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ANN FOR THE ENERGY CONSUMPTION FORECASTING IN BUSINESS BUILDING

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Abstract :-

In recent years, analysing the data gathered during production process of the energy has become an important issue in the energy sector in order to increase the efficiency of the produced energy. In the predictive machine learning approach, the main goal is generalisation. This means the ability of the model to give sensible predictions for situations not identical to what has already been observed in the training data. The main factors determining the predictive performance are the relevance of the sensory features, the amount of training data available and the adaptation of the complexity of the model to the task at hand. For the purpose of energy conservation, we present in this paper an introduction to the use of learning machines used as a data mining tool applied to buildings energy consumption data from a measurement campaign. The learning stage was done for a first part of the data and the predictions were done for the last month. Performances of the model and contributions of significant factors were also derived. The results show good performances for the model.

Keywords: data mining; predictive modelling; energy efficiency; energy consumption

Introduction:

Global energy demand rose by 1.9% in 2017 – the fastest annual increase since 2010. The forces driving up energy demand, led by strong economic growth, outpaced progress on energy efficiency. As a result, energy intensity – primary energy use per unit of GDP – fell by just 1.7% in 2017, the slowest rate of improvement this decade.

From the discovery of the computer to the present, a large amount of data has been quickly produced and become the source of inspiration for the future research. The importance of bigdata has increased with the spread of (Industry 4.0's component) the internet of things (IoT), cloud computing and smart devices. Nowadays, big data is produced by heterogenous sources such as health, government, social networks, marketing, and financial sectors. Big data tools are advanced mobile devices, digital sensors, communication tools, computing and storage devices.

Even though big data created great opportunities for several sectors, it is extremely hard to be analysed. These challenges are; the complex nature of the big data, scalability, performance requirements and real-time response analysis of the big heterogenous datasets. Therefore, it is important to perform an advanced data analysis to understand and study the relationships between data and its properties. As a result of the big data analysis, positive or negative, controllable parameters or valuable information can be obtained.

Machine learning and deep learning approaches that can explore the information, make smart decisions and solve the difficulties encountered due to the size of the data volume while applying the current analytical methods, are being used. Machine learning is used in real-world applications such as data mining and information, search engines, recognition systems, and autonomous control systems. In this sense, study used a statistical method and machine learning techniques for the analysis of large amounts of data. Today, renewable energy sources often use machine learning techniques. In previous years, the importance of renewable and sustainable energy sources has increased due to the rapid increase in the disadvantages of fossil fuels. The combined effects of the rapid loss of fossil fuels and its damage to the environment has presented the urgency to the use of traditional and renewable energy sources such as solar, hydro, wind, geothermal and bioenergy sources. Increasing problems related to environmental pollution have increased the importance of renewable energy. Renewable energy sources are a cheap and never-ending type of energy in every country in the world. The renewable energy sector will continue to grow rapidly within the next years.

Compressed Air Systems with Energy Efficiency

The use of compressed air in the factory environment is an important issue in energy efficiency. Additionally, it requires only minor maintenance efforts since they are very robust and cost efficient. They are usually suitable for installations that run 24 h a day/365 day of the year. Pneumatic systems are criticised for their poor energy efficiency and the research community is extremely interested in measuring the air consumption in machines and in assessing the energy efficiency and the optimisation of devices and systems. The low efficiency of compressed air systems (CAS) is the result of the total losses that are caused by compressors, dryers, pneumatic installations and the use of side devices.

Energy Efficiency Assessment

Increasing interest in the analysis of production data has caused an increasing amount of data to be collected from sensors and field devices. This results in huge datasets that not only need to be stored and aggregated properly but, most of all, to be processed and computed. One of the main groups of methods that are capable of finding dependencies between the objects in a dataset is clustering. Clustering comes out of data mining and machine learning and is one of the methods of unsupervised classification. Its groups objects into homogenous subsets (clusters) and is based on finding similarities between features of objects.

