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Automatic Fault Detection Baseline Construction for Building HVAC Systems using Joint Entropy and Enthalpy

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Abstract

Studies indicate that a large energy saving can be realized by applying automatic fault detection and diagnosis (AFDD) to building systems, which consumes more than 40% of the primary energy in the U.S. To enable AFDD, a baseline depicting the normal operation mode is needed to detect whether the building operation deviates from normality. Different from many other systems, a building system behaves differently under different weather conditions and hence needs its baseline model to reflect such weather dependence. Existing research shows baseline constructed using nonlinear mathematical models has performed well. However, determining the sample size, which is necessary to capture the totality of data space needed for accurate baseline construction, relies on trial-and-error experiments conducted offline. There is a lack of easy-to-use method that can provide guidance on whether enough sample size has been collected for baseline construction. In this research, we have developed a data-driven approach for AFDD baseline model construction based on information entropy, in conjunction with enthalpy, a measurement of outdoor air conditions to reflect weather conditions. The developed method is compared with our previously-reported baseline construction method using real building data.

Keywords

Information Entropy, Building Engineering, Energy, Fault Detection and Diagnosis, Data-driven approach

1. Introduction

Buildings are complex, integrated systems involving multiple sensors, subsystems, and automatically controlled components, such as Heating, Ventilation, Air-conditioning (HVAC), lighting, fire, and safety systems. It has been reported that approximately 40% of global energy consumption and energy-related carbon dioxide emission is attributed to buildings and construction [1]. Among these components, the HVAC system is responsible for 20% of this energy use [2]. Almost 30% of this primary consumption is energy waste due to operation faults, malfunctional equipment, and controls in the building systems [3]. Consequently, faults in HVAC lead to significant wasted energy if they are not handled properly. Studies have indicated that automatic fault detection and diagnosis (AFDD) in HVAC systems have a great potential for energy savings [4]. AFDD thus becomes a necessity in building operations.

AFDD is the process to detect, identify, and isolate faults, which are deviations from the normal operating conditions in the building systems [3]. There are many AFDD methods developed for component level and whole building level for the building systems over the past years, and existing AFDD methods can be generally categorized as model-based approaches, rule-based approaches, and data-driven based approaches [3,5]. Regardless of any methods mentioned above, a baseline, typically developed from collected building data (ground truth data), is necessary to enable fault detection and to depict the normal operational conditions because an exact fault-free status may rarely exist in a real building [6]. In this research and many other AFDD research for building systems, the term “normal”, rather than fault-free is used to reflect such difficulty. “Normal” here then reflects a satisfied building operation, rather than a complete “fault-free” status. A normal status typically exists after a building is freshly commissioned. Data are then collected for baseline construction, which are denoted as historical normal data. Another unique feature of building HVAC system is that it reconfigures and performs differently under different weather conditions. For example, a HVAC system during cooling mode is completely different, using different components with different parameters, from heating mode. Yet such mode transition could happen within an hour and for many times during a day. When judging whether an incoming sample contains faults or not, corresponding baseline that reflects similar weather (hence similar operation) as the incoming sample is needed.

Therefore, to enable a reliable baseline establishment for a real building AFDD from historical datasets, two principles are followed: (1) this baseline should be under similar external weather conditions as the corresponding fault test case, and (2) sensor readings of this baseline should be as independent from each other as possible. Extensive research works on AFDD have been performed to construct baselines in the past certain decades. For example, Miller et al. introduced a day-typing process using Symbolic Aggregate ApproXimation (SAX) to extract and cluster the most common daily profiles to create the baseline [7]; Chen et al. developed weather information-based Pattern Matching incorporating SAX model to establish the baseline by clustering time-series with the same weather motif [6]. While promising, the research reviewed above heavily relies on building domain knowledge. Additionally, since trial-and-error approaches are taken to evaluate the effectiveness of the baseline, there is a lack of guidelines on whether a sufficient number of samples are collected, which makes existing methods for online AFDD implementation challenging.

