Predictive Energy Analytics on Institutional Buildings using integrated wavelet transformation and deep learning algorithms

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The paper presents a novel integrated technique to predict energy utilization using data-driven methodology at a sustainably-elevated institution in Arizona. An improved forecasting technique based on the Wavelet Transform (WT) and Deep Learning (DL) algorithms contribute to the methodology of this paper. The paper tests the robustness of the integrated WT-DL algorithms to predict the electricity consumption of institutional buildings. The cases of the institutional building that possess similar utilization pattern are examined. Four campuses' buildings' data has been collected for five consecutive years on their electricity consumption. Discrete WT (DWT) is used to decompose the original signal into several frequency components, and then DL algorithms are employed to provide electricity forecasting of the test case buildings. The approach provides a better Demand Side Management (DSM) strategy and facilitates the regulatory authorities, energy managers and decision makers with a simplified yet accurate forecasting technique. Findings of the paper demonstrate the energy forecasting of the buildings at different campuses and examine the efficiency of the proposed infused WT-DL technique using the Mean Absolute Percentage Error (MAPE).

Key Words: Predictive Analytics, Deep learning, Conditional Restricted Boltzmann Machine (CRBM), Electricity Consumption, Institutional buildings, Wavelet Transformation.

Introduction

According to Energy Information Administration (EIA), buildings account for 40% of the total primary energy consumption with 18% consumed by the commercial sector (Lanzisera et al., 2013). The improvement of building energy efficiency has not reduced the demand for energy but has increased with increase in renewable consumption (Naganathan, Chong, & Chen, 2016). Electricity consumption in commercial sectors accounts for 35 percent of the total electricity consumption in the U.S., and it is expected to encounter an increase of 40% from 2010 to 2030 (DOE, 2009). Sustainability has changed into a major component of the university campuses because of their increased environmental impact. With different types of buildings and their utilization, college campuses are considered a medium to large size cities (Deb, Eang, Yang, & Santamouris, 2016). Nguyen et al. (2010) add that electricity demand forecasting provides fundamental information on elevating pricing strategies, supply-demand characteristics, and marketing to maximize their benefits. Computer-based simulation models have also been used for building energy simulations (Naganathan et al., 2016). Because of the expansion of smart grid infrastructures, a lot of new prospects have come up recently, such as new data-driven methods for their flexibility and their ability to automatic fit new datasets (Cugliari, Goude, & Poggi, 2016).

Universities make constant efforts to ameliorate sustainability and conserve energy by better demand management strategies, automating building management system, promoting the need for sustainability to the younger citizens through education. The paper presents a novel integrated technique to predict energy utilization using data-driven methodology at a sustainably-elevated institution. The paper is organized into sections that include the objective of this study, a review of existing energy forecasting models, the relevance of wavelet transforms and deep learning concepts, research methods, WT-DL framework, predictive analytics and finally, the results and discussions to conclude the paper.

Relevant Work

Existing Energy Models

Predicting electricity consumption is a challenging task since it is a complex, time series values with non-linear dependencies and possess both periodic and random components (Rana & Koprinska, 2016). Suganthi & Samuel (2012) presented thorough research on different energy models for demand forecasting that includes time series, regression, econometrics, decomposition, co-integration, Autoregressive integrated moving average (ARIMA), expert systems, grey predictions, input-output models, integrated models, and bottom-up models. Pao (2009) developed a hybrid model that includes an exponential form of the autoregressive model that can predict the consumption of electricity and petroleum. Yokoyama et al., (2009) identified model trimming method to remove noises and periodic change in the time series data and later introduced the treated or preprocessed data into the neural network algorithm to predict the input values. Azadeh et al. (2006) forecasted the annual energy consumption of the commercial industries using Artificial Neural Network (ANN) and regression models and the accuracy is validated using the Analysis of Variance (ANOVA) test. The paper focuses on deep learning methods inspired by the structure of the artificial neural network integrating Boltzmann algorithms.

Wavelet-based approaches for Energy Prediction

With real-world applications on noise suppression, fingerprint detection, seismic analysis and medical signals such as Electrocardiogram (ECG), the wavelet transform is one of the most efficient methods for fault detection, data enhancements, and image recognition. Several studies explain the use of wavelet transform in short-term, medium-term and long-term electricity prediction. Catalão et al., (2009) developed a Neural Network Wavelet Transform (NNWT) framework and forecasted the electricity pricing using the test case dataset of Spain. Vu (2014) utilized wavelet to decompose both demand data and temperature data into low and high-frequency components and then, the Fourier transform is adapted to identify the demand patterns. Wavelet analysis has additional advantages of compressing and de-noising a signal without appreciable degradation (Frimpong & Okyere, 2010). Benaouda & Murtagh, (2006) utilized Haar wavelet transform and a nonlinear multi-resolution autoregressive method must forecast one-hour electricity load of the New South Wales electricity market. Thus, wavelet transform has been extensively used in the preprocessing the data for higher accuracy of the electricity prediction. It is important to note that the most widely used machine learning techniques for energy prediction are ANN and Support Vector Machines (SVM) (Fan & Hyndman, 2012).

