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MONTHLY ENERGY CONSUMPTION FORECASTING USING WAVELET ANALYSIS AND RADIAL BASIS FUNTION NEURAL NETWORK

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ABSTRACT
Monthly energy forecasts help heavy consumers of electric power to prepare adequate budget to pay their electricity bills and also draw the attention of management and stakeholders to electricity consumption levels so that energy efficiency measures are put in place to reduce cost. In this paper, a wavelet transform and radial basis function neural network based energy forecast model is developed to predict monthly energy consumption. The model was developed using the monthly energy consumption of Kwame Nkrumah University of Science and Technology (KNUST), Kumasi, Ghana for a 9-year period. A mean absolute percentage error of 7.94% was achieved when the forecast model was tested over a 60-month period.

Keywords: *Load forecasting, artificial neural network, radial basis function, wavelet transform*

INTRODUCTION
Monthly energy forecasts help heavy consumers of electric power such as manufacturing industries, universities, mining companies and hospitals to predict their monthly energy consumption. Such consumption forecasts help them to prepare adequate budget to pay their electricity bills and also draw the attention of management and stakeholders to electricity consumption levels so that energy efficiency measures are put in place to reduce cost. They can also use the forecast output to cross check if they are being correctly billed.

Energy cost and environmental concerns have created the need to minimise power generation. One of the methods used to keep power generation low while meeting demand is Demand Side Management. For DSM to be effective, it is imperative that forecast of electricity consumption is not left to the electric utility provider alone but must also be encouraged among heavy consumers of electric power such as manufacturing industries, universities, mining companies and hospitals.

Load forecasts can be divided into three categories: short-term forecasts which are usually from one hour to one week, medium-term forecasts which are usually from one week to one year and long-term forecasts which are longer than one year. A number of methods have been used for electric energy forecasting. These include statistical methods such as time series, econometric modeling, regression and similar-day approach as well as artificial intelligence techniques such as fuzzy logic, expert systems and artificial neural networks. Artificial intelligence algorithms based on artificial neural networks have however proven more accurate (Feinberg *et al.*, 2005).

This paper proposes a combination of radial basis function neural network (RBFNN) and wavelet transform as a tool to forecast monthly energy consumption.

METHODOLOGY

Wavelet Analysis

Wavelet analysis was considered for the model because it is capable of revealing aspects of data that other signal analysis techniques miss. These aspects include trends, breakdown points, discontinuities in higher derivatives, and self-similarity. Wavelet analysis has additional advantages of compressing and de-noising a signal without appreciable degradation (El-Keib *et al.*, 1995). There are essentially two types of wavelet decomposition: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT) (Lee *et al.*, 2000). CWT is mainly used for theoretical research, but DWT is more popular in the field of engineering, because the observed time series are discrete in real world, including short-term load series.

DWT uses mother wavelets such as Haar, Daubechies and Coefiman in its analysis (Zun-Xiong, 2005). With DWT, a signal is analysed at different frequency bands with different resolutions by decomposing the signal into high-scale, low-frequency components called approximate coefficients and low-scale, high-frequency components called detailed coefficients (Misiti *et al.*, 2004). Thus, the wavelet transform is an implementation of a bank of filters that decompose a signal into multiple signal bands. It separates or retains the signal features in one or few levels or scales as shown in Fig. 1 (Akujuobi *et al*., 2007).

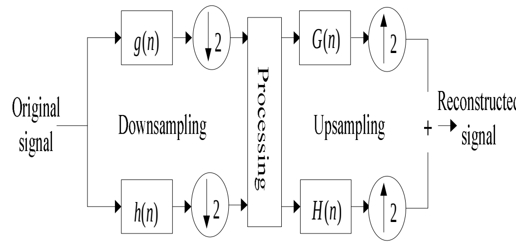

Fig. 1: Wavelet decomposition and reconstruction of a signal

DWT employs two sets of functions called scaling functions and wavelet functions, which are associated with lowpass and highpass filters, respectively. The filters are employed for down sampling (decomposing) or up-sampling (reconstruction) of the signal. Separately, the lowpass and the highpass filters are not invertible.

