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A deep learning framework for building energy consumption forecast

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Highlights

- *k*CNN-LSTM, a deep learning based energy consumption forecast model, is presented.
- Timestamp based features generated from the timestamp provides parameter-rich data.
- *k*-means clustering analyzes the trend in energy consumption data.
- CNN-LSTM captures spatio-temporal characteristics in energy consumption data.
- A case study on KReSIT building energy consumption data is presented.

Abstract

Increasing global building energy demand, with the related economic and environmental impact, upsurges the need for the design of reliable energy demand forecast models. This work presents *k*

CNN-LSTM, a deep learning framework that operates on the energy consumption data recorded at predefined intervals to provide accurate building energy consumption forecasts. kCNN-LSTM employs (i) $\boldsymbol{k}$—means clustering – to perform cluster analysis to understand the energy consumption pattern/trend; (ii) Convolutional Neural Networks (CNN) – to extract complex features with non-linear interactions that affect energy consumption; and (iii) Long Short Term Memory (LSTM) neural networks – to handle long-term dependencies through modeling temporal information in the time series data. The efficiency and applicability of kCNN-LSTM were demonstrated using a real time building energy consumption data acquired from a four-storeyed building in IIT-Bombay, India. The performance of kCNN-LSTM was compared with the k-means variant of the state-of-the-art energy demand forecast models in terms of well-known quality metrics. It is also observed that the accurate energy demand forecast provided by kCNN-LSTM due to its ability to learn the spatio-temporal dependencies in the energy consumption data makes it a suitable deep learning model for energy consumption forecast problems.

Introduction

A nation's total energy demand can be estimated by aggregating three main economic sectors: buildings, industry, and transport [1,2]. According to World Watch Institute data, buildings as the largest energy consumer, accounts for 40% of the global annual energy consumption and 36% of the total carbon emissions, especially in urban areas [3,4]. The growth rate of building energy consumption in Organisation for Economic Co-operation and Development (OECD) and non-OECD nations for 2012 and 2040 is 1.5% and 2.1% per year, respectively [5]. Specifically, the total energy consumption of higher education institutional and commercial buildings are 45% and 30% higher than the residential buildings [6]. The proper use of energy through the implementation of appropriate energy management systems and end-user energy efficiency control strategies [7] provides lower operational costs by reducing energy use and avoiding penalties imposed by the utilities [[8], [9], [10]]. In this regard, several nations have augmented the implementation of energy regulations and codes for buildings, such that new energy-efficient building designs ensure reduced energy consumption, energy costs, and environmental impact (carbon emissions). According to the World Energy Council, “While overall per capita energy demand would begin to fall, demand for electricity would double by 2060”, which necessitates the need for larger investments in smart infrastructures that promote energy efficiency [11]. From the smart grid perspective, buildings have become more intelligent with the integration of advanced information and communication technologies, electric vehicles, decentralized generation and storage systems, and energy management systems. Therefore, the design and implementation of smart technologies for power grids and buildings to meet the global energy demand in an effective and economically sustainable way with reduced carbon emissions have become extremely important.

Recently, research on energy consumption forecast in buildings has become increasingly significant as buildings are equipped with smart meters to monitor energy consumption of buildings at fine-

