# Mining Building Energy Management System Data Using Fuzzy Anomaly Detection and Linguistic Descriptions

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***Abstract*—Building Energy Management Systems (BEMSs) are essential components of modern buildings that are responsible for minimizing energy consumption while maintaining occupant comfort. However, since indoor environment is dependent on many uncertain criteria, performance of BEMS can be suboptimal at times. Unfortunately, complexity of BEMSs, large amount of data, and interrelations between data can make identifying these suboptimal behaviors difficult. This paper proposes a novel Fuzzy Anomaly Detection and Linguistic Description (Fuzzy-ADLD)-based method for improving the understandability of BEMS behavior for improved state-awareness. The presented method is composed of two main parts: 1) detection of anomalous BEMS behavior; and 2) linguistic representation of BEMS behavior. The first part utilizes modified nearest neighbor clustering algorithm and fuzzy logic rule extraction technique to build a model of normal BEMS behavior. The second part of the presented method computes the most relevant linguistic description of the identified anomalies. The presented Fuzzy-ADLD method was applied to real-world BEMS system and compared against a traditional alarm based BEMS. Six different scenarios were tested, and the presented Fuzzy-ADLD method identified anomalous behavior either as fast as or faster (an hour or more), than the alarm based BEMS. Furthermore, the Fuzzy-ADLD method identified cases that were missed by the alarm based system, thus demonstrating potential for increased state-awareness of abnormal building behavior.**

***Index Terms*—Anomaly detection, building energy management systems (BEMSs), clustering, fuzzy systems, linguistics**

## I. Introduction

BUILDINGS consume more than 20% of world energy production and around 40% of US energy production [1], [2]. Such energy consumption means buildings are one of the major causes of greenhouse gas production as well [3]–[6]. Due to various reasons, the energy usage in buildings has been steadily growing [2]. And this number has been projected to further increase [1], [7].

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The largest energy consumer in buildings is Heating, Ventilation and Air Conditioning (HVAC) systems, consuming 30-50% of building energy [2], [4], [6], [8]–[10]. It has been shown that energy efficiency in HVAC systems can be improved by more than 5% by implementing very low cost building management strategies [4]. Research has shown that the energy efficiency can be improved by up to 40% by closely monitoring the state of the building and improving control strategies [11].

Building Energy Management Systems (BEMSs) are responsible for monitoring building state and controlling HVAC systems. BEMSs are highly complex information gathering and control systems and implement advanced control strategies to improve energy efficiency while maintaining occupant comfort [12]. BEMSs enable significant energy savings in buildings when properly tuned and controlled [13]–[15].

Modern BEMS are extremely complex and consist of thousands of components such as sensors, controller and actuators [16]. BEMSs provide data about the current state of the system to building managers, who are responsible for maintaining uninterrupted operation of the HVAC and lighting systems without compromising the occupant comfort or impacting temperature-sensitive equipment. The information provided by the BEMS should allow the building managers to gain an understanding of the current state of the building operation and to quickly focus on inefficiencies and anomalous behavior [17].

However, due to the complexity and the overwhelming amount of the acquired data it is difficult to identify important and abnormal building behavior and resolve them accordingly [18], [19]. Furthermore, it has been shown in previous work that information representation and visualization of building state can lead to significant savings in energy and identification of hardware faults [15]–[22].

Therefore, in order to improve the understandability of the BEMS data and to enhance the state-awareness of building managers, this paper presents a novel method for extracting relevant actionable information via fusing multiple heterogeneous sources of BEMS data using Computational Intelligence (CI) techniques [23]. The presented method utilizes Fuzzy Anomaly Detection and Linguistic Descriptions (Fuzzy-ADLD) for mining BEMS data. The anomaly detection enables identification of anomalous behavior which is otherwise difficult to identify. The linguistic descriptions of anomalies provide the capability to present identified behavior in easy to understand natural language form.

