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Procedia Manufacturing 33 (2019) 176–183

Procedia MANUFACTURING

www.elsevier.com/locate/procedia

16th Global Conference on Sustainable Manufacturing - Sustainable Manufacturing for Global Circular Economy

Non-linear autoregressive neural network (NARNET) with SSA filtering for a university energy consumption forecast

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Abstract

Energy consumption forecast is essential for strategic planning in achieving a sustainable energy system. The hemispherical seasonal dependency of energy consumption requires intelligent forecast. This paper uses a non-linear autoregressive neural network (NARNET) for energy consumption forecast in a South African University with four campuses, using three-year daily energy consumption data. Singular Spectrum Analysis (SSA) technique was used for the data filtering. Three window lengths (L=54, 103 and 155) were obtained using periodogram analysis and R-values of network training at these window lengths were compared. Filtered data at L=103 gave the best R-values of 0.951, 0.983, 0.945 and 0.940 for campus A, B, C, and D respectively. The network validation and a short-term forecast were performed. Forecast accuracies of 85.87%, 75.62%, 85.02% and 76.83% were obtained for campus A, B, C and D respectively. The study demonstrates the significance of data filtering in forecasting univariate autoregressive series.

Keywords: Non-linear Autoregressive Neural Network; Singular Spectrum Analysis; Energy Forecast

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10.1016/j.promfg.2019.04.022

1. Introduction

Energy consumption forecasting is highly essential for strategic and operational planning in academic institutions. Reports shows that about 10% of the electricity consumption in South Africa will continue to be attributed to the commercial sectors, to which universities belong [1]. With a 200% increase in electricity cost in South Africa between 2008 to 2014 [2], an intelligent energy consumption forecast is essential, even for universities, to enhance strategic planning and policy making. Multi-campus universities exhibit a form of complexity which makes their energy consumption different from other commercial buildings [3]. The complexity, however, is more pronounced in cases where the campuses are dependent on one another for resources. Furthermore, increase in technological development has consequentially increased plug load devices used in offices, school residences and research [4]. These devices consume energy during operation. Hence, energy consumption forecasting is essential in achieving a sustainable energy system, as this fosters data-driven decision-making.

Nomenclature

$\boldsymbol{Y_T}$ = Time series data over time $\boldsymbol{T}$

$\boldsymbol{K}$= Window size embedding the original series

$\boldsymbol{L}$ = Window length

$\boldsymbol{X}$ = Trajectory matrix

$\boldsymbol{p}$ = Lag length

$\boldsymbol{R^L}$ = Dimensional space L

$\boldsymbol{a_i}$ = autoregressive parameters at i

$\boldsymbol{\varepsilon_t}$ = normally distributed error term over time t

Several approaches have been developed in forecasting energy consumption. Its forecast—short-term, medium-term or long-term—is approached using three extended techniques: the engineering techniques, statistical techniques and the artificial intelligent techniques [5]. Recent works focus on the use of intelligent techniques in forecasting energy consumption, some of which include Autoregressive Integrated Moving Average (ARIMA) [6], Artificial Neural Network (ANN), Support Vector Machine (SVM) [5] and Hybrid Algorithms (HA) [7]. Each technique possesses its uniqueness. While some are highly efficient with large datasets e.g. ANN [8], some with sparse dataset still give good forecast e.g. SVM [9]. Aside from the popularly known autoregressive integrated moving average (ARIMA), the non-linear autoregressive neural network (NARNET) gives good forecast, most especially when series are non-linear. This technique uses lagged input; whose forecast uses historical data according to the number of lags in the series. As a variant of ANN, it consists of interconnected network of neurons which simulates the biological nervous system of impulse processing [8], [10], [11]. Autoregressive neural network with exogenous input is another variant of autoregressive models, where autoregression is influenced by an external variable [12], [13].

Most time series data in real life applications possess temporary variability and spatial fluctuation [8], [14], [15], making them a mix of noise and signal. To solve these problems, data pre-processing using decomposition, smoothing, extraction of seasonality components, and de-trending is performed on the data using known techniques. One of the potent tools in solving variability problems in time series data is singular spectrum analysis [16], [17].