The decomposition of the signal into different frequency bands is simply obtained by successive highpass and lowpass filtering of the time domain signal. The original signal *x(n)* is first passed through a halfband highpass filter *g(n)* and a lowpass filter *h(n)* After the filtering, half of the sam-ples can be eliminated according to the Nyquist's rule, since the signal now has a highest frequency of half the frequency of the original signal. The signal can therefore be sub-sampled by 2, by discarding every other sample. This constitutes one level of decomposition and can mathematically be expressed as follows:

$$y_{high}[k] = \Sigma_n x(n)g(2k - n)$$
$$y_{low}[k] = \Sigma_n x(n)h(2k - n)$$

where $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the highpass and lowpass filters, respectively, after subsampling by 2. Fig. 2 illustrates a two-level decomposition of a signal.

Radial Basis Function Neural Network

Artificial Neural Networks (ANNs) are mathematical tools originally inspired by how the hu-

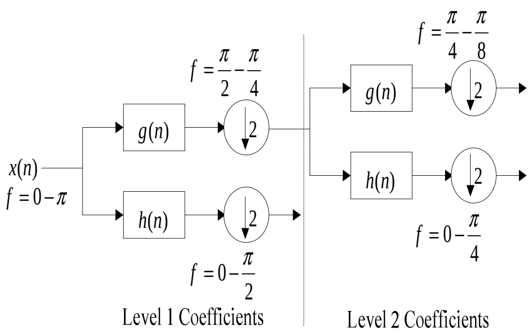

Fig. 2: A two-level discrete wavelet transformation of a signal

man brain processes information. ANNs are composed of simple elements or neurons operating in parallel with connections or weights between them. The network function is determined largely by the weights between neurons. ANNs can be trained to perform a particular function by adjusting the values of the weights between neurons. Fig. 3 illustrates the ANN training concept.

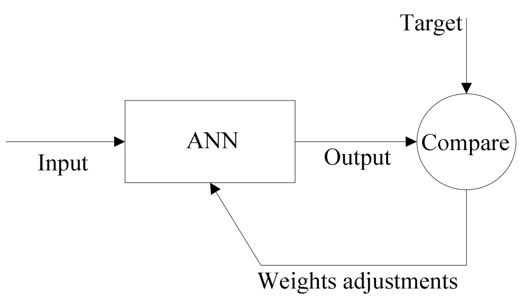

Fig. 3: ANN training concept

Typically, a number of input/target pairs are needed to train a network. A neuron receives numerical information through a number of input nodes, processes it internally, and puts out a response. The processing is usually done in two stages: first, the input values are linearly combined, and then the result is used as the argument of a nonlinear activation function. The combination uses the weights attributed to each connection, and a constant bias term. Fig. 4 shows one of the most used schemes for a neuron.

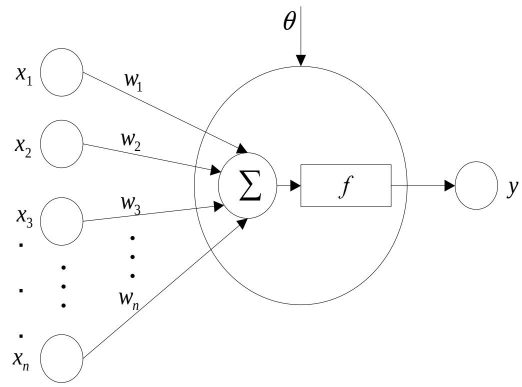

Fig. 4: An artificial neuron

The neuron output y is given by:

$$y = f\left[\left(\sum_{i=1}^{n} w_i x_i - \theta\right)\right] \quad i = 1,2,3,\ldots,n$$

where x_i *is* the neuron input; w_i is the weight, θ is the characteristic neuron offset (bias) and f is the activation function (Al-Shareef *et al*., 2008).

Neural networks are able to derive meaning from complicated or imprecise data and can be used to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques (Gershenson, 2001).

