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Building Energy Consumption Modeling with Neural Ensembling Approaches for Fault Detection Analysis

Fiorella Lauro[1], Alfonso Capozzoli[1], Stefano Pizzuti[2]

[1]*TEBE Research Group, Department of Energy (DENERG), Politecnico di Torino, Corso Duca degli Abruzzi 24, 10129 Torino, Italy*
[2]*Energy New technologies and sustainable Economic development Agency (ENEA), Casaccia R.C., Via Anguillarese 301, 00123 Rome, Italy*

Abstract

In the paper a fault detection analysis through neural ensembling approaches is presented. Experimentation was carried out over two months monitoring data sets for the lighting energy consumption of an actual office building located at ENEA 'Casaccia' Research Centre. Using a fault free data set for the training, the Artificial Neural Networks Ensembling (ANNE) were used for the estimation of hourly lighting energy consumption in normal operational conditions. The fault detection was performed through the analysis of the magnitude of residuals using a peak detection method. Moreover the peak detection method was applied directly to the testing data set. Finally a majority voting method to ensemble the results of different ANN classifiers was performed. Experimental results show the effectiveness of ensembling approaches in automatic detection of abnormal building lighting energy consumption.

1. Introduction

In the energy optimization field, the evaluation of an actual building energy consumption data is a demandable and emerging area of building energy analysis. Therefore, developing automatic, accurate and reliable fault detection and diagnosis (FDD) methods is necessary in order to ensure the optimal operations of systems and to save energy. Different intelligent methods have been used to obtain useful information from building energy consumption data. A number of papers on the application of Artificial Neural Networks(ANNs) for FDD have been published. In this paper the capability of different Artificial Neural Networks Ensembling (ANN) approaches for artificial lighting fault detection of a real office building is demonstrated. The fault detection has been performed analyzing the magnitude of the residual generated by ANNE using a peak detection method. Moreover a majority voting method has been performed to ensemble the results of different ANN classifiers. In the first part of the paper a brief theoretical description of the methods analyzed is presented. Then the application of a fault detection analysis for the lighting energy consumption is showed with the aim to compare the capability of neural ensembling approaches in detecting two artificial faults created in the testing period.

2. Consumption modeling by Artificial Neural Network basic ensembling method

Artificial Neural Networks (ANNs) [1,2] are data modeling or decision making tools which can be used to model complex relationships between inputs and outputs or to find patterns

in data. ANNs essentially contain masses of parallel, interconnecting information processing units, technically known as neurons which interact with one another and can be located in multi-layers: for example an input layer, an output layer, and the intermediate layers consisting of hidden neurons. The connections between units define the network topology or architecture. Although neurons can be combined in various ways to form different types of interconnecting structures, only feedforward structures are mainly featured in fault diagnostic research papers. This structure generally has no connections from the output neurons back to the input neurons.
The term "ensemble" describes a group of learning machines working together on the same task: the goal is obtaining better performances than those which could be obtained from any of the constituent models. The non-generative ensembling method seeks to combine the outputs of the machines in the best way. In the case of ANNs, they are trained on the same data, they run together and their outputs are combined in a single one. Basic Ensemble Method (BEM) is the simplest way to combine M neural networks as an arithmetic mean of their outputs.

3. Peak Detection Method

Identifying and analyzing *peaks* in a given time-series is important in many applications such as building energy consumptions. In order to avoid subjectivity and to devise algorithms for the automatic detection of peaks in any given time-series, it is important to define the notion of peak. A peak is defined as an observation that is inconsistent with the majority of observations of a data set. Not all local peaks are true peaks: a local peak is a true peak if it is a reasonably large value even in the global context. The implemented method, *Peak Detection Method*, is based on the use of a *peak function S*, which associates a score with every element of the given time-series [3]: a given point is a *peak* if its score is positive and it is greater or equal than a user-specified (or suitably calculated) threshold value. Particularly, a *peak function S* computes the average of the maximum among the signed distances of a given point x_i in a time-series T from its k left neighbors and the maximum among the signed distances from its k right neighbors. The *function S* is an index that allows to quantify the severity of outliers and then provides information about the priorities for actions to be associated with each outlier. In addition to the *function S*, another synthetic index is the *modified z score* (*mzscore*). This index is based on the distance and direction of each outlier compared to the average value of normal observations (observations that do not contain outliers).

4. ANN classifier and majority voting ensemble method

Pattern recognition is the study of how machines can observe the environment, learn to distinguish patterns of interest from their background and make decisions about the categories of the patterns [4]. In this study, the recognition problem is posed as a classification task, where the classes are defined by the system designer (supervised classification). A supervised learning scheme uses a database which consists of a set of input patterns (a sample from the set of possible inputs) with the corresponding targets (classifications). The aim of the training is to ensure that the machine learns to extract relevant information from the database in order to classify future input patterns.