Deep learning and Energy Predictions

Mocanu et al., 2016 investigates the application of Conditional Restricted Boltzmann Machines (CRBM) and Factored Conditional Restricted Boltzmann Machines (FCRBM) to understand the prediction accuracy of these latest deep learning concepts. These concepts of deep learning are considered to be the future of computational intelligence by few researchers because of its ability to resemble human brain networks better than traditional machine learning techniques (Mocanu, Nguyen, Gibescu, & Kling, 2016b). Deep learning has become the new state-of-the-art technique for many difficult artificial intelligence tasks (Naganathan et al., 2016). This technique discovers the inner data structure by exploring unlabeled data and use labeled data for fine-tuning for improved discrimination power and classification accuracy. Similarly, the study suggests that deep learning algorithms are the future of artificial intelligence. The paper aims at integrating these two techniques that can elevate the prediction accuracy of energy consumption. Thus, a novel framework with a combined algorithm of pre-processing and predictive analytics can be utilized by the energy managers and decision makers to get more insights on building consumption characteristics and ameliorate sustainability through optimizing their production rates.

Research Objective

The primary objective of this paper is to test the robustness of the integrated WT-DL algorithms to predict the consumption characteristics of institutional buildings. The data used in this paper are the consumption data of electricity, heating, cooling collected from seven buildings (at the 15-minute interval) for five years. The extensive database over five years of 15-minute interval data requires a thorough pre-processing technique that can elevate the data quality before performing predictive analytics using deep learning techniques. Preprocessing can provide insights for the energy managers to understand the ideal consumption of buildings based on their consumption values (Deb et al., 2016). The significant contribution of this paper is on integrating a framework of wavelet transform and deep learning algorithms that would preprocess the data into comprehensive dataset and provide predictions of buildings' energy consumption through modified Boltzmann deep learning technique.

Research Methods

The proposed WT-DL framework has three essential processes. The first phase includes data representation and collection, while the second phase details on data pre-processing. During this phase, the process of Wavelet transformation is explained, and the data pre-processing takes place. The third and the final phase includes the predictive analytics using deep learning CRBM technique that predicts the energy using the reconstructed data from wavelet transformation. Data collected from the campuses include electricity consumption, heating, and cooling loads. The time interval of the data is 15 minutes and is collected over five years at four different campuses. Figure 1 describes the stepwise procedure of the methodology.

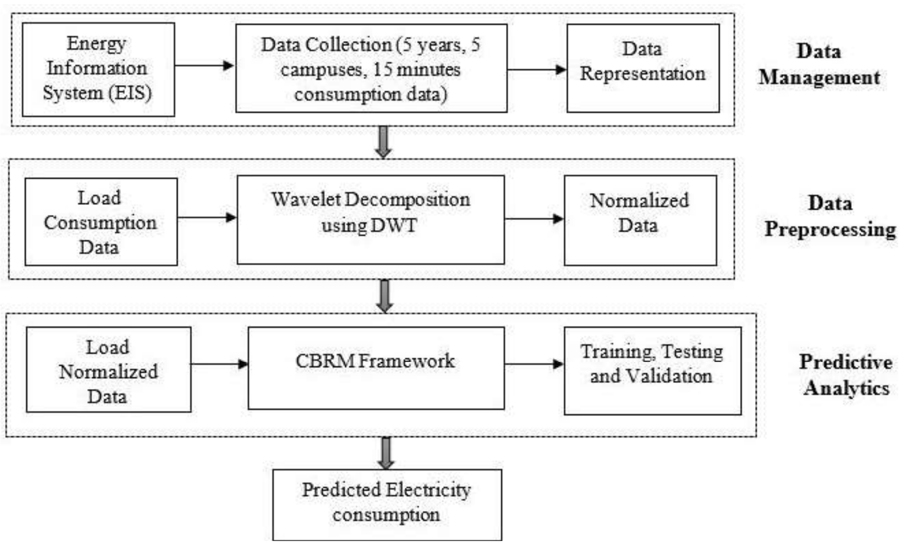

Figure 1: Research Methodology

Data Management

Data collection from Energy Information System (EIS) includes 15 minutes data on electricity consumption for all the buildings at the 4-year college institution. The figure below indicates the sample raw energy consumption representation of a couple of buildings. The figure is three dimensional with x-axis indicating time (15 minutes), y-axis indication consumption and z-axis indicating months.

