

Review on Electricity Consumption Forecasting in Buildings: using Artificial Intelligence

Aditya Sonar¹, Vinita Galande²

¹Student, ²Faculty of Department,

^{1,2}Department of Computer Engineering, R.M.D. Sinhgad School of Engineering, Warje, Pune, Maharashtra, India

ABSTRACT

During the past century, energy consumption have increased drastically due to a wide variety of factors including both technological and population-based. Therefore, increasing our energy efficiency is of great importance in order to achieve overall sustainability. Forecasting the building energy consumption is important for a wide variety of applications including planning, management, optimization, and conservation. Data-driven models for energy forecasting have grown significantly within the past few decades due to their increased performance, robustness and ease of deployment. Amongst the many different types of models, among the most popular data-driven approaches applied to date. This paper offers a review of Electricity consumption forecasting in office buildings: an artificial intelligence approach for forecasting building energy use and demand, with a particular focus on reviewing the applications, data, forecasting models, and performance metrics used in model evaluations. Based on this review, existing research gaps are identified and presented.

KEYWORDS: energy, data-driven, artificial intelligence, electricity consumption, energy, neural network, forecast;

INTRODUCTION

The need in electricity generation and management continues to increase each year. This growth is primarily the result of the rapid increase in the world's population and the upward trend in the number of electronic devices per person. World electricity consumption could significantly increase in the near future.

Over the past few decades, researchers have dedicated themselves to improving building energy efficiency and usage through various techniques and strategies. The forecast of energy use in an existing building is essential for a variety of applications like demand response, fault detection and diagnosis, model predictive control, optimization, and energy management.

Many studies have been published during the past years to improve the prediction models in power energy systems. In has been presented a study that uses forecasting methods to

identify correlations between electricity consumption behavior and distributed photovoltaic (PV) output.

This paper presents a day ahead vitality utilization forecast approach for buildings. The estimating demonstrates contains five determining algorithms, to be specific Artificial Neural Network (ANN), Support Vector Machines (SVM) and Fuzzy Rule Based Systems (FRBS).

This article is composed of three main sections. In Section , the methodology used to model electricity consumption and management is described. Many simulation results are discussed to demonstrate the possibility to decrease the cost of electricity consumption, while at the same time smoothing the peak demand.

In below Section, Artificial Neural Network is explained. Many simulation results are discussed to prove the relevance of such an approach.

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Sr. No	Name of journal/ Year of publication	Paper Title	Author Name	Abstract
1.	IEEE transaction/2016	Energy Management System with PV Power Forecast to Optimally Charge EVs at the Workplace	Dennis van der Meer, Gautham Ram Chandra Mouli	This paper presents the design of an energy management system (EMS) capable of forecasting photovoltaic (PV) power production, that optimizes power follows between PV system, grid and battery electric vehicles (BEVs) at the workplace.
2.	NDPI energies transaction/2017	The Fuzzy Logic Method to Efficiently Optimize Electricity Consumption in Individual Housing	Sébastien Bissey, Sébastien Jacques	This article points out the relevance of a fuzzy logic algorithm to efficiently predict short term load consumption Home energy management (HEM) algorithm used to optimize cost of electricity consumption, while smoothing the peak demand.
3.	IEEE transaction/2010	Decision Making under Uncertainty in Electricity Markets.	L. A. Barroso, A. J. Conejo	This paper considers stochastic programming models for decision-making under uncertainty in the context of electricity markets.
4.	IEEE transaction/2006	Applying Support Vector Machine Method to Forecast Electricity Consumption	Shu-xia Yang, Yi Wang	Electricity consumption reflects the electricity usage of the whole society, so the prediction study and analysis to electricity consumption have important realistic and theoretical significance.

➤ **A Brief Explanation of Forecasting and Artificial Neural Networks**

In this section, a definition of forecasting is provided, along with a brief overview of ANNs, their overall structure, different varieties of ANN, and ANN architecture selection methods. Machine learning (ML) may be a branch within the general tree of AI (AI). Within the machine learning domain, one among the foremost prominent techniques to-date is that the artificial neural network. a man-made neural network (ANN) is an information science system that was inspired by interconnected neurons of biological systems. McCulloch and Pitts wrote a paper hypothesizing how neurons might work, and that they modeled simple neural networks with electrical circuits supported their hypotheses. In 1958, Rosenblatt modeled an easy single-layer perceptron for classifying endless valued set of inputs into one among two classifications. Since then, ANNs have gained significant complexities and breakthroughs which have added to their growth and recognition . Two prominent applications of ANNs include pattern recognition, and prediction/forecasting. An ANN learns to perform tasks without being explicitly programmed with task-specific rules. Rather it learns by being presented with data and modifying the interior ANN parameters to attenuate the errors.