To address the challenges, we propose a data-driven approach for reliable baseline construction. Specifically, our proposed method is based on correlation information entropy extracted from multiple building sensor readings. Moreover, outdoor air enthalpy (or enthalpy) is used in our method to reflect weather conditions, which further indicates HVAC operation mode. Enthalpy is a property of moist air that reflects the heat needed to condition such air, and can be calculated from air temperature and humidity measurements. Given a library of historical normal ("fault-free") datasets collected from multiple sensors in the real building systems, we can develop a baseline candidate set by identifying samples from this normal dataset library that match the incoming fault test case in terms of enthalpy. Then we calculate correlation information entropy within these candidate samples and determine the final samples consisting of baseline. Finally, we validate the efficacy of the baseline using fault detection accuracy. Compared to existing works which highly rely on mathematical modeling, our proposed entropy-based method shares the following advantages: (1) it is model-free, fully relying on the data information; (2) besides weather conditions, it uses information entropy to measure all features of data integrated; (3) information entropy can provide a guideline on the determination of a sufficient number of samples for baseline construction.

The main contents of this paper are organized as follows. The design of baseline construction using correlation information entropy is described in section 2, details of experiments are introduced in section 3, and the conclusion is drawn in section 4.

2. Design of baseline construction using correlation information entropy

In this section, we describe our proposed data-driven method using correlation information entropy as a guideline to establish a baseline for AFDD.

2.1 Correlation information entropy

Proposed by Shannon, information entropy theory is a field of study concerned with information measurement [8]. The fundamental behind is the quantification of the amount of information in things such as events, random variables, and distributions. Information quantification requires the use of probability, and thus information theory is linked to event probability. Given a single random variable takes n values with corresponding probabilities $p_1, \ldots, p_n$, its entropy is defined as:

$$H = -\sum_{i=1}^{n} p_i \log p_i \tag{1}$$

Consequently, information entropy measures information in terms of the average degree of uncertainty for a random variable. Since this theory integrates with probability, statistics, computer science, and other relevant fields, it plays an important role in data and signal processing [9]-[11].

Correlation information entropy is a measurement representing the degree of uncertainty of the correlation between variables. The higher value of the correlation information entropy is, the greater the degree of independence between the variables is [11]. For a dataset with n samples, each sample with m features, its covariance matrix is structured by:

$$R = \begin{bmatrix} cov(1,1) & cov(1,2) & \cdots & cov(1,m) \\ cov(2,1) & cov(2,2) & \cdots & cov(2,m) \\ \vdots & \vdots & \ddots & \vdots \\ cov(m,1) & cov(m,2) & \cdots & cov(m,m) \end{bmatrix} \tag{2}$$

where $cov(j,k) = \sum_{i=1}^{n}(x_{ij} - \bar{x}_j)(x_{ik} - \bar{x}_k)$, $j = 1, \ldots, m, k = 1, \ldots, m$.

Then, the correlation information entropy is defined as:

$$H_R = -\sum_{i=1}^{m} \frac{|\lambda_i^R|_2}{\Lambda} \log \frac{|\lambda_i^R|_2}{\Lambda} \tag{3}$$

where $|\lambda_i^R|_2$, $i = 1, \ldots, m$ are corresponding eigenvalues of the matrix R in L2-norm, and $\Lambda = \sum_{i=1}^{m}|\lambda_i^R|_2$.

Correlation information entropy has been extensively studied for applications with multi-sensor information fusion. One example is feature selections of pattern classification systems and bioinformatics [10,11]. It shares advantages, including the realization of correlation measurement for high-dimensional data and consistency with the basic nature of information entropy. Since building systems are integrated, involved in multiple sensors and components, it is expected that correlation information entropy may have the potential for baseline construction in building AFDD. The next subsections present the detailed baseline construction procedure.

2.2 Development of baseline construction

Algorithm 1 Entropy-based baseline construction in conjunction with enthalpy for a fault test case

Input: A fault test case and historical datasets containing fault-free samples (FF), both with snapshot window SW_j, $j = 1, \ldots, 48$, each SW_j with 6 samples, each sample with enthalpy (ENL) and p measurements from multiple sensors.