Among the many types of neural networks is the radial basis function (RBF) which is employed in this paper. RBFs are able to model complex mappings which perceptron neural networks can only model by means of multiple layers. They also have non-linear approximation properties. RBFs also have advantages such as interpolation, functional approximation, localization and cluster modeling. These properties lead to quicker learning in comparison to multilayer perceptrons trained by back propagation (Topchy *et al*., 1998; Bors, 2001).

Fig. 5 shows a radial basis network. The expression for the net input of a radial basis (radbas) neuron *a=radbas(||w-p||b)* is different from that of other neurons. The net input to the radial basis transfer function is the vector distance between its weight vector *w* and the input vector *p*, multiplied by the bias *b*. The || dist || box in the figure accepts the input vector *p* and the single row input weight matrix, and produces the dot product of the two. The transfer function *f* for a radial basis neuron is e^{-n2} (Demuth *et al.*, 2006).

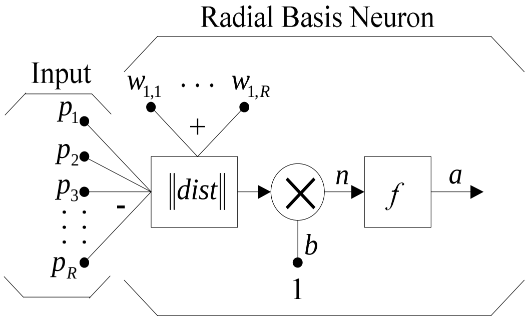

Fig. 5: A radial basis network

Input Data to Model

For the RBFNN to be able to approximate the energy consumption function and make meaningful predictions, the input data must take into consideration a set of inputs which have significant effects on the consumption values to be predicted. The input parameters if well chosen improve the performance of the network.

A study of the energy data collected showed that the energy consumed in a particular month depended on the specific month whose consumption was to be predicted and other parameters such as the previous year's consumption of the target month and the consumption of the month proceeding the target month. Hence for any month whose consumption is to be predicted, the following will be the input data required:

1. The target month
2. Previous month's energy consumption
3. The target month's previous year's energy consumption
4. The previous month's, previous year's energy consumption

Pre processing of Input Data

Since using the raw data will reduce the accuracy of the forecasting model, pre-processing of the data into refined form was done. The preprocessing stages were;

1. Smoothing of historical monthly consumption curve
2. Wavelet decomposition of data
3. Normalization of the decomposed values between zero and one.

Smoothing of consumption Curve

A graph of the historical energy consumption against the months of the year revealed a lot of data inconsistencies which could be due to load shedding programmes, frequent power outages and instrumentation errors. The existence of such bad data in the historical data has significant effect on the accuracy of the forecasting results. It can be thought that the energy curve is the sum of two energy curves: an essential energy curve, representing the basic consumption requirement, and a vibrating curve showing the sudden change in a large consumer's state. Hence in smoothing the energy curve, the vibrating curve is removed from the essential curve by replacing sections that showed severe irregularities with the average of their preceding and succeeding energy values (Gross *et al.*, 1987). This stage is only required during the development of a forecast model.

Wavelet Decomposition

The decomposition of the raw energy data makes it possible to extract essential components of the input data, thus improving the forecast output. Using the Daubechies db3 mother wavelet, the raw data was decomposed into approximate and detailed coefficients using a two level decomposition. The coefficients were then added to obtain coefficients that describe the original signal more accurately.

Normalization
After the energy data had been decomposed, they were normalized so that their values ranged between 0 and 1. This was achieved by using the square two norm implemented in MATLAB. The effect of this was to avoid the saturation of the neural network. For this same purpose the months of the year which were given indexes from 1 to 12 were each converted to binary.

Neural Network Architecture
A radial basis function neural network (RBFNN) was adopted for the development of the model. The four raw input data chosen were pretreated, resulting in eight input parameters. The RBFNN thus had eight input neurons. The monthly energy consumptions of 2000, 2001, 2005 and 2006 were used to train the network while the testing data were those for the years 2002, 2003, 2004, 2007 and 2008.

