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Development of an RDP neural network for building energy consumption fault detection and diagnosis

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ABSTRACT

Fault detection and diagnosis (FDD) is an important issue in building energy conservation. This paper proposes a new option for solving this problem at the building level by using a recursive deterministic perceptron (RDP) neural network. Results show a higher than 97% level of generalization in all the designed experiments. Based on this high detection ability of RDP model, a new diagnostic architecture is proposed. Our experiments demonstrate that it is able to not only report correct source of faults but also sort sources in the order of degradation likelihood.

1. Introduction

Buildings play an important role in the total energy use and environmental implications in the world. In Europe, it accounts for 40% of the total energy used and 36% of the total CO_2 emissions [9]. The energy usage of buildings is not always done under normal conditions. For example, in order to keep a room temperature at a comfortable level, more than the normally required heating energy is used. Another example might be one on which normal energy is consumed but room temperature has not reached its expected value. Together with heating energy, electricity and cooling energy consumption may also experience abnormality. We call these abnormal energy consumptions faults. They might be caused by performance degradation, poor maintenance or improper operation of the installed electrical systems. The early detection of these faults in energy usage is crucial for building operation and energy conservation. Based on this information, building users and engineers are able to adjust their corresponding equipment for enhancing energy usage as well as saving energy.

This type of non-abrupt faults are difficult to monitor and even more difficult to diagnose. This paper therefore introduces an effective artificial neural network (ANN) model, based on the recursive deterministic perceptron (RDP) neural network, to implement fault detection and diagnosis (FDD) of building energy consumption. Based on the knowledge from previous faulty consumption, this model is able to report faults automatically and with a high degree of accuracy. It also shows high performance in a newly designed fault diagnosis procedure.

This paper is organized as follows. Section 2 introduces the recent work related to FDD of building energy consumption. Section 3 describes RDP neural network model. Section 4 presents how to do fault detection with RDP and reports the experimental results. Section 5 proposes a new diagnosis approach involving RDP neural networks. The last section concludes this paper.

2. Related work

FDD of building energy consumption has been widely investigated in recent decades. Previous work concerned various system levels, ranging from subsystem equipment to whole building level, mainly including air-handling units (AHUs), air-conditioning systems, vapor compression systems, and higher level systems such as heating, ventilation and air-conditioning (HVAC) systems. Many advanced methods or techniques have been used. These include simulation, ANNs, principle component analysis (PCA), residual analysis, fuzzy model, transient pattern analysis, support vector machines (SVMs), expert rule-based method and hybrid method.

The most direct fault detection approach is to calculate normal consumption and to compare it with a measured real one. We can report a fault when they are not consistent and exceed some threshold. The calculation can be done by using engineering methods or simulation, such as the work in [19,25,22].

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The classification ability of ANNs makes them applicable to distinguish normal and abnormal energy consumptions. Lee et al. [17] introduced an ANN for FDD of an AHU. They used this method to treat eleven faults including fan failure and sensor failure. Bailey and Kreider [2] used ANN to FDD of chillers. Tassou et Grace [28] applied ANNs for FDD purposes in vapor compression refrigeration systems. Du et al. [5] used a dynamic fuzzy-neural approach to perform fault diagnosis for an AHU. Lee et al. [16] proposed general regression neural networks to detect faults in sensor values and control signals for AHUs. The faults were determined when residuals exceeded pre-defined thresholds. When residuals are small, detection might be inaccurate. To solve this problem, Yang et al. [33] suggested to adopt fractal correlation dimension deviation instead of direct residual. They showed that the novel method was able to detect relatively small bias faults under noise conditions.

PCA was adopted by Du et al. [6] and Wang et al. [29] in fault diagnosis for air dampers, VAV terminals and AHUs. An expert-based multivariate decoupling method was proposed in [32,31] to enhance the capability of the PCA-based method in fault diagnosis of AHUs.

Liang and Du [18] used residual analysis method to detect three faults in a HVAC system, i.e., recirculation damper stuck, cooling coil fouling/block and supply fan speed decreasing. A multi-layer SVM classifier was developed to diagnose these three kinds of faults. To improve the performance, Han et al. [12] adopted a feature selection technique while using multi-class SVM as a FDD tool for chillers.

Schein et al. [24] used twenty-eight expert rules, which were derived from mass and energy balances, to detect faults in AHUs. Kim and Kim [15] used two different rule-based modules for an easy diagnosis of faults in vapor compression systems.