A neural network consists of the many interconnected neurons. Each node performs an independent computation joined together by connections which are typically weighted. During the training phase of an ANN, the weights of every connection are adjusted and tuned supported being presented with data.

ANNs are one among the foremost used and known forecasting methods. This method is inspired by the human brain and their number of neurons with high interconnectivity. ANNs are several combined nodes or neurons, divided into different levels and interconnected by numeric weights. They resemble the human brain in two fundamental points: the knowledge being acquired from the encompassing environment, through a learning process; and the network's nodes being interconnected by weights (synaptic weights), wont to store the knowledge. The ANN is implemented in R using the “neuralnet” package.

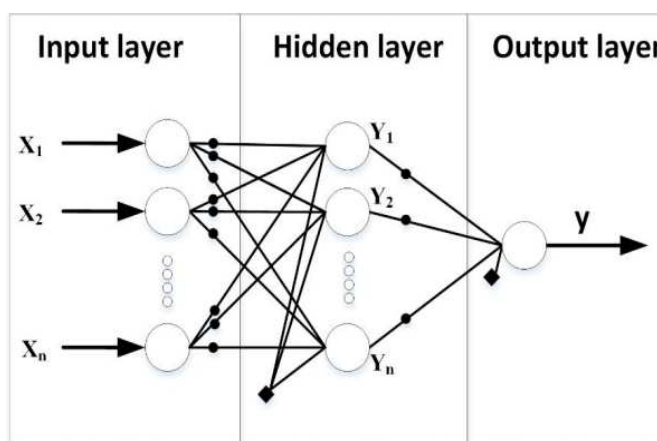


Figure 2. A typical feedforward neural network topology.

➤ **Types of Artificial Neural Networks**

The This section presents a brief description of the five main sorts of standard ANNs found applied to building energy forecasting, and a general overview of deep ANNs, which are a classification unto themselves. The feed forward neural network (FFNN), often called multilayer perceptron (MLP) or back propagation neural network (BPNN), is one among the foremost common sorts of neural networks which are applied so far . this sort of ANN model was previously described in Section shown in Figure 1. A radial bias function neural network (RBNN) may be a three-layer neural network almost like that of a FFNN, but it contains a bigger number of interconnected neurons. These types are predominately used for classification purposes, but they need also been applied to forecasting in buildings. The RBNN differs from the FFNN therein the input layers aren't weighted, and thus the hidden layer nodes receive each full input value with none alterations/modifications. additionally , the unique feature of the RBNN is that the activation function. Often, an RBNN network uses a Gaussian activation function. Radial basis neural networks are often simpler to coach as they contain fewer weights than FFNNs, provide good generalization and have a robust tolerance to input noise. the most disadvantage of these models is that they will grow to large architectures, requiring more neurons (compared to a FFNN), thus, they will become computationally intensive. A general regression neural network (GRNN) may be a variation of the RBNN suggested by Specht .A GRNN may be a one-pass learning algorithm which will be used for the estimation of target variables. A nonlinear autoregressive neural network (NARNN) may be a sort of recurrent neural network. The NARNN model is different from the previously mentioned neural networks in such the outputs are fed back as an input for future forecasts. Once training is completed, the loop is closed, initial inputs are presented, then the primary estimated value is forecasted. The output is then fed back as an input, removing the last most input file sample from the previous estimation so as to supply the next forecasted value. the method continues until the specified forecast horizon has been achieved. NARNN have the advantage of not requiring many various input variables, have similar training times to FFNN, and supply good results. Should the info for theonly variable become unavailable the forecasting model can fail. additionally , forecasting errors are propagated back in as inputs for future forecasts, thus, because the forecast horizon increases, these models can subsided accurate. In many applications, there's a crucial correlation between a target variable and other variables. Thus, integrating multiple variable inputs and autoregressive inputs may benefit the modeling process to supply more accurate estimations. In such cases, the nonlinear autoregressive with exogenous (external) input, or NARXNN, is used. Deep learning is a neighborhood in AI which has received recent advances. Breakthroughs occurring in 2010–2012 have led to the advancements in many fields and applications . Deep-learning ANNs are models which contain a minimum of two non-linear transformations (hidden layers). the advantages of deep-learning models dwell two main aspects: the power to handle and thrive in big data, and automated feature extraction . Within the deep learning ANNs, different varieties have emerged, however, this paper limits the outline of ANN to the five previous presented ANN types, which constitute the bulk of models applied so far . However, for the cataloging and analysis portion of this work, all neural networks which have developed two or more hidden layers are categorized as deep artificial neural networks.