PROPOSED LOAD FORECAST MODEL

A flow chart of the proposed forecast model is shown in Fig. 6. The input energy data is decomposed into two levels using db3 mother wavelet giving rise to three coefficients vectors. The three coefficient vectors are then added to obtain a single vector. The resulting vector is normalised. The target month is converted into binary and fed into the RBFNN together with the normalised vector. The output of the RBFNN is reconstructed using wavelet analysis to obtain an energy forecast.

RESULTS AND DISCUSSIONS

The load of KNUST is basically domestic loads which increase gradually with increasing student and worker population. The loads consist mainly of lighting loads, heating loads and air-conditioning loads. The energy consumption increases in the months when students are on campus and is low when students are on vacation. Thus the monthly peak occurs during months when students are on campus. That is between February and April and between September and November of every year. The peaking is as a result of a rise in learning and other student activities which involve the use of electricity. The daily consumption peaks early in the morning around 6am to 8am when students are preparing for lectures and in the evening between 6pm and 10pm. Other seasonal variations such as pertain to weather conditions have little effect on the composite KNUST consumption. Fig. 7 shows the energy consumption of KNUST for the year 2006.

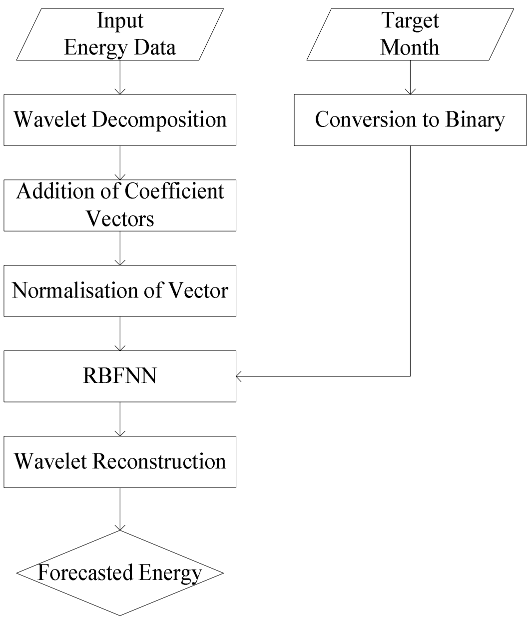

Fig. 6: Flow chart of proposed load forecast model

Fig. 7: Monthly energy consumption of KNUST for year 2006

Table 1 shows the actual monthly energy consumption and forecasted monthly energy consumption for the year 2008. Figures 8, 9, 10, 11 and 12 show respectively the graphs of monthly energy forecasts using the proposed model against actual monthly consumptions for years 2002, 2003, 2004, 2007 and 2008. Table 2 also shows the mean absolute percentage errors (MAPEs) for the testing years. The MAPEs were determined using the following formula:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{E_{actual,i} - E_{predicted,i}}{E_{actual,i}}\right| \times 100$$

Table 1: Actual and forecasted energy for 2008

Month	Actual energy (MWh)	Fore-casted Energy (MWh)	Percen-tage Error(%)
January	345.84	233.5	32.4832
February	964.564	965.4	0.0867
March	1118.847	1210.7	8.2096
April	985.318	976.1	0.9355
May	901.512	880.5	2.3308
June	732.032	776	6.0063
July	580.041	517.8	10.7304
August	694.563	700.7	0.8836
September	851.23	723.6	14.9936
October	950.169	854.9	10.0265
November	1235.07	1296.7	4.9900
December	840.01	837.3	0.3226