Some hybrid approaches took advantage of two or more effective models, achieving higher flexibility and suitability. Qin and Wang [23] proposed a hybrid method which combines expert rules, performance indexes and statistical process control models, to implement FDD for ten faults in air-conditioning systems. Also for air-conditioning systems, Hou et al. [13] combined data mining, a rough set approach and an ANN model to detect and diagnosis sensor faults. Norford et al. [22] applied two methods for FDD in HVAC equipment. One was based on first-principles models of system components, and the other one was based on semiempirical correlations of submetered electrical power with flow rates or process control signals. Namburu et al. [20] developed a generic FDD scheme for centrifugal chillers, in which fault classification techniques were chosen from support vector machines, principal component analysis, and partial least squares. House et al. [14] compared five models in detecting and diagnosing seven faults of an AHU system, i.e., ANN, nearest neighbor, nearest prototype classifier, rule-based classifier and Bayes classifier.

There are also some less commonly used approaches. A fuzzy model was used by Dexter and Ngo [4] in fault diagnosis of air-conditioning systems. A transient pattern analysis approach was proposed by Cho et al. [3] for FDD of fan, sensor and damper. Song et al. [11] developed an easy-to-use FDD method for the whole building air-conditioning system based on indoor air temperature changes. Wu and Sun [30] proposed a spatial-temporal partition strategy to allow cross-level FDD for HVAC systems, such as detecting faults on AHU level and on VAV level. Ghiaus [10] proposed a bond graph model for FDD in air conditioning systems. Navarro [21] used a dynamic adaptive model and operating variables dynamic thresholds to detect real-time faults in chillers.

System level FDD still needs improvement. Although several techniques have been adopted, a more reliable, accurate model is always required. This paper proposes an alternative but highly effective approach which is based on an RDP neural network for solving FDD in system level. RDP models offer several advantages over more popular neural network algorithms such as Backpropagation. The used data includes certain real-time physical variables that are measured by sensors and meters installed throughout the building. In addition, a new architecture for diagnosing the detected faults is proposed. Given a sample of faulty consumption, the system is able to point out which electric equipment causes this fault. Furthermore, it can list all of the possible causes in order of descending probability, making it easy to deal with broader problems. This method is based on the evaluation of several RDP models, each of which is designed to be able to detect a unique device fault. The experimental result shows that this method can diagnose faults correctly.

3. RDP model

RDP feed-forward neural networks can solve any two-class classification problems and the convergence is always guaranteed [27]. It is a multi-layer generalization of the single layer perceptron topology and essentially retains the ability to deal with non-linearly separable sets.

The construction of RDP does not require pre-defined parameters since they are automatically generated. The basic idea is to augment the dimension of the input vector by addition of intermediate neurons (INs), i.e., by incrementing the affine dimension. These INs are added progressively at each time step, obtained by selecting a subset of points from the augmented input vectors. Selection of the subset is done so that it is linearly separable from the subset containing the rest of the augmented input points. Therefore, each new IN is obtained using linear separation methods. The algorithm stops when the two classes become linearly separable at a higher dimension. Hence, RDP neural networks reports completely correct decision boundary on the training dataset, and the knowledge extracted can be expressed as a finite union of open poly topes [26]. The following are some fundamental definitions of RDP neural network.

Definition 1. A RDP ($\in \mathbb{R}^d$, denoted by P) is defined as a sequence $[(w_0, t_0), \ldots, (w_n, t_n)]$ such that $w_i \in \mathbb{R}^{d+i}$ and $t_i \in \mathbb{R}$, for $0 \le i \le n$.

- (w_i, t_i) for $0 \le i \le n$ is termed as an IN of P,
- $height(P)$ is determined by the number of INs in P,
- $P(i, j)$ stands for the RDP $[(w_i, t_i), \ldots, (w_j, t_j)]$ where $0 \le i \le j \le height(P) - 1$. $P(i, j)$ is on $\mathbb{R}^{d+i}$. So $P = P(0, n)$.

Definition 2 *(Semantic of RDP).* Let P be a RDP on $\mathbb{R}^d$. The function $\mathcal{F}(P)$ is defined in $\mathbb{R}^d$, such that:

- if $height(P) = 1$ then:

$$\mathcal{F}(P)(x) = \begin{cases} -1, & \text{if } w^T x + t < 0 \\ 1, & \text{if } w^T x + t > 0 \end{cases}$$

- and if $height(P) > 1$ then:

$$\mathcal{F}(P)(x) = \begin{cases} \mathcal{F}(P(1, n))(Adj(x, -1)), & \text{if } w_0^T x + t_0 < 0 \\ \mathcal{F}(P(1, n))(Adj(x, 1)), & \text{if } w_0^T x + t_0 > 0 \end{cases}$$

Definition 3. Let X, Y be two subsets of $\mathbb{R}^d$ and let P be a RDP on $\mathbb{R}^d$. Then, X and Y are linearly separable by P if $(\forall x \in X, \mathcal{F}(P)(x) = c_1)$ and $(\forall y \in Y, \mathcal{F}(P)(y) = c_2)$ where $\{c_1, c_2\} = \{-1, 1\}$, denoted by $X \parallel_P Y$.

The last definition provides the criterion of termination of RDP training. Different choice of the linear separability testing method