Methodology

Building characteristics

Building were chosen at random from the dataset and a process to collect building characteristics data was then undertaken. The data collection process adopted a desktop approach rather than, for example, site surveys—in order to maximise the sample size. Sources of data included digital map software, satellite images, publicly available databases.

Final Dataset

Upon the completion of the data collection process, energy use outliers were removed. Machine learning algorithms are sensitive to the range and distribution of the training data. Outliers in the training data can “mislead” the training process of a neural network and can result in less accurate models. Therefore, a process to remove outliers was undertaken on the energy use figures. Energy use data1.5 times the interquartile range below the lower quartile and above the upper quartile were used as boundaries for identifying outliers. Outliers were identified using interquartile ranges to account for the possibility of skewed distributions. The outlier removal procedure was carried out on the thermal and electrical energy use figures separately.

Single Machine Learning Models for Building Cooling Load Prediction

This study applied the ANNs model for predicting building energy loads in the early design stage due to two reasons. Firstly, they are the powerful and most commonly used techniques. Secondly, they are potential models to solve nonlinear problems which are affected by numerous factors. Inputs for the models in this study are general information of buildings, the building envelops and internal loads which are presented. The cooling loads of buildings are outputs of these models in this study.

The ANNs uses the processing of the brain as a basis to develop models that can identify complex patterns and solve prediction problems. The ANNs models are powerful tools that can solve nonlinear problems such as prediction of cooling loads in buildings, prediction of thermal loads of commercial buildings. The multilayer perception neural networks model is a typical ANNs model, which has three main layers including an input layer, a set of hidden layers, and an output layer.

Artificial Neural Networks

The multilayer feed forward network with a backpropagation learning algorithm is among the most common neural network architectures, which have been widely studied and used in many disciplines. Three main layers included in a neural network are: (1) an input layer; (2) an output layer; and (3) an intermediate or hidden layer. The input vectors are, D <- Rn and D= (X1; X2;...;Xn)T; the outputs of q neurons in the hidden layer are Z = (Z1;Z2;...;Zn)T; and the outputs of the output layer are Y<- Rm, Y = (Y1;Y2;...;Yn)T. Here it is assumed that the weight and the threshold between the input layer and the hidden layer are wij and yj respectively, and the weight and the threshold between the hidden layer and output layer are wjk and yk respectively. The outputs of each neuron in a hidden layer and output layer are as follows:

$$Z_j = f\left(\sum_{i=1}^{n} w_{ij} \cdot X_i\right)$$

$$Y_k = f\left(\sum_{j=1}^{q} w_{kj} \cdot Z_j\right)$$

Where f is a transfer function, which is the rule for mapping the neuron's summed input to its output, and using a suitable choice as the instrument for introducing a non-linearity into the network design. One of the most commonly used functions is the sigmoid function, which is monotonically increasing and ranges from zero to one.

Learning Algorithm

The purpose of the learning algorithm is to train the network to predict the output parameter(s) given one or more input parameter(s). There are many types of neural network learning rules. There are three kind of learning algorithm, the first is known as supervised learning, in this case the algorithm allows to predict the output parameter on the basis of a set of known input-output pairs. Second algorithm is unsupervised learning, in this case the output is not given, the aim consisting of inferring a function in order to describe a hidden structure (e.g., clustering, anomaly detection, etc.). Therefore, the output parameters are considered ‘unlabelled’ (the observations are not classified) and is not provided any evaluation about the pre-diction reliability ensured by the ANN. Third algorithm is named reinforcement learning, in this case a continue interaction between the learning system and the environment allows to identify the input-output mapping minimizing the performance scalar index. In most cases, the unsupervised learning allows to ensuring lower cost function. Three different methods, usually considered to be supervised learning methods, are described in this work: Quick Propagation (QP), Conjugate Gradient (CG) and Levenberg-Marquardt algorithm (LM).