The presented Fuzzy-ADLD method has been integrated with a graphical user interface and applied to real-world BEMS data demonstrating potential for increased state-awareness of building managers. The Fuzzy-ADLD method was compared to a traditional alarm based system using six abnormal scenarios. In all cases tested, the Fuzzy-ADLD method was at least as good as or better than the alarm based system in identifying the abnormal behavior. Furthermore, the Fuzzy-ADLD method was able to identify certain abnormal behavior that was not identified by the alarm based system.

The rest of the paper is structured as follows. Section II discusses the problems in BEMS data and details the presented Fuzzy-ADLD method for BEMS. Section III elaborates on the developed anomaly detection algorithm for BEMS. The method for generating linguistic descriptions of the identified anomalies is described in section IV. The implementation of the presented Fuzzy-ADLD method and its integration with a suitable graphical interface is explained in section V. Finally, the experimental results are presented in section VI and the paper is concluded in section VII.

## II. Mining BEMS Data

This section first identifies prevalent shortcomings in existing BEMS data, and then, a detailed overview of the novel Fuzzy-ADLD method for BEMS is presented.

### *A. Existing BEMS data*

BEMS uses a large array of sensors installed within the building, outside the building and throughout the air handling systems to gather information about zone temperature, air quality, occupancy, and even lighting [16], [24], [25]. BEMS uses this information to control the heating, cooling and lighting of the building [14], [26], [27]. This type of control has the potential of large energy savings when compared to conventional systems, without sacrificing occupant comfort [13], [17], [28]. Furthermore, gathering and analyzing sensor data allows the identification of previously unknown building performance characteristics [13].

Significant impact of uncertain factors such as weather and occupancy on building state also make it difficult to identify and predict such behavior using traditional methods [31], [32]. The large number of sensors and the interdependency of measurements make it difficult to identify and locate abnormal behavior or malfunctions.

Therefore, inspection of reported data and identification of anomalous behavior and inefficiencies is a daunting task for building managers.

Current BEMS tools lack the capability of providing actionable information by processing and integrating gathered data [13]. Some tools specifically created for monitoring and analyzing BEMS data exist in the industry [30]–[33]. However, these tools commonly require additional training in order for it to be utilized effectively, and may require a service contract with the supplier to access [22], [28]. Furthermore, most of these tools need to be customized for specific applications and thorough understanding of the system is required to operate them.

Advanced CI based techniques have been previously used for improving BEMS [35], [36], [37], [38], [39]. However, to the best of authors' knowledge, the combination of anomaly detection and linguistic descriptions used to generate actionable information for increasing the state-awareness of building managers have not been previously considered.

A framework that utilizes all the sensors in a building along with energy consumption data for identifying specific events was presented in [40]. In [40] the authors present a method for manually and semi-automatically acquire rules for classifying building performance according to the energy consumption. The Fuzzy-ADLD method presented in this paper differs from the framework presented in [40] by providing completely automated anomaly detection that is not restricted to energy consumption. Furthermore, linguistic descriptions of anomalies are automatically generated and the use of fuzzy logic derived computation enables handling of human understandable linguistic terms while maintaining uncertainty inherent to system measurements.

### *B. Fuzzy-ADLDs for BEMS*

This paper presents a novel methodology for mining BEMS data that leads to improved state awareness of building managers. The presented Fuzzy-ADLD method is based on a two part approach: 1) detecting abnormal behavior patterns by fusing multiple sources of data, 2) providing easy to understand descriptions of the identified behavior in a linguistic form.

The first part of the Fuzzy-ADLD method utilizes modified nearest neighbor clustering (NNC) algorithm and a fuzzy logic rule extraction technique to build a model of normal BEMS operations based on the provided normal behavior training data [41]. The anomaly detection algorithm then compares the current behavior of the BEMS to the established normal behavior to identify abnormal BEMS behavior.

The second part of the Fuzzy-ADLD method presents the identified anomalies in an intuitive, easy to understand manner in the form of linguistic descriptions. This is done by using a predefined fuzzy representation of the input attributes to autonomously compute the relevant and compact linguistic description of the identified anomalies. The Fuzzy-ADLD method also enables building managers to adjust the complexity of the linguistic descriptions for increased understandability.

The presented Fuzzy-ADLD method was implemented in a software prototype that incorporates an easy to understand intuitive Graphical User Interface (GUI), which is further discussed in section V.