Combining the decision of several classifiers can lead to improve recognition results. The basic idea is to run not a single network but an ensemble of networks (each of which have been trained on the same data), in order to classify a given input pattern by obtaining a classification from each network and then using a combination scheme to decide the collective classification. Among all the combination methods, the majority vote is by far the simplest one for implementation, and it is as effective as the other more complicated schemes (Bayesian, logistic regression, fuzzy integral, etc.) in improving the recognition rate for the used dataset [5]. By combining the decisions of n experts, the majority vote assign the sample to the class for which at least k of the experts are agreed on the identity.

5. Experimentation

An actual office building, located at ENEA Research Centre (Rome, Italy) was considered as a case study. The hourly energy consumption and maximum power for artificial lighting of the building first floor were monitored and used as targets (outputs) of the analyzed models. A data set of about two months (Dec.12- Jan.13) was considered. Other variables have been monitored and considered as inputs of the neural models: day of the week (1-7), time, people presence, “active” rooms (a room is “active” when there is at least one person inside), global solar radiation. The considered ANN features are feed-forward MLP, 1 hidden layer consisting of 15 neurons, hyperbolic tangent as activation function for the hidden neurons, and linear for the output. In order to verify the reliability and the effectiveness of the proposed fault detection approach, two artificial faults were created on 24th and 25th of January. In those days at the end of the working time with a low people presence between 17:30 and 18:00 all the offices artificial lights of the first floor were switched on creating a peak of energy demand. The ANN ensemble was built according to BEM. The data set was split in a training (approximately 4 weeks) and testing (approximately 1 week) parts. Training was performed with MATLAB through the Levenberg-Marquardt algorithm stopping after 1000 iterations. The reported results are averaged over 10 different runs (standard deviation in brackets) and the ensemble was built for the same 10 models. Performance has been evaluated according to the Mean Absolute Error (MAE) and the Maximum Absolute Error (MAX) (Table 1):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - \hat{y}_i\right| \tag{1}$$

$$MAX = \max\left\{\left|y_i - \hat{y}_i\right|\right\}_{i=1}^{N} \tag{2}$$

where y_i is the real output, $\hat{y}_i$ is the estimated output and N is the size of the real data set.

	TRAINING	**ANN**	**BEM**	**TESTING**	**ANN**	**BEM**
Active Energy	MAE (kWh)	0.33 (±0.01)	0.31	MAE (kWh)	0.66 (±0.04)	0.63
	MAX (kWh)	1.41	1.06	MAX (kWh)	4.26	3.75
Maximum Active Power	MAE (kW)	0.35 (±0.02)	0.33	MAE (kW)	0.81 (±0.05)	0.78
	MAX (kW)	1.76	1.40	MAX (kW)	4.78	4.51

Table 1. Experimental results (training and testing)

As shown in Table 1, the results obtained with ANN BEM are always better than those obtained with individual networks. In the following sections only the analysis performed on the maximum power for lighting is presented.

In order to estimate a normal pattern of the maximum electrical power for the artificial lighting, the training of the ANN BEM was performed considering a fault free data set. The training dataset was cleaned through an outlier detection. The lighting power demand was estimated with an high accuracy through the ANN BEM in the training period. In the testing period the estimated power follow quite well the monitored power demand, with the exception of some evident abnormal values. The magnitude of the difference over the time between the actual and estimated power demand was analyzed for detecting faulty operation or anomalous values. To this purpose the peak detection method has been applied to the residuals data set in the testing period. In Figure 1 the trend of residuals over the time is shown and the abnormal detected power demand values are highlighted. The identified residual peaks include potential early morning faults for which very high power demand was observed with few people and the two artificial faults. The results confirm that the analysis of residual generated through the ANN BEM represents a useful and powerful technique for the peak building lighting fault detection.

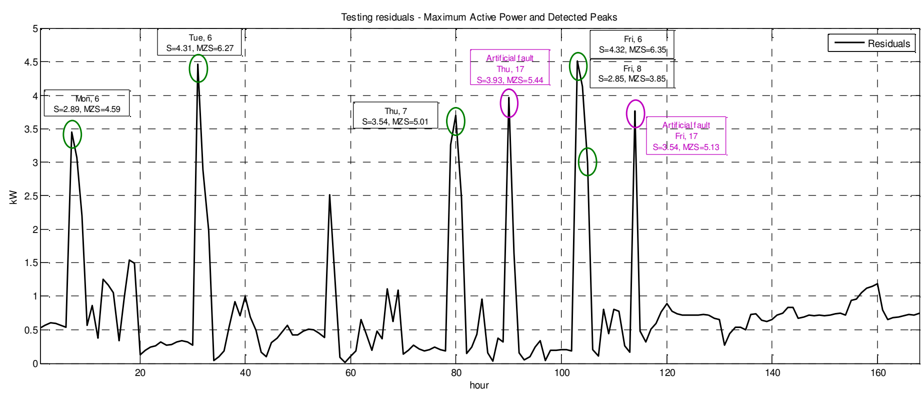

Figure 1. Testing residuals (maximum active power) and detected peaks

The Peak Detection Method was also directly applied to the sequence maximum power demand data. In figure 2 the outliers detected for testing period are shown with the relative values of *mzscore* and *S function* indices. It can be observed that the method allows to detect the two artificial faults and some other real faults in early morning. In this situations the relative severity indices correctly assume higher value. However, the data show that power is related to other variables i.e. people, solar radiation, day and active rooms, so it can be inferred that the extreme values are not always definite faults. Therefore some false positives can be found when an univariate outlier detection method is applied without taking into account the effect of the independent variables on the pattern recognition.