QP is a heuristic modification of the standard back propagation, the output of the mth output node for the pth input pattern is given by opm

$$o_{pm} = f\left(\sum_{k=1}^{K} \varpi_{km}\, o_{pk}\right)$$

where f is the activation sigmoidal function (Eq. (2)), ω¯km is the weight between the mth output neuron and the kth hidden neuron. The value of opk depends by two parameters: the first is given by the weight between kth hidden neuron and the nth input neuron (ω¯nk). The second parameter is xpn given by pth input pattern of nth neuron.

$$f(x) = \frac{1}{(1 + e^{-x})}$$

All network weights are updated after presenting each pattern from the learning data set. As far as concern CG method, the learning algorithm starts with a random weight vector that is iteratively updated according the direction of the greatest rate of decrease of the error evaluated as ω(τ)

$$\Delta\omega^{(\tau)} = -\eta \nabla E_{\omega(\tau)}$$

where E is the error function evaluated at ω(τ) and η is the arbitrary learning rate parameter. For each step (τ) the gradient is re-evaluated in order to reduce E. The performance of the gradient descent algorithm is very sensitive to the proper setting of the learning rate, in case η is too high the algorithm can oscillate and become unstable, for η too small the algorithm takes too long to converge. In this case an adaptive learning rate allows to keep the learning step size as large as possible, ensuring, in this way, the learning rate stable. The LM algorithm allows to minimize the squares of the differences (E) between the desirable output, identified as yd(t), and the predicted output yp(t). 'E' is given by the follow equation:

$$E = \frac{1}{2}\sum_{t=1} (y_p(t) - y_d(t))^2$$

LM algorithm is also adopted, which blends the 'Steepest Descent' method and the 'Gauss-Newton', therefore it can converge well even if the error surface is much more complex than the quadratic situation; ensuring, in many cases, speed and stability. LM algorithm can be presented as:

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k$$

where J is Jacobian matrix, μ is the 'combination coefficient' (always positive), I is the identity matrix and e represents the error vector. When μ is very small (nearly zero), Gauss-Newton algorithm is used. On the other hand, when μ is very large, steepest descent method is used.

Results and Discussion

The prediction of energy consumption of one building based on historical data has led to promising results. After training for 180 epochs with 180 neurons in the hidden layer, the measured root mean square errors was 17.78 for building 1 and 2.78 of building 2. The results of more experiments on building 2 can be found in table

Epochs	No. of Neuron in hidden layer	RMSE	MAE
60	60	4.26	2.92
60	120	4.12	1.80
60	180	4.01	2.21
120	60	4.35	1.02
120	120	4.06	2.45
120	180	4.25	2.47
180	60	4.62	1.98
180	120	4.21	1.05
180	180	4.10	2.54

The results obtained for building 2 show that the optimal number of epochs is approximately 120. The higher error scores that result from longer training may be caused by overfitting, although the scores are only slightly higher. The approach on which this first part of this project was based, obtained slightly better results with the ANN: a mean absolute error of 9.52 for building 1. The hybrid approach in which ARIMA was used to create features for the ANN, resulted in a MAE score of 7.33. The results of the hybrid approach for building 2, where this project obtained the best results, are unknown.

The results of ANN for all 180 simulations. The results obtained from ANN are annual energy use for heating and cooling for all groups. Annual energy use for interior lighting and equipment are the same for all buildings as the default inputs for lighting and equipment are constant in all models. These values are eliminated in this evaluation. The output data from the simulations indicate that the variations in building energy consumption are significantly affected by the properties of the insulation materials rather than the changes in different groups, i.e., different thickness configurations of wall materials. By increasing the thickness of the insulating material, the effects of other materials' properties on building energy performance decreases, i.e., the changes in thickness of other materials happen to become less effective.

Conclusions

Energy-efficient building design has attracted researchers and practitioners in adopting green building solutions. An early prediction of building energy use in the design stage is imperative to provide designers with various building design options. This study attempts to propose an alternative approach to energy loads in buildings. The dataset of buildings was used to construct and evaluate prediction performance of the single and ensemble ML models in this study.

This article presents research carried out to develop a machine learning method of predicting a building's energy use as an exploration of an alternative to traditional, physics based, building energy simulation at the early design stages. ANNs were trained to predict the energy consumption of building designs by electrical energy consumption data to a range of collected design and briefing parameters.

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