Singular Spectrum Analysis (SSA) is a non-parametric multi-step filtering and smoothing technique for time series data disintegration into noise and signal [18]. SSA operates on the assumption that the dataset satisfies the linear recurrent formula for predicting new data points. The SSA technique consists of two steps. The first, being data decomposition, consists of two steps: the data embedding and Singular Value Decomposition (SVD) [16]. The data embedding stage involves mapping a one-dimensional time series data $Y_T = (y_1, y_2, \dots\ y_T\ )$ into a multi-dimensional lagged vector, $X_K = (y_K, \dots\ y_{K+L-1}\ )' \ \in\ R^L$ where $K = T - L + 1$. There exists a single parameter, an integer, called the window length, L. The window length takes a value in the domain of 2 and T: $\in\ 2 \leq L \leq T.$ Embedding stage produces a trajectory matrix, X. The trajectory matrix X obtained is expanded using SVD into a sum of rank-one biorthogonal matrices [16]. The second step in SSA is the reconstruction of the trajectory matrix X. The matrix is split into different groups, with data in each group summed. This represents the grouping stage. Each resulting matrix is transferred into an additive component of the initial time series data, Y_T. A more detailed explanation of this technique can be found in [19]. The capability of SSA technique for forecasting [17] and filtering [20] has been explored. However, its use for filtering in energy studies is sparse in the literature.

The success of SSA technique largely depends on the choice of window length. Some techniques have been used by researchers in the selection of optimal window length [21], [22]. Among these techniques, the periodogram analysis offers a better result in identifying the spectral density of a signal for proper regrouping [16]. Sun and Li experimented with this to identify possible peaks in a precipitation data collected over 30 years [22]. These peaks were used as window lengths in the SSA process. The study concluded that larger values of window length do not always give a better result in SSA.

Energy study in the university environment is not new. A quintessential study is that of Rad *et al.,* [18] where Penn State University Park Campus buildings were examined to identify which has a prospect of higher energy cost savings as well as lowest greenhouse gas emission. Another study, which emphasizes ways of promoting energy efficiency in the university is that of Maistry and McKay [2]. The study used a case study of a university in South Africa and suggested ways by which energy demand side of energy system could be efficiently managed to achieve good results. However, studies on multi-campus institutions have received less attention.

This study applies SSA technique for filtering, decomposing the time series data into noise and signal. The non-linear autoregressive neural network is used as a forecasting tool for the resulting signal. Section two of this paper presents the methodology used. The results obtained from SSA and neural network model are presented in section three while section four concludes the work.

2. Methodology

2.1. Data Collection

A typical multi-campus university consisting of four campuses located in South Africa was considered in this study. Daily energy consumption data (in Kilowatt-hour) for the campuses under the university from 2015 to 2017 was used. The energy consumption data was obtained from the energy management department of the university, which oversees the four campuses. This department, through a data logger, archives the historical energy consumption of each campus in the university in real time. Campuses with the highest and lowest energy consumption were identified. The seasons of maximum and minimum energy consumption were also identified at each campus. The South African Weather Service, based on climatological and sociological grounds classified the seasons in the southern hemisphere as shown in Table 1. This classification was used to determine seasons where high, and low energy consumption occur. In building the model, the data was divided into training and testing data sets in the ratio of 70:30 respectively.

Table 1: Calendar Dates in the Southern Hemisphere

Southern Hemisphere	Calendar Dates
Autumn	1 March to 31 May
Winter	1 June to 31 August
Spring	1 September to 30 November
Summer	1 December to 28/29 February

Source: [23]

2.2. Singular Spectrum Analysis

Selecting an appropriate window length predicates a successful result in singular spectrum analysis [21]. Window length inappropriately selected could imply improper decomposition [24]. In order to forestall this, periodogram analysis was used to determine different periods in the data. These identified periods were used as window lengths. Three peaks, 54, 103, 155 were identified from the periodogram analysis and used as window lengths on the data from each campus. The window length with the highest R-value was selected for use in the non-autoregressive artificial neural network model. SSA was applied to the training dataset prior to feeding it into the network.