Output: Baseline B

```
Determine the operation mode for a fault test case and corresponding training start date.
Under this operation mode and the determined training start date, select n fault-free samples from m-day historical datasets, FF_i, i = 1,…, n (n = 288m).
B = ∅
for j = 1,…,48 do:
    Calculate average enthalpy for SW_j, ENL‾_{SW_j}.
    Pick up samples that covers SW_j and its neighborings (SW_{j−3}, SW_{j−2}, SW_{j−1}, SW_j, SW_{j+1}, SW_{j+2}, SW_{j+3}), with total l samples (l = 42m, m historical days, each day with 7 SWs, each SW with 6 samples). Calculate difference between ENL_{FF_k} and ENL‾_{SW_j} (ΔENL_{FF_k}), where ΔENL_{FF_k} = |ENL_{FF_k} − ENL‾_{SW_j}|, k = 1,…, l.
    Standarize and rank all FF_k in ascending order according to ΔENL_{FF_k}, k = 1,…,l, to obtain a ranked historical data pool for SW_j, RH_j = {FF_(1), …, FF_(l)}.
    Take s samples from RH_j after a pre-defined cut-off to construct baseline candidate (C_j^s), where C_j^s = {FF_(1), …, FF_(s)}.
    Choose C_j^6 = {FF_(1), …, FF_(6)} to calculate correlation information entropy (ENT) using equations (2)-(3), ENT(C_j^6).
    ENT = {ENT(C_j^6)}
    C_j^r = C_j^6
    for q = 7, …, s do:
        C_j^r = C_j^r ∪ FF_(q)
        ENT = ENT ∪ ENT(C_j^m)
    end for
    Pick up t samples resulting in the max (ENT) within this cut-off for SW_j: B_j = C_j^t.
    B = B ∪ B_j
end for
return B
```

Detailed steps for baseline construction are shown in **Algorithm 1**.In our study, there are two types of data provided: incoming fault test cases (cases with artificially injected faults) and historical datasets (normal conditions). Our goal is to construct a baseline by selecting samples from historical normal datasets for each fault test case. Note samples in each dataset are collected for one day period under a 5-min sample rate. We divide the 24-hour period into 48 equal-sized segments, termed snapshot window (SW). Thus each fault case and each historical dataset have 48 SWs, each SW with a size of 30 minutes and 6 samples. Each sample consists of multiple features besides enthalpy. Since building systems have various operation modes in different seasons, both historical datasets and features of samples vary accordingly. Hence the first step is to determine the operation mode for each fault case so as to choose what historical datasets and features. Next, for a specific SW in fault test case, corresponding and neighboring SWs in historical datasets should be explored. Taking SW #7 in a fault test case as an example (line 4 in **Algorithm 1**), both corresponding SW #7 and neighboring SWs (#4-6 and #8-10) in historical datasets should be considered (lines 5-8 in **Algorithm 1**). Lines 1-2 are initialization for fault test case and historical datasets, lines 4-9 are for sample selection from historical datasets, and lines 10-17 are to determine the final samples for each SW in the baseline.

2.3 Evaluation

To validate the efficacy of baseline, we use Hotelling statistics (T^2) incorporating the PCA method to indicate whether a systematic abnormality occurs [12]. T^2 can be calculated for each sample by:

$$T^2 = X^T P \sum a \; P^T X \tag{4}$$

where X is feature space in the sample, P is a loading matrix obtained from PCA and $\sum a$ is a set of the non-negative eigenvalues corresponding to the a principal components. Because T^2 follows F distribution, its upper bound can be obtained as:

$$T^2_{threshold} = \frac{a(n-1)}{n-a} F_{a,n-a,\alpha} \tag{5}$$

where n is the number of samples, and α is the level of significance.

Therefore, in our study, an abnormal sample is flagged by T^2value when its $T^2 \geq T^2_{threshold}$, and α is set at 0.05. Because for each fault test case, the fault was artificially injected in a specific period, our fault detection accuracy is then defined as the fraction of samples detected to total samples within this fault injection period. When fault detection accuracy is greater than 0.5, we can conclude that the fault test case is successfully detected.

3. Experiments

3.1 Datasets

Our experimental datasets are collected from Nesbitt Hall at Drexel University, which include15 fault test cases and 2 libraries of historical normal datasets under two different operation modes according to stable chilled water supply period, namely mode 1 (all-day period) and mode 2 (partial-day period) [6]. Among these 15 cases, 4 are under mode 1, while 11 are under mode 2 (See **Table 1**). As is described above, the number of historical datasets and selected features vary from one mode to another (See **Table 2**).