## III. Anomaly Detection for BEMS

This section first discusses the feature extraction from BEMS data. Next, an algorithm for normal behavior modeling and anomaly detection using online clustering and fuzzy logic rule extraction is presented.

### *A. Feature Extraction*

Typical BEMS provides measurements from multiple sensors throughout the building. Some measurements are associated

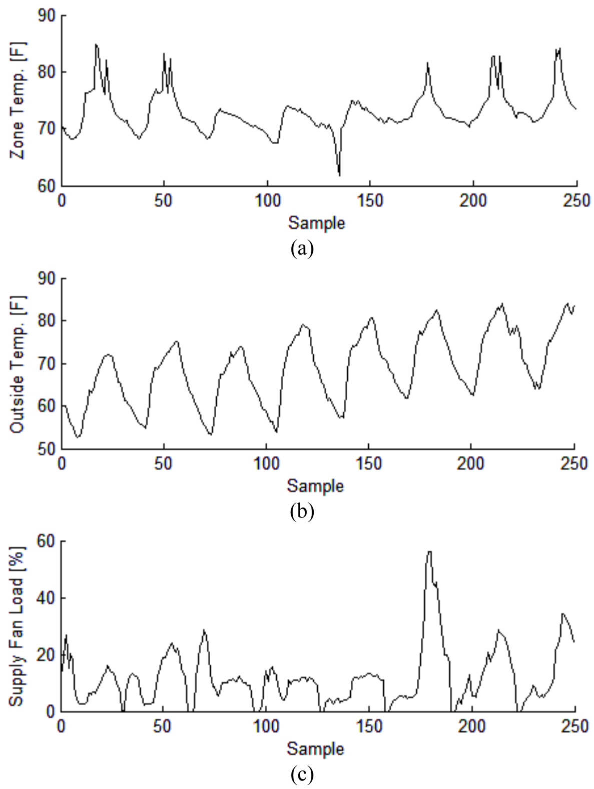


Fig. 1 Example of BEMS sensor data, occupant zone temperature (a), outside air temperature (b) and supply fan load (c).

with the entire building (e.g. outside air temperature), some are associated with individual floors (e.g. return air temperature or supply air fan load for an air handling unit at a given floor) and some are associated with individual occupants' zones on the floor (e.g. zone temperature). The sensor measurements collected over time constitute a time-series data describing the behavior of each occupant zone. Different patterns of zone behaviors can be experienced in a typical building. A common pattern for winter climates, for instance, exhibits pre-heating of the rooms in the morning, regulating appropriate human comfortable temperatures during a day [42], and reducing the set point to maintain lower temperatures at night. An example of BEMS data recorded from a real building over a one week period, namely the occupants zone temperature, the outside air temperature and the supply fan load is depicted in Fig. 1. The alternations between day time (e.g. increased outside air temperature) and night time hours is clearly visible.

The behavior of each building zone can be described as a feature vector extracted from the sensor measurements. This feature $X(t)$ extracted at time $t$ can then be expressed as:

$$X(t) = \{x_1(t),\ x_2(t), \ldots, x_n(t)\} \tag{1}$$

Here, $x_i(t)$ denotes the specific value of the $i^{th}$ attribute sampled at time $t$ (e.g. zone temperature) and $n$ denotes the dimensionality of the feature vector.

### B. Rule Extraction via Online Clustering

The behavioral patterns in a specific building zone can be extracted using online fuzzy rule extraction technique, which was previously proposed in [41]. This method uses a computationally efficient one-pass algorithm for unsupervised modeling of input data. One of the major advantages of the proposed algorithm is that it is capable of online learning, which means that the model can be updated without the need to relearn the entire training data set. In addition the algorithm requires only a single pass through the training data, which is suitable for large data sets.

The obtained model of normal zone behavior is composed of a set of fuzzy rules. Each rule is extracted using a modified NNC algorithm [41]. The original NNC algorithm was modified to maintain additional information about the spread of data points associated with each cluster throughout the clustering process.