2.3. Non-linear Autoregressive Artificial Neural Network (NARNET)

Autoregressive models harness hidden patterns in data-driven predictions by leveraging the use of historical data to predict future values. The autoregressive process for a series y_t can be described by:

$$y_t = a_1 y_{t-1} + a_2 y_{t-2} + \cdots + a_n y_{t-n} + \varepsilon_t \quad (1)$$

where $a_1, a_2, \ldots a_p$ are called the autoregressive parameters and ε_t are normally distributed error term with a mean of zero and a finite variance σ^2. The lag length, p, of 30 was selected for all campuses.

Autoregressive neural network models with different architectures were developed for each campus. Data consisting of 11 seasons (summer, winter, autumn and spring) was used to train the network using Levenberg Marquardt back propagation algorithm. The network was re-trained until a lower mean square error is obtained and over fitting avoided in each case. A dataset of 120 elements, which represents a complete spring time (September to November) and one month into the summer season (December) for the last year in the series was forecasted. The predicted values were compared with the observed values for each campus. The SSA and autoregressive neural network algorithm were written using MATLAB R2015a.

3. Results and discussion

Energy consumption statistics for each of the campuses within the period of study is presented in Table 2.

Table 2: Energy Consumption Statistics

Campus	Mean (KWh)	Maximum (KWh)	Season of Maximum Consumption	Minimum (KWh)	Season of Minimum Consumption
Campus A	71,501.95	103,064.9	Winter	29,423.56	Summer
Campus B	15,913.89	31,345.86	Winter	1,955.40	Summer
Campus C	14,405.51	23,495.22	Winter	2,775.98	Summer
Campus D	23,334.64	34,780.94	Winter	10,179.26	Summer

From Table 2, Campus A has the highest average energy consumption (71,501.95KWh) while the Campus D has the least (14,405.51KWh). Winter season is associated with high energy consumption in the southern hemisphere [25]. This can be attributed to space heating other heating equipment, in the process of adjusting to the decrease in temperature associated with this season. Similarly, the highest consumption of electricity occurred during the winter season in all the campuses, while the least occurred in the summer season. Campus A has the highest number of students and student residents compared to other campuses.

3.1. Singular Spectrum Analysis

Singular spectrum analysis was used to filter the training dataset before being used to train the autoregressive neural network.

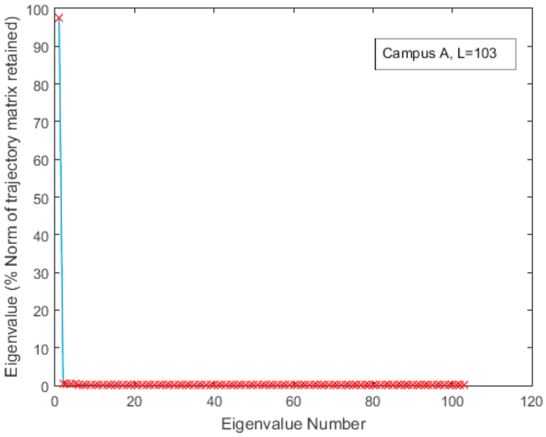

Figure 1. Eigen values from SVD at Window Length L=103 (Campus A)

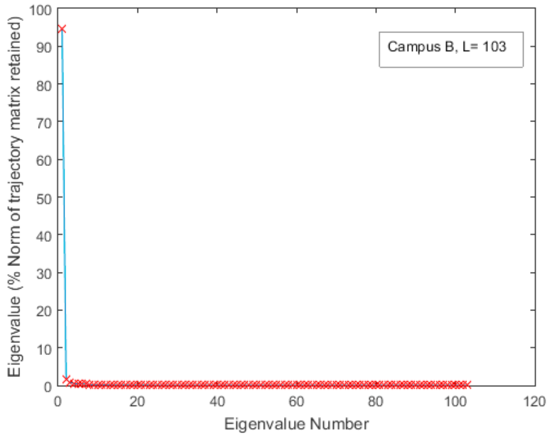

Figure 2. Eigen values from SVD at Window Length L=103 (Campus B)