Table 1: Summary of 15 fault test cases

Operation mode	Fault test case	Whole building fault description
Mode 1	Case 1	System stopped at 4:00 PM to 11:00 PM
	Case 2	AHU-1 supply air temperature sensor negative bias 4°F
	Case 3	AHU-2 supply air temperature sensor negative bias 4°F
	Case 4	Change weekend occupied schedule to end at 08:20PM
Mode 2	Case 5	Operator fault, chiller off
	Case 6	AHU-2 outdoor air damper stuck at 90% open
	Case 7	AHU-2 outdoor air damper stuck at 100% open
	Case 8	Chiller CHWS temperature sensor negative bias 4°F
	Case 9	AHU-2 cooling coil valve position override at 100% open
	Case 10	Chilled water differential pressure sensor positive bias 0.1 psi
	Case 11	AHU-2 supply air temperature sensor negative bias 3.5°F
	Case 12	AHU-2 OA damper stuck at 30% open
	Case 13	AHU-2 cooling coil valve stuck at 80%
	Case 14	AHU-2 OA damper stuck at 60% open
	Case 15	CHWS temperature sensor negative bias 3°F

Table 2: Summary of libraries of historical datasets

Library	Operation mode	No. of datasets	No. of samples in each dataset	No. of features
Library 1	Mode 1	45	288	100
Library 2	Mode 2	55	288	182

3.2 Parameters settings

We need to ensure that baseline samples share similar weather conditions with a fault test case, equivalently to say that the enthalpy difference between baseline and fault case samples should be as small as possible. However, the literature does not have a set rule on how large the difference is acceptable. Therefore, we test on 3 quantile values, saying 15%, 20%, and 25%, on enthalpy difference (e.g., 15% quantile means to take the first 15% samples from the historical datasets with small enthalpy difference). In each fault test case, we follow correlation information entropy calculation procedures (shown in **Algorithm 1**) to determine samples from historical datasets to construct the baseline. Then we compare fault detection performances using baselines under these quantile values.

3.3 Results

Experimental results are shown in **Tables 3&4**. For comparison purposes, we also include AFDD results from SAX model developed by Chen et al. [6]. Observing from **Table 3**, baselines constructed by both our proposed entropy-based method (under different quantiles) and the SAX model are able to successfully detect 11 out of 15 fault test cases. As the quantile value increases, fault detection accuracy increases. In **Table 4**, 4 fault test cases are undetected by neither SAX method nor our proposed method. It is worth noting that baselines developed by our proposed method contain more samples than that by SAX, and as quantile values increases, the average number of samples in each snapshot window increases. Among models with different quantiles, the model with 25% quantiles outperforms others as 2 out of 4 cases are detected. This result is better than that from the SAX method (only 1 out of 4 is detected). Moreover, one key advantage of our proposed method is to provide information on whether existing historical normal datasets contain enough samples to construct baselines for incoming fault cases, because experimental results indicate that at most 15 historical normal datasets are used for baseline construction. We conclude because baselines by our proposed approach can detect at least 11 cases, comparable to those by SAX model, entropy-based approach may be a viable solution to guide the baseline construction for building AFDD.

Table 3: 11 fault test cases successfully detected by SAX and our proposed method under different quantile values. ACC – fault detection accuracy; MS – average number of samples in each SW; HD – the number of historical normal datasets used for baseline construction.

Fault test case	Fault detection performance											
	SAX			15% quantile			20% quantile			25% quantile		
	ACC	MS	HD	ACC	MS	HD	ACC	MS	HD	ACC	MS	HD
Case 1	1.00	217	12	1.00	179	12	1.00	249	14	1.00	311	15
Case 3	1.00	153	8	1.00	164	10	1.00	244	12	1.00	304	14
Case 4	1.00	174	9	1.00	179	11	1.00	235	12	1.00	292	13
Case 5	0.92	123	6	0.68	155	8	0.96	209	10	0.88	276	11
Case 6	0.90	150	7	0.89	166	10	0.90	211	11	0.93	255	13
Case 10	1.00	167	8	1.00	157	10	1.00	207	12	1.00	255	13
Case 11	1.00	152	7	1.00	180	10	1.00	245	12	1.00	310	13
Case 12	1.00	221	10	0.99	166	11	0.99	223	12	1.00	282	13
Case 13	1.00	215	11	1.00	179	12	1.00	235	13	1.00	285	14
Case 14	1.00	173	9	1.00	172	11	1.00	236	12	1.00	292	13
Case 15	1.00	88	4	1.00	178	7	1.00	245	9	1.00	311	12

Table 4: 4 fault test cases undetected by SAX or our proposed method under different quantiles. ACC – fault detection accuracy; MS – average number of samples in each SW; HD – the number of historical normal datasets used for baseline construction.