Each cluster $P_i$ of normal zone behavior is described by its center of gravity $\vec{c}_i$, weight $w_i$ and a matrix of boundary parameters $M_i$:

$$P_i = \{\vec{c}_i, w_i, M_i\},\ \vec{c}_i = \{c_i^1, \ldots, c_i^n\},\ M_i = \begin{vmatrix} \overline{c}_i^1 & \cdots & \overline{c}_i^n \\ \underline{c}_i^1 & \cdots & \underline{c}_i^n \end{vmatrix} \tag{2}$$

Here, $i$ is the index of particular cluster, $c_i^j$ is the attribute value in the $j^{th}$ dimension, $\overline{c}_i^j$ and $\underline{c}_i^j$ are the upper and lower bounds on the encountered values of the $j^{th}$ attribute for data points assigned to cluster $P_i$ and $n$ denotes the dimensionality of the input vector.

The algorithm is initialized with a single cluster $P_1$ created at the position of the first supplied training data point $X(0)$. Upon acquiring a new data point $X(t)$ the nearest cluster $P_a$ is identified by calculating the Euclidean distance to all available clusters with respect to the new data point $X(t)$. The set of clusters is then updated according to the NNC algorithm: if the computed nearest distance is greater than the established maximum cluster radius parameter, a new cluster is created, otherwise the nearest cluster $P_a$ is updated as:

$$\vec{c}_a = \frac{w_a\,\vec{c}_a + X(t)}{w_a + 1},\ \ w_a = w_a + 1 \tag{3}$$

$$\overline{c}_i^j = \max(x_i(t), \overline{c}_i^j),\ \ \underline{c}_i^j = \min(x_i(t), \underline{c}_i^j) \quad j = 1 \ldots n \tag{4}$$

As can be seen in (4), the modified NNC algorithm also keeps track of the lower and upper bounds of the encountered input values in each dimension for every cluster.

### C. Fuzzy Rule Based Behavior Modeling

Once the clustering process is completed (i.e. all available data has been processed by the algorithm), the set of extracted clusters is transformed into a set of fuzzy rules [41]. Each fuzzy rule describes the belonging of a particular sub-region of the multi-dimensional input space to the class of normal building zone behavior.

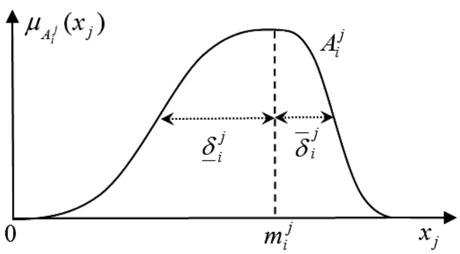


Fig. 2 Illustration of the non-symmetric input Gaussian fuzzy set $A_i^j$

A fuzzy rule $R_i$ corresponding to cluster $P_i$ is composed of $n$ antecedent fuzzy sets: $A_i^j$, $j = 1..n$. Each fuzzy set $A_i^j$, located in the $j^{th}$ dimension of the input space, is modeled using a non-symmetrical Gaussian fuzzy membership function. As shown in Fig. 2 this membership function is defined using three parameters: mean $m_i^j$ and the left and the right standard deviations $\overline{\delta}_i^j$, $\underline{\delta}_i^j$. The parameter values are extracted based on the computed cluster $P_i$ as follows:

$$m_i^j = c_i^j \tag{5}$$

$$\overline{\delta}_i^j = \alpha(\overline{c}_i^j - c_i^j) \tag{6}$$

$$\underline{\delta}_i^j = \alpha(c_i^j - \underline{c}_i^j) \tag{7}$$

Here, symbol $\alpha$ denotes the fuzziness parameter, which is used to adjust the spread of the membership functions.