grained intervals. Massive and high dimensional energy consumption data from the smart meters collected at different granularities helps in understanding the energy consumption patterns for its application to energy demand forecasting, demand response, heating ventilation and air conditioning (HVAC) optimization, and fault diagnosis and detection. Accurate and reliable energy demand forecasts enable the utilities to plan resources and balance supply-demand, thereby ensuring stability and security of the power grid & reliability of service provisions [12]. Overestimation and underestimation of the energy demand lead to a severe impact on the economic and industrial developments [13]. Accurate modeling and prediction of energy demand help in efficient energy management in smart buildings, accurate demand response strategies, electricity supply management, and context aware control strategies [14]. Therefore, energy consumption forecast models have become an integral part of Building Energy Management System (BEMS) to improve the buildings' energy efficiency for a sustainable economy through a conservation-minded society, reasonable use of available energy resources, and efficient national energy strategy [15]. However, the non-linear, dynamic, and complex nature of energy consumption data, along with the presence of trend, seasonal & irregular patterns, and dependence on various exogenous factors like climatic conditions, nature of the day, socio-economic factors, etc. presents accurate and reliable energy consumption forecast as an interesting research problem.
Energy consumption forecast models in the literature fall into three categories: (i) **Engineering methods:** Uses physical and thermodynamic laws & require complex building and environmental parameters; Difficult and time-consuming; Examples-EnergyPlus, Ecotect, etc [2]. (ii) **Statistical methods:** Correlates energy consumption with relevant factors like climate data, occupancy, etc.; Lacks accuracy and flexibility; Examples-Time series (autoregressive models) [14] and regression models (linear regression) [16,17], and (iii) **Artificial intelligence methods:** Learns the consumption patterns from the historical energy consumption data, i.e., discover the non-linear relationship between the input (historical data) and output (target consumption) [18,19]; Examples-artificial neural network [20], support vector regression [4], etc. Among these, artificial intelligence approaches have become 'active research hotspot' due to their efficiency and flexibility over engineering and statistical methods (Table 1) [21,22].

From Table 1, it is evident that ANN and its variants have been widely explored and applied for energy consumption forecast since they are non-linear, self-adaptable, and can approximate any function, given the sufficient number of hidden layers and nodes in the hidden layer [39]. However, the inability to handle historical data dependencies and several factors like parameter initialization, trap at local minima, slow convergence, and scalability of network architecture provoked the researchers to actively work on these issues or explore deep learning approaches for building energy consumption forecast. Further, a considerable amount of information collected over various sensors deployed in buildings has transformed energy forecasting research into a "big data" research problem [40]. Interestingly, recent advancements in deep learning theory have resulted in efficient tools to handle massive and high dimensional energy consumption data, which can outperform traditional machine learning tools [41]. In this way, this work presents kCNN-LSTM, a deep learning framework which employs $k-$means clustering, CNN, and LSTM for trend analysis, energy-related feature identification, and modeling long term dependencies in the energy consumption data, respectively.

From the brief literature survey on the building energy consumption forecast models designed for residential, academic, and commercial buildings, the following *research gaps* were identified.

1. Most of the energy consumption data used in the literature are multi-featured (occupancy, temperature, humidity, building schedule, etc.) and data-rich (massive and high dimensional data). The research challenge in building energy demand forecasting is to achieve high forecast accuracy using the energy consumption data recorded at each timestamp.

2. The energy consumption in an academic building does not reveal the trend and seasonality during the time series analysis. It might be due to several factors like high dynamics in schedules, occupancy related status, operations, etc.

3. Moreover, the existing energy forecasting models follow static learning, where its performance is entirely dependent only on the historical energy consumption data. However, the inclusion of recent observation with the historical data with the help of a sliding window approach would result in better forecast accuracy.

4. Further, the existing research works on LSTM based building energy consumption forecast model operates over static data (benchmark datasets) instead of real time building operation data obtained from the BEMS.

What makes kCNN-LSTM different from the existing building energy consumption models? The distinctive features of kCNN-LSTM are.

1. **Feature generation from timestamp:** The considered building energy consumption data is a nxm dimensional data, where n denotes the rows (energy consumption records) and m represents the columns ($m = \mathbf{2}$**;** timestamp in dd-mm-yyyy HH: MM: SS format and energy consumption). As a data preprocessing step, seven features (day of the year, season, month, day of the week, hour of the day, minute of the hour, type of the day) were generated from the timestamp, which enables the learning model to gain better insight on the trend and seasonality of the energy consumption data.

2. **Clustering algorithms:** An academic building's energy consumption is quite complex and dynamic, which does not exhibit an apparent trend and seasonality in the initial analysis. In such cases, the application of clustering algorithms to the energy consumption data before data modeling provides better insights into the trend and seasonal characterization of the data through the generation of clusters.

3. **Multi-input and multi-output sliding window:** The application of multi-input and multi-output sliding window to kCNN-LSTM provides robust and reliable forecasting by moving through the window of historical and recent energy consumption observations.

4. **Static or live data:** kCNN-LSTM has been implemented as an energy consumption forecast model in the BEMS designed for Kanwal Rekhi School of Information and Technology (KReSIT), IIT-Bombay, India.