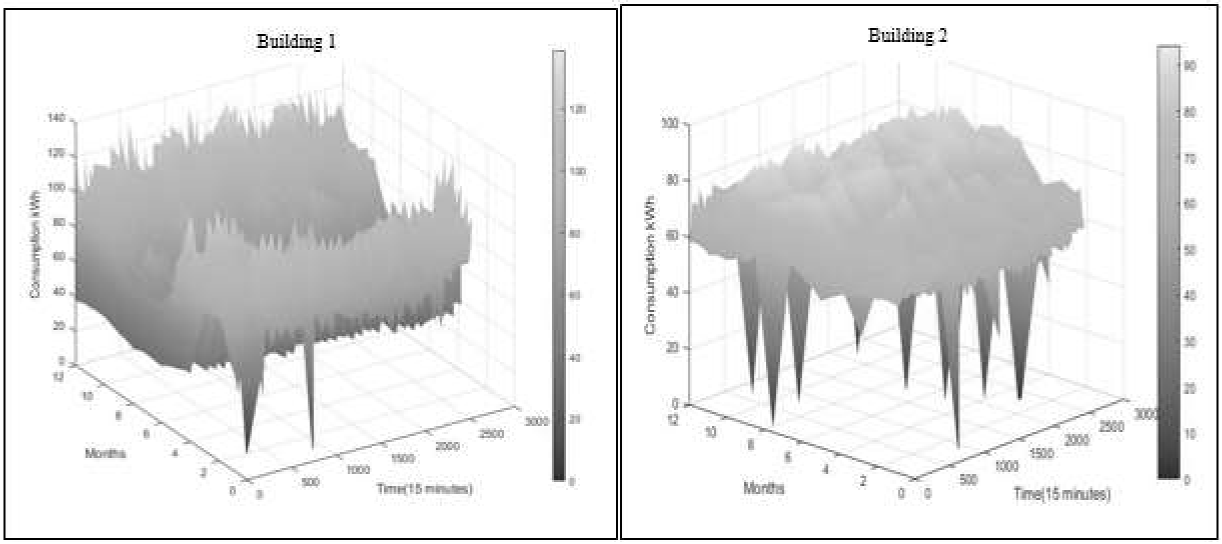

Figure 2: Data representation of Campus Buildings' electricity consumption

In addition to weekend and holiday spikes, Figure 2 shows that the raw data from the campus that has many high and low spikes indicating data quality issues during various times of the day over five years Thus, the figure shows the need for data preprocessing and cleaning before doing predictive analytics using these institutional buildings.

Data Preprocessing

Analyzing data that has not been carefully screened for such problems can produce misleading results (Naganathan, Chong, et al., 2016). The dataset representation from figure 2 indicates noisy samples and has significant variations over the period. Data-gathering methods are often loosely controlled, resulting in out-of-range values, impossible data combinations, missing values, redundant information, noisy and unreliable data (Naganathan, Seshasayee, Kim, Chong, & Chou, 2016).

Wavelet Transformation

The process of wavelet transformation includes two different steps. The first step is to decompose the raw data, which is passed through high pass and low pass filters. The outputs are approximate and detailed components. The summation of these two components will provide a more explicit representation of the original datasets.
In this paper, discrete wavelet transforms of level 3 has been chosen for the decomposition. Once the data is decomposed, the components derived are introduced to deep learning CBRM framework for training and testing and predicting the decomposed components.

Deep learning framework

In this paper, a deep learning algorithm of Conditional Restricted Boltzmann Machines (CRBM) is employed. While CRBM is the extension of RBM, the process includes the adding a conditional layer to improve the accuracy of the framework. The novel WT-DL framework aims at performing predictive analytics of institutional buildings' electricity consumption, which can provide predictions of consumptions that are more accurate than other ANNs, SVMs, and Recurrent Neural Network (RNNs).