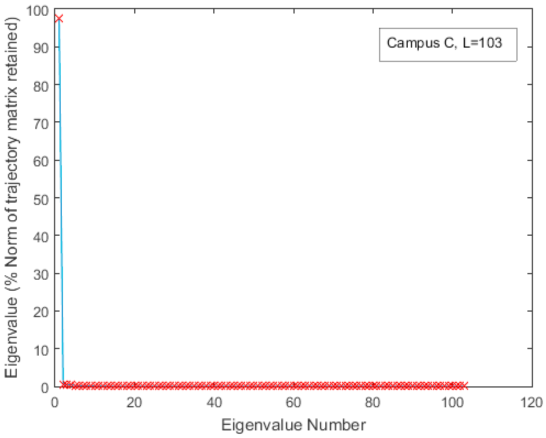

Figure 3. Eigen values from SVD at Window Length L=103 (Campus C)

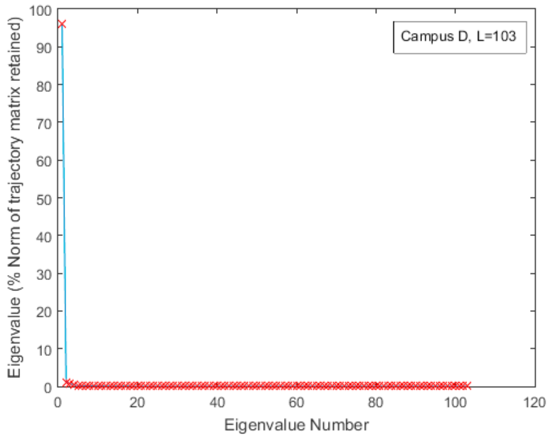

Figure 4. Eigen values from SVD at Window Length L=103 (Campus D)

Shown in Figure 1 to 4 are the singular values of the trajectory matrix obtained from SVD; a step in singular spectrum analysis (SSA) at window length, L=103. The percentage number of trajectory matrix retained was plotted against their respective eigen values. The eigen values were plotted in decreasing order for all the campuses. In Figure 1 to 4, there is a grouping of the first eigen value located at the peak, at different percentages for all the campuses.

3.2. Non-Linear Autoregressive Neural Network (NARNET)

The network architectures, which gave the best result after multiple trainings are presented in Table 3. The architectures may be noticed to change between campuses. The same network architecture was used for all the campuses before variation was introduced to obtain a better prediction.

Table 3: Network Structure and Result

Campus	Network Structure	R-Value at Window Length (L)		
		L=54	L=103	L=155
Campus A	1- [10-25]-1	0.9297	0.9513	0.9345
Campus B	1-[25]-1	0.9823	0.9832	0.9816
Campus C	1-[10-25]-1	0.9443	0.9448	0.9443
Campus D	1-[20-10]-1	0.9130	0.9399	0.9135