The key *contributions* of this paper are.

1. kCNN-LSTM, a deep learning framework, is presented to provide reliable and accurate building energy consumption forecasts.

2. As a data preprocessing step, seven timestamp based features were generated to enrich the energy consumption data recorded at regular time intervals as parameter rich data.

3. The complex trend and seasonality in the energy consumption data are analyzed using the $k-$means clustering algorithm that uses the LB-Keough distance metric to identify the similarity between the time series (energy consumption data) of different months in the considered annual energy consumption data.

4. The spatio-temporal dependencies in the energy consumption data are learned and modeled by the convolutional neural networks and long short term memory neural networks, respectively.

5. Multi-input and multi-input sliding window mechanism is deployed to provide accurate and reliable energy consumption forecast.

6. Further, effective modeling of higher order and non-linear dependencies in the energy consumption data enables kCNN-LSTM to provide accurate forecasts in real time for a long period without retraining.

7. The effectiveness of kCNN-LSTM for reliable building energy consumption forecast is validated through a case study using the real time building operational data acquired from the BEMS deployed at KReSIT, IIT-Bombay. Further, the performance of KCNN-LSTM over the $k-$means variant of existing energy demand forecast models was assessed in terms of MAE, MSE, MAPE, and RMSE for the considered year, weekdays, and weekend.

The paper follows the following structure. Section 2 introduces the basic principles of $k-$means, energy consumption forecasts, LSTM neural networks, and convolutional neural networks. Section 3 presents a brief description of the formulation of the energy consumption forecast problem and the proposed deep learning framework to forecast the energy consumption of the buildings. Section 4 provides a detailed analysis of the performance of kCNN-LSTM and state-of-the-art energy demand forecast models in terms of MAE, MSE, MAPE, and RMSE. Section 5 concludes the paper.

Section snippets

Preliminaries

This section presents a clear view of the formulation of energy consumption forecast problem, $k-$means clustering, long short term memory, and convolutional neural networks. …

CNN-LSTM: proposed deep learning framework for building energy consumption forecast

Fig. 5 presents the architecture of kCNN-LSTM to forecast the energy consumption of buildings. The overall workflow of kCNN-LSTM consists of (i) **Data source and preprocessing layer:** Transform the raw energy consumption data into a compatible format, (ii) **Data clustering and analytics layer:** cluster the data into different groups for trend analysis, (iii) **Dataset generation layer:** generate datasets for train, valid, and test, and (iv) **Model building and evaluation layer:** create models to …

Case study

This section presents a detailed description of the considered energy consumption data, data preprocessing techniques, and evaluation metrics. Further, a detailed analysis of the performance of kCNN-LSTM over the $k-$means variant of the state-of-the-art building energy consumption forecast model. …

Results and discussions

The implementation of kCNN-LSTM and the experimental analysis was carried out in Operating system - Windows 10; System configuration - i7 processor and 64GB RAM; and Framework - Python 3.6. The experiments carried to analyze the efficiency of kCNN-LSTM for the energy consumption forecast problem can be divided into three phases, namely (i) Data clustering, (ii) Energy consumption trend analysis, and (iii) Energy demand forecast analysis.

(i) Phase1: Clustering …

In general, the application of …

Conclusions

This work presented kCNN-LSTM, a deep learning framework for robust and reliable building energy consumption forecast. kCNN-LSTM employed $k-$means clustering, CNN, and LSTM for trend characterization, energy-related feature identification, and to model temporal information in the energy consumption data. The hyperparameters of kCNN-LSTM model were optimized using ISCOA, which uses Haar wavelet based mutation operator to update position, thereby avoiding premature convergence. A case study using …

Credit author statement

Nivethitha Somu: Conceptualization, Methodology, Investigation, Data curation, Writing (Original, Review and Editing), and Visualization, Gauthama Raman: Conceptualization, Software, Writing (Review and Editing), Krithi Ramamritham: Conceptualization, Validation, Resources, Writing (Writing – review & editing), Supervision, and Funding acquisition.

. Energy consumption patterns in Cluster 1 for different days (a) Tuesday (b) Thursday (c) Saturday

. Energy consumption patterns in Cluster 2 for

…

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. …

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References (56)

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