian, 2013. Study on the Importance of Wind Energy Development. Applied Mechanics and Materials, 268: 958-961.

Zhao, Z.Y., H. Yan, J. Zuo, Y.X. Tian, G. Zillante, 2013. A critical review of factors affecting the wind power generation industry in China. Renewable and Sustainable Energy Reviews, 19: 499-508.