Fig. 8: Actual and forecasted energy consumption for 2002

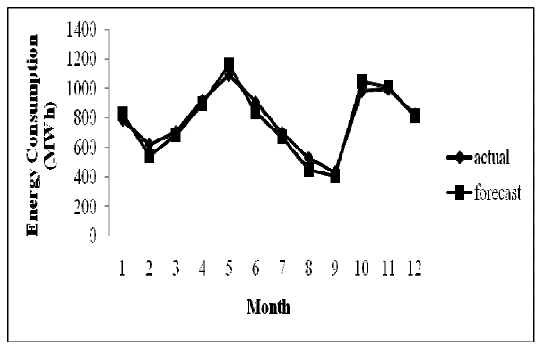

Fig. 9: Actual and forecasted energy consumption for 2003

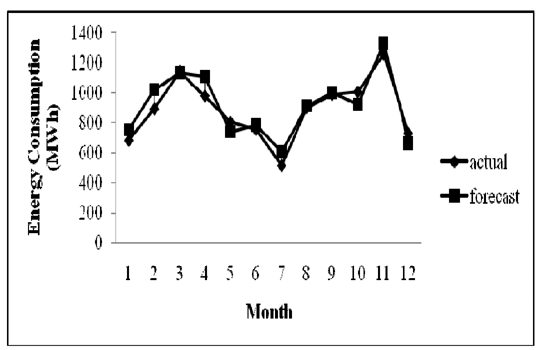

Fig. 10: Actual and forecasted energy consumption for 2004

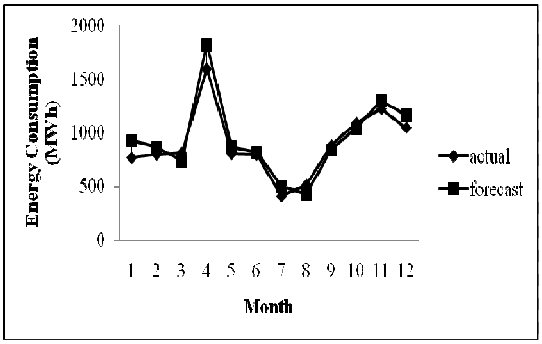

Fig. 11: Actual and forecasted energy consumption for 2007

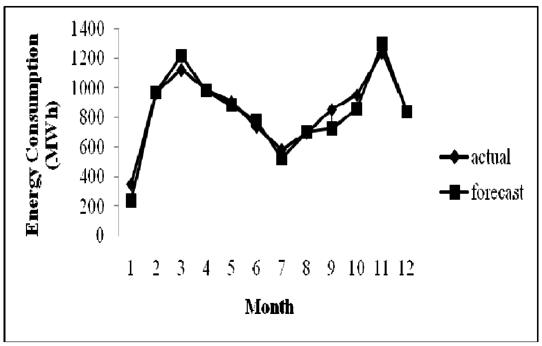

Fig. 12: Actual and forecasted energy consumption for 2008

Table 2: Mean absolute percentage errors for testing years

YEAR	MAPE (%)
2002	7.07
2003	6.19
2004	7.81
2007	10.94
2008	7.67
AVERAGE	**7.94**

Table 1 typifies how well the forecasted energies match the actual energies. The major exception to this close matching is in January 2008. The 32.5% percentage error for this month is due to the uncharacteristically low value of energy consumed in this month due to power outage. Figures 8, 9, 10, 11 and 12 also show that the forecasted monthly energy consumptions closely follow the actual. In 2002 and 2003, May recorded the highest energy consumption. November recorded the highest energy use in 2004 and 2008 while in 2007; the highest energy consumption was recorded in April. The best model performance was recorded in February 2008. The average percentage error for this month was 0.09%. The MAPE for the twelve months of the year 2002 was 6.19%, which was the least, and the highest MAPE of 10.94% was recorded in 2007 as shown in Table 2.

CONCLUSION

A wavelet transform and radial basis function neural network based monthly energy forecast model has been developed in respect of the Electrical Energy consumption time series data of KNUST. The model used the approximate and detailed coefficients obtained from a two level decomposition using the Daubechies db3 mother wavelet. A mean absolute percentage error of 7.94% was obtained when the model was tested over a 5-year period, which is good. Only the historical load of KNUST was used for the forecast model, demonstrating that the composite KNUST load does not depend on seasonal variations.

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