[ ]- number of neurons in each hidden layer

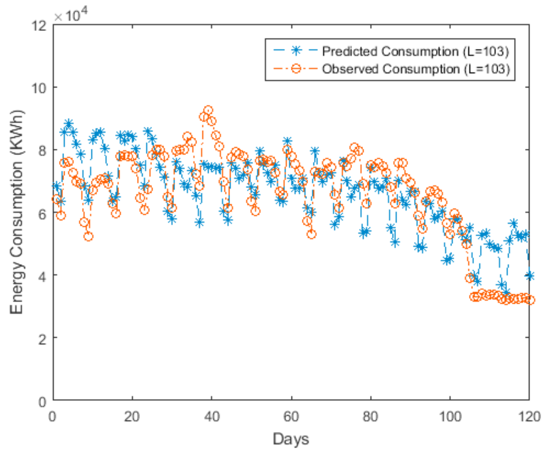

Figure 5. Energy Consumption Forecast for Campus A

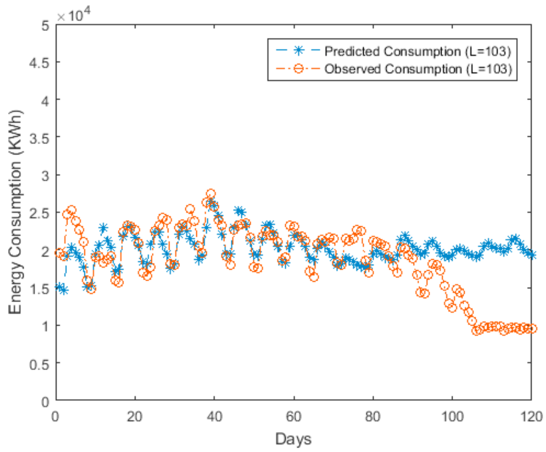

Figure 6. Energy Consumption forecast for Campus B

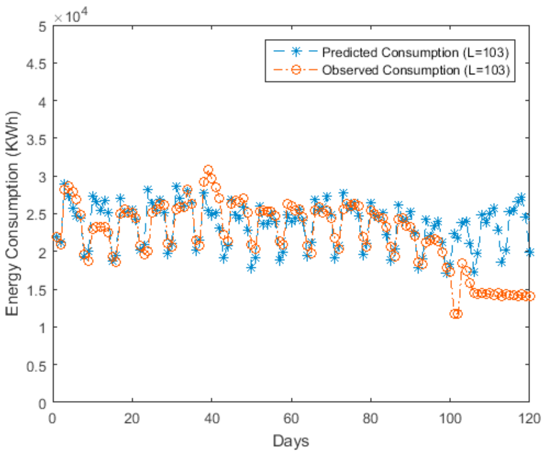

Figure 7 Energy Consumption Forecast for Campus C

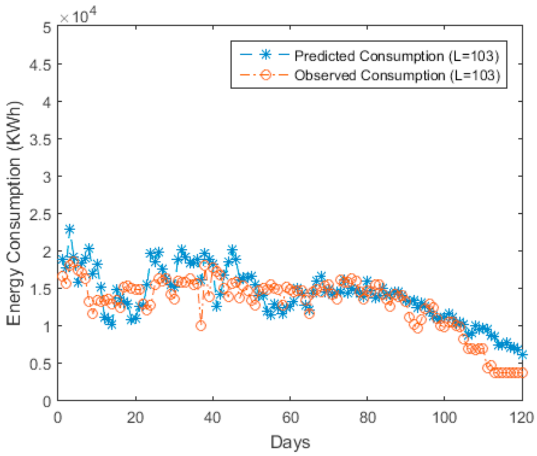

Figure 8. Energy Forecast for Campus D

Figure 5-8 present a forecast of energy consumption for each campus at window length L=103. The predicted values for the springtime in the series (Day 1 - 90) is closer to the observed compared to a month into the summer time (Day 91 -120) for all campuses. Energy consumption during the springtime as predicted exhibits a trend, with a sinusoidal fluctuation in all the campuses as shown in Figure 5-8. Energy consumption during the first month in the summer is relatively low compared to the springtime. SSA being a non-parametric model is not restricted by assumptions for stationarity peculiar to parametric models [17]. Its integration with NARNET enables a good performance without test for stationarity of the time series data, which is seen in this study.

As a measure of forecast accuracy, the mean absolute percentage error (MAPE) was used. This was calculated using;

$$MAPE = \frac{1}{N}\sum_{k=1}^{N}\left|\frac{y_k - \widehat{y_k}}{y_k}\right| \times 100\% \quad (2)$$

where y_k is observed energy consumption in the testing dataset k, $\widehat{y_k}$ is the predicted energy consumption and N is the total number of testing datasets.

For campus A, a MAPE of 14.13%, which translates to a forecast accuracy of 85.87% was obtained. Similarly, a MAPE of 24.38% was obtained for campus B. This means an energy consumption forecast accuracy of 75.62% for the model developed for the campus. Campus C and D recorded a MAPE of 14.98% and 23.17% respectively. These values translate to a forecast accuracy of 85.02% and 76.83% respectively. On the average, the models developed for each campus can forecast above 75% accuracy.

4. Conclusion

Strategic energy planning is highly essential in the service industry, as in the university, to achieve its sustainability. Singular spectrum analysis used in this study has proved to be a good tool for filtering data with noise. This study used three values of window length obtained from periodogram analysis (L=54, 103, 155). Window length of L=103 gave a more accurate result. Prediction accuracy in campus A model is highest (85.87%), and the lowest being campus B (75.62%). Up until now, the choice of window length for a series Y_T, still remains open. However, from this study, window length of $\frac{T}{10} < L < \frac{T}{11}$ gave a better filtering. In using SSA for filtering time series data, it is recommended that different values of window length be chosen based on known metrics, one of which is periodogram analysis. Data filtering before forecast enhances data quality, most especially when the forecast is a step ahead using the same series as input, i.e. an autoregressive model.

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