Development of Wavelet and CRBM learning framework

The discrete wavelet transforms (DWT) decomposes the data into low-frequency components called approximate coefficients and high-frequency components called detail coefficients. The detail coefficients indicate the irregularities and fluctuations whereas the approximate coefficient indicates the regular signals. The selection of buildings was based on the availability of valuable data for all three factors which are electricity consumption (kWh), heating (mmBtu), and cooling (tonHr). Thus, the data is preprocessed using the wavelet transform for each building, and their respective approximate and detail coefficients are obtained. Finally, the combination of the decomposed components will be employed to determine the prediction of electricity consumption. The feedforward networks possess an input layer, a hidden layer, and an output layer. In this paper, the input data is labeled, and thus the learning algorithm for this article is supervised learning. In other words, the learning algorithm for this section is determined by the backpropagation method. In this paper, the collected data highlights the electricity consumption, heating and cooling loads of ten buildings. The means absolute error percentage is identified for all the buildings to understand the accuracy percentage error of the actual versus predicted values.

Results and Discussion

The process of WT-DL includes wavelet transformation and then utilizing deep learning CRBM algorithms to predict the electricity consumption of the institutional buildings. The first step, which is wavelet decomposition enhances the data quality by reducing noises and removing instabilities. After decomposition, the decomposed data utilized with Boltzmann's learning algorithm to predict the decomposed data for predicting the consumption values of 2015. Figure 3 shows the buildings from the campuses and their actual and predicted values.

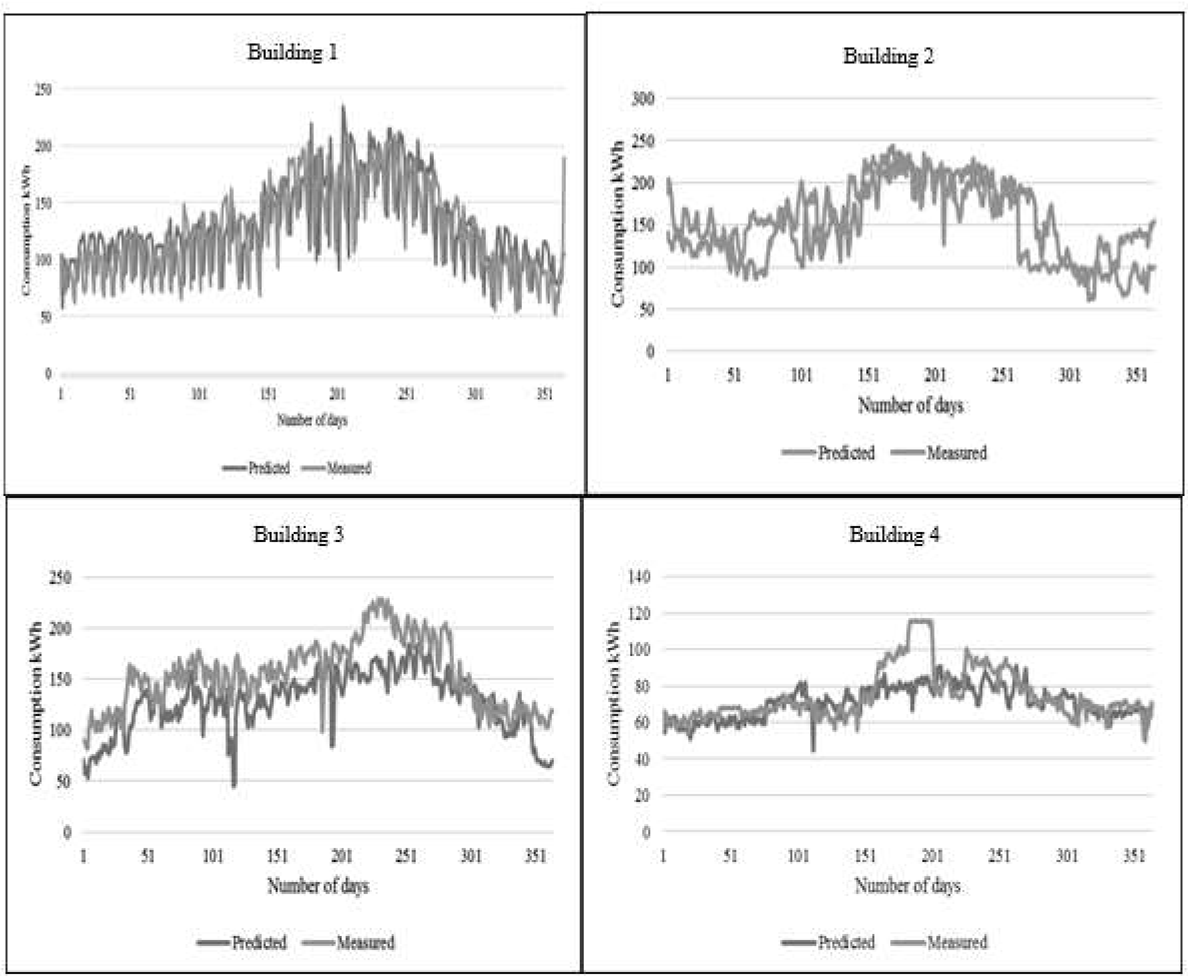

Figure 3 Predicted versus Measured Consumption values of Campus buildings (2015)