Fault test case	Fault detection performance											
	SAX			15% quantile			20% quantile			25% quantile		
	ACC	MS	HD	ACC	MS	HD	ACC	MS	HD	ACC	MS	HD
Case 2	0.38	156	8	0.52	173	10	0.45	232	11	0.36	301	13
Case 7	0.46	186	10	0.44	156	11	0.49	202	12	0.51	251	14
Case 8	0.57	165	9	0.42	162	11	0.42	215	12	0.50	277	13
Case 9	0.38	189	10	0.27	144	11	0.17	203	13	0.12	251	14

4. Conclusion

The goal of this paper is to explore AFDD baseline construction by an entropy-based data-driven approach. To ensure a reliable baseline construction, enthalpy, a measurement of weather conditions, should be well-matched with fault test cases. Our proposed method involves two phases. Given a fault test case and historical fault-free datasets collected from different sensors in the real building systems, we construct a baseline candidate dataset by identifying samples from these historical fault-free datasets that match the faulty test case in terms of enthalpy. Given the candidate dataset, we then calculate the correlation information entropy on sensor reading to determine the final samples consisting of the baseline. Experimental results show that baselines by our proposed method can reach comparable fault detection accuracy to those by an existing nonlinear mathematical model (SAX); plus, compared to SAX, our proposed method is purely data-driven and able to tell whether existing historical datasets contain sufficient samples for baseline construction. Therefore, evaluations suggest that our proposed approach provides a useful guideline on baseline constructions for building AFDD.

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References

[1] International Energy Agency and the United Nations Environment Programme, "2018 Global Status Report: towards a zero-emission, efficient and resilient buildings and construction sector," 2018. [Online]. Available: https://www.worldgbc.org/sites/default/files/2018%20GlobalABC%20Global%20Status%20Report.pdf. [Accessed December 21,2020].

[2] L. Pérez-Lombard, J. Ortiz and C. Pout, "A Review on Buildings Energy Consumption Information," *Energy and Buildings*, vol. 40, no. 3, pp. 394–98, 2008, doi:10.1016/j.enbuild.2007.03.007.

[3] S. Katipamula and M. Brambley, "Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—A Review, Part I," *HVAC&R Research*, vol. 11, no. 1, pp. 3–25, 2005, doi: 10.1080/10789669.2005.10391123.

[4] K.W. Roth, D. Westphalen, M.Y. Feng, P. Llana and L. Quartararo, "Energy Impact of Commercial Building Controls and Performance Diagnostics: Market Characterization, Energy Impact of Building Faults and Energy Savings Potential," Tech. Rep. 200612, 2005.

[5] S. Katipamula and M. Brambley, "Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—A Review, Part II," *HVAC&R Research*, vol. 11, no. 2, pp. 169–187, 2005, doi: 10.1080/10789669.2005.10391133.

[6] Y. Chen, "Data driven Whole Building Fault Detection and Diagnostics," Ph.D. dissertation, Dept. Civ. Archit. Env. Eng., Drexel Univ., Philadelphia, PA, USA, 2019.

[7] C. Miller, Z. Nagy, and A. Schlueter, "Automated daily pattern filtering of measured building performance data," *Automation in Construction*, vol. 49, Part A, pp. 1-17, 2015, doi: 10.1016/j.autcon.2014.09.004.

[8] C.E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, vol. 27, pp. 379-423, 1948, doi: 10.1002/j.1538-7305.1948.tb01338.x.

[9] D. Erdogmus, K. E. Hild and J. C. Principe, "Online entropy manipulation: stochastic information gradient," *IEEE Signal Processing Letters*, vol. 10, no. 8, pp. 242-245, 2003, doi: 10.1109/LSP.2003.814400.

[10] X. Wang, Y. Yan, and X. Ma. "Feature Selection Method Based on Differential Correlation Information Entropy," *Neural Processing Letters,* vol.52, pp. 1339–1358, 2020, doi:10.1007/s11063-020-10307-7.

[11] J. Xu, T. Li, L. Sun, F. Liu, R. Lagoa, K. Sandeep and D. Lee, "Feature gene selection method nased on logistic and correlation information entropy," *Bio-Medical Materials and Engineering*, vol. 26, no. s1, pp. S1953–S1959, 2015, doi:10.3233/BME-151498.

[12] M. Kano, S. Hasebe, I. Hashimoto, H. Ohno, "A new mulitivariate statistical process monitoring method using principal component analysis," *Computers & Chemical Engineering*, vol. 25, no. 7, pp. 1103-1113, 2001, doi: 10.1016/S0098-1354(01)00683-4.