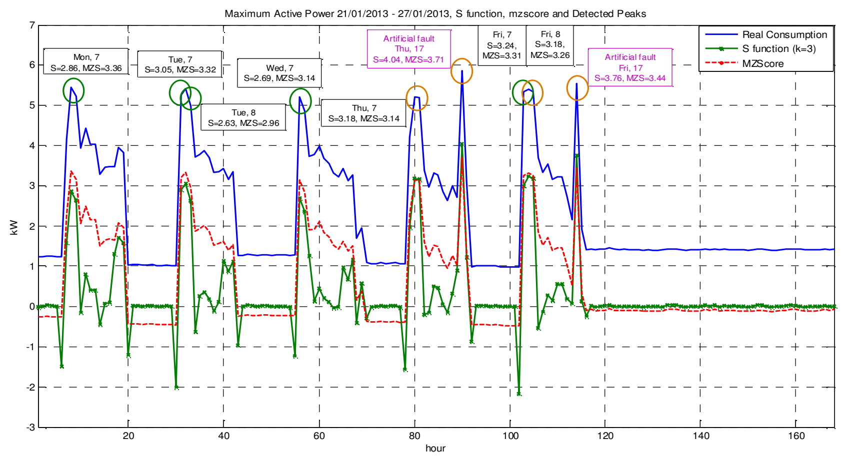

Figure 2.Maximum active power (testing period), S function values, mzscore and detected peaks (common peaks are orange)

In order to develop an ANN ensemble for classification of operational data, the ANN itself has been trained using data that are representatives of normal as well as faulty operating conditions on the basis of the results above discussed; once the ANN was trained, the detection and diagnosis of faults becomes a pattern recognition task. The inputs of the ANN are a set of features that define the output of the network, i.e., the operating state of the system as "normal" or "anomalous". The output data associated were chosen to enable the ANN to perform pattern recognition. Thus, by codifying the output data using a unique numerical pattern, the condition 'normal operation' was defined. In order to codify output data, the numerical values 0 (normal operation) and 1 (faulty operation) have been used to develop a totally single numerical pattern.

Therefore, maximum active power and active energy consumptions, day of the week, time, people presence, "active" rooms and solar radiation were considered as inputs of the ANNs. The ensemble technique used is the Majority Voting. The neural classifier has been built and applied, using hourly data in the testing period.

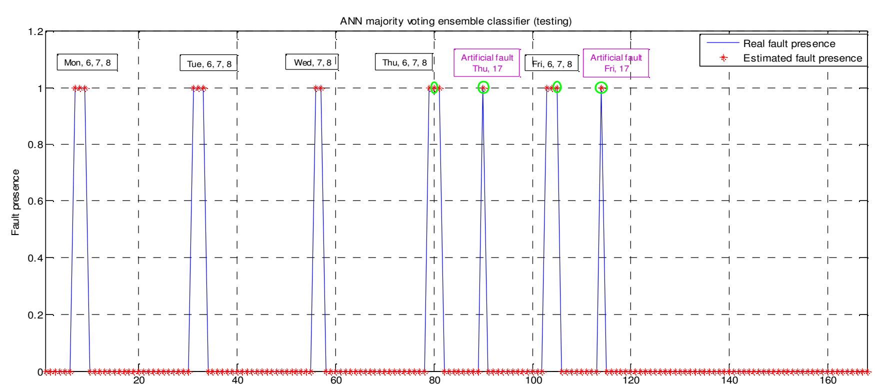

Figure 3. ANN majority voting ensemble classifier (common peaks are highlighted)

As shown in Figure 3, using the majority voting method to combine the results of ANN classifiers, the two artificial faults and some other real abnormal energy consumption values were detected. In the figure, the common outliers (among the methods analyzed) are highlighted in green. In table 2 the classification error (defined as the percentage relative magnitude of classification error) is reported. It can be observed that a majority voting ensemble of neural networks performs better than using a single network.

TRAINING	PERCENTAGE ERROR (%)	TESTING	PERCENTAGE ERROR (%)
BEST ANN	0.00	BEST ANN	0.00
WORST ANN	0.35	WORST ANN	0.60
CLASSIFIER	0.00	CLASSIFIER	0.00

Table 2. Classification error percentage (training and testing)

Conclusions

In the paper the effectiveness and usefulness of the ensembling techniques for fault detection has been demonstrated. The results show that ANN BEM always outperforms individual networks in artificial lighting power demand estimation of an office building. The fault detection, performed trough the analysis of the magnitude of residuals using a peak detection method, allowed to detect the two artificial faults and some other actual anomalous power values in the testing data set.
Finally, an ANN ensemble for classification of operational data was developed considering as output of the network the operating state of the system as “normal” or “anomalous”. A very high accuracy of the developed classifier has been verified in detecting abnormal artificial lighting power values using Majority Voting ensembling.

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