➤ **Survey**

This study proposes a day-ahead energy consumption forecasting approach for the energy consumption of an office block, which the energy consumption of the building N of GECAD facilities located in Porto, Portugal has been chosen for this purpose. The proposed model includes five forecasting algorithm namely as ANN so as to get the simplest possible results. The proposed forecasting approach contains two forecasting strategies that are supported using different variables and different data structures to coach the forecasting methods. Both strategies divide the entire energy consumption of the building into three values of consumption which correspond because the three existed types of consumers within the building like HVAC, Lights, and Sockets. The Energy consumption of every one among these consumers are going to be forecasted separately and therefore the methods are going to be trained ones for every sort of consumers. For the case of Lights only the consumption from 11:00 to 19:00 is taken into account because out of this interval the lights consumption is zero. These strategies first selected 14 days before the target day that have an equivalent day type because the target day. The test data set which is the main input of the methods includes the info from these selected 14 days. And because the train data, an equivalent day of the past week because the target day from the past 10 weeks are considered because the targets.

This way, for of these 10 days an equivalent data set because the test data setis created and therefore the methods train supported this data set. a special data set is made for each hour of the target day and each consumer type. this suggests to predict the energy consumption of the next 24 hours; 72 different data sets are created, and the methods are going to be trained 72 times by these data sets. The structure of the same is given below

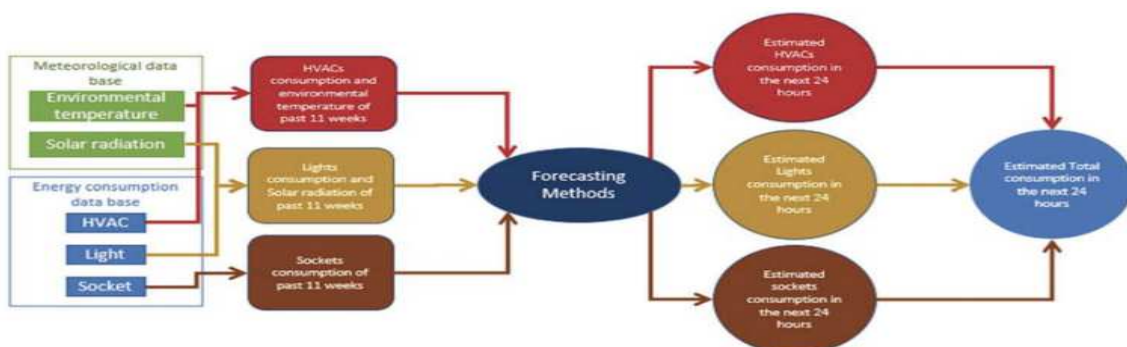


Figure 2 - The structure of the second proposed forecasting strategy

➤ Conclusion

Due to the increasing involves sustainability, concerns about emissions, and their large energy utilization, there's a growing got to improve the energy efficiency and performance of buildings. Underpinning many approaches for improving energy usage are accurate and reliable forecasts. Thus, this article focuses on one among the foremost prominent forecasting machine learning algorithms being applied, the synthetic neural network. Previous literature reviews focused on the comparison of data-driven models with physics-based models, compared machine learning to statistical techniques, evaluated ensemble methods, and analyzed machine learning as an entire with regards to forecasting and prediction of building energy use. additionally, such papers didn't differentiate between forecasting and prediction. While the previous work is vital and relevant, there remains a niche strictly that specialize in how ANNs have been applied for forecasting future energy use and demand in buildings. This paper aimed to deal with this gap by that specialize in the subsequent questions. The potential to assist mitigate future problems associated with duplicate research and supply a benchmark to assist gauge performance of the ML technique. In order to answer the aforementioned questions, a strategy was followed which collected relevant papers, screened them supported a specified criteria, then cataloged parameters within the papers supported a typical feature set. Such features included application properties, data properties, forecasting model properties, and therefore the performance used for model evaluations. Limitations for this work included papers accessible through available journals, written in English, and published over the year range of January 2000 to January 2019. After cataloguing the accumulated papers, an analysis was conducted. Our conclusion supported the analysis found the bulk of ANN models are a black-box-based model, employing a feed forward neural network with its hyper parameters manually found. the bulk of the applications were found to be applied to commercial buildings, using hourly data, and applied to an entire building energy load. additionally, performance of the ANN models was found to be 0.001–36.5% (MAPE) for single step ahead forecasting and 1.04–42.31% (MAPE) for multistep ahead forecast supported the analysis, a couple of areas which may benefit from additional research are highlighted. These include long-term prediction, ensemble models, deep learning models, lighting models, component-based target variables, grey-box models, window re-training, and automated architecture selection methods. Effective incorporation of occupant information can also help improve energy forecasting. Future research directions may cause improvements in ANN forecasting models, improve energy

usage, and may potentially cause wider contributions in big data analytics and data science.

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