Figure 3 shows four different buildings and their consumption prediction. Hence, deep learning requires many attributes to train the machine to its best and to have higher accuracy. The paper aims at developing a predictive analytics model, and from Figure 3 and 4, it is evident that the predicted value and actual values are close to each other. Hence the predictive algorithm developed proves to be accurate indicating the success of this framework.

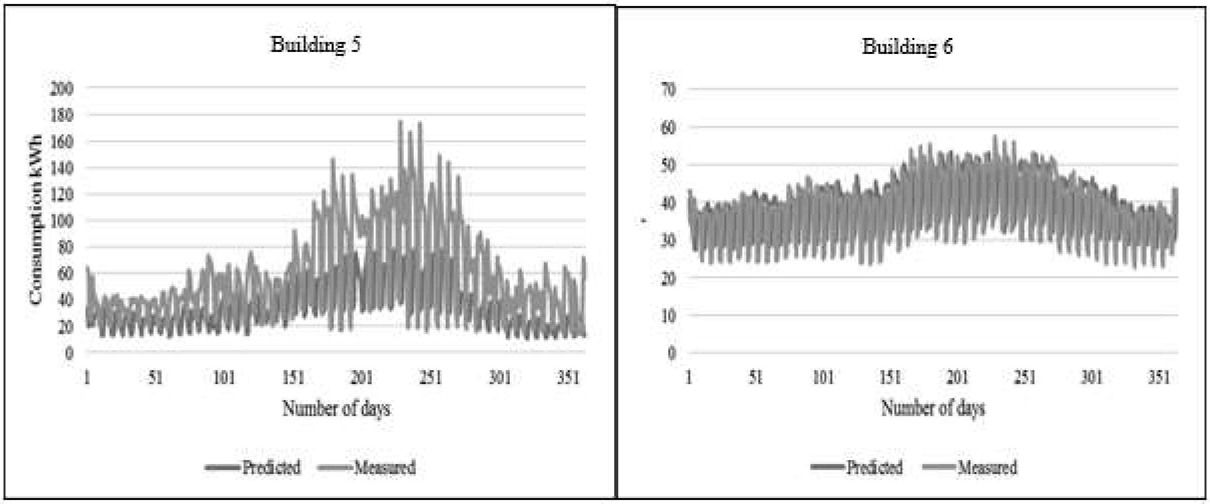

Figure 4 Predicted versus Measured Consumption values of other Campus buildings (2015)

Figure 4 shows the predicted and measured values of other two institutional buildings. To better understand the prediction errors, the authors performed MAPE to identify and rectify errors in predictive analytics. Table 1 provides information on buildings and their MAPE values. It is notable that Building 4 and 5 has a more significant deviation from the original value. However, building 6 and 7 perform better regarding the mean absolute percentage error. The percentage errors of other buildings range from 2.3%-2.7%. Institutional buildings have more uncertainties on their energy consumption characteristics because of sudden events, occupancy and another unexpected surge.

Table 1

Buildings and their mean MAPE values

Building Number	MAPE
1	2.7 %
2	2.5 %
3	2.3 %
4	1.9%
5	1.0 %
6	6.2 %
7	5.6 %

Thus, electricity prediction for an institutional building is a challenging task since the prediction accuracy can always be questionable. With the latest smart grids, the solution is to integrate real-time data with more accurate techniques. The paper proposes a new integrated framework of WT and DL to preprocess and predict data. The institutions can predict their consumption values using this framework by integrating this framework with their Building Automation System (BAS), which can collect every minute data. It is the first step towards developing a whole model that track, preprocess, detect anomalies, predict and finally visualize the data. Also, the process of automation is one of the future scopes of this paper. Though the results have been demonstrated and validated, there are some limitations to this article. Hence, the complexities must be eliminated to give better human experience. The other limitation is the data quality. Information is available in abundance, but it is essential to have a comprehensive dataset for better outputs. The focus of this research will be by adding more attributes to the deep learning algorithm to improve predictive learning strategies and to elevate accuracy. It can help the industry practitioners, and any infrastructure developers to know and understand their energy strategies beforehand by using predictive analytic model.

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