The firing strength of fuzzy rule $R_i$ can then computed using the minimum operation as:

$$\mu_{R_i}(X(t)) = \min_{j=1..n}\{\mu_{A_i^j}(X_j(t))\} \tag{8}$$

The output of the fuzzy rule is a singleton fuzzy set assigning the input pattern to the normal behavior class. Hence, the fired output of a particular fuzzy rule is its own firing strength $\mu_{R_i}(X(t))$. The final output decision $y$ of the anomaly detection system is obtained by applying the maximum operator to the output of all available fuzzy rules:

$$y(t) = \max_{i=1..C} \mu_{R_i}(X(t)) \tag{9}$$

Here, $C$ denotes the number of extracted fuzzy rules, which is equal to the number of extracted clusters. The value of the output $y$ denotes the degree of belonging of input pattern $X(t)$ to the class of normal behavior. In other words, the output value $y$ expresses the confidence of the algorithm in how likely does the current input pattern belong to the class of normal behavior. A specific sensitivity threshold can be used for the final classification into the normal/anomaly class.

It should be noted here that the main assumption of the anomaly detection algorithm is that a representative normal behavior data set has been collected and used for training. In case that the used training data set was not a good representation of the class of normal behavior, the detection of an anomaly might only signalize that the input data is normal but it has not been included in the training data set. This assumption constitutes a fundamental concept underlying the use of anomaly detection techniques.

## IV. Linguistic Description of Anomalies

To further improve the state-awareness of building managers, the presented method provides compact and easy to understand linguistic descriptions of the identified anomalies. It has been previously shown that using linguistic terms rather than precise numbers for describing data increases the understandability of the descriptions [43], [44]. Therefore the provided descriptions linguistically characterize the identified anomaly [45], [46]. Each detected anomaly can be automatically described using a linguistic description encoded as a fuzzy rule in the following form:

**IF** $x_{f(1)}$ is $B_{f(1)}$ **AND** … **AND** $x_{f(m)}$ is $B_{f(m)}$
**THEN** *Anomaly* **WITH** *Confidence* is $C$ (10)

Here, $m$ is the complexity of the linguistic description that can be set by the user. It expresses how many antecedents participate in the linguistic description, typically set to 1 or 2. The linguistic description thus contains the first $m$ antecedents of the overall $n$ available antecedents ranked according to their importance as expressed by the indexing function $f(i)$. Symbols $B$ and $C$ denote the linguistic labels that are modeled as fuzzy sets and assigned to individual input dimensions as well as the confidence of the linguistic description. Thus a typical linguistic description can be written as:

**IF** Zone Temperature **IS** *Low* AND Chiller temperature *High* **THEN** Anomaly **WITH** Confidence **IS** *Very High*

The following sections explain the ranking of the available input attributes followed by a description of the method for assigning linguistic labels to individual attributes.

### A. Ranking of Antecedents

In applications such as BEMS, the number of available input attributes is typically significantly larger than the desired complexity of the generated linguistic descriptions. As the number of antecedents, $m$ increases, the linguistic rule becomes more difficult to interpret [46]. For a linguistic description to be comprehensible, the number of antecedents, $m$ should be kept low [44], [46]. For instance, the complexity of linguistic descriptions generated based on building zone behavior described using 10-dimensional input vector, should not exceed 2 or 3 antecedents in order to provide easy to understand linguistic descriptions for the building manager. Hence, it is important to select $m$ most important and descriptive antecedents out of the $n$ available input attributes with respect to the detected anomaly [46].

This selection is performed via first ranking individual input attributes and then selecting the first $m$ dimensions. The permutation of the input antecedents according to their rank is denoted by function $f(i)$ in (10). The main idea of the antecedent ranking process is based on the assumption that the more a specific input attribute contributes to the classification of particular input vector as an anomaly, the more it is important for the linguistic description.

This ranking is then computed based on the fuzzy rule based behavior modeling algorithm presented in section III.C. The classification of the given input vector is performed according to the fuzzy rule with the highest firing strength as denoted in (9). This firing strength was calculated as the minimum among the antecedent membership degrees of particular fuzzy rule. Hence, the smaller the membership degree of specific antecedent with respect to the winning fuzzy rule, the more important is the respective attribute for the classification.

Hence, the antecedent dimensions are ranked based on the membership degree of the input vector to the fuzzy rule with the maximum firing strength sorted in an increasing order. The resulting permutation of indexes $f(i)$ can be denoted as follows:

$$\forall i,j \quad i<j \Rightarrow \mu_{A^k_{f(i)}}(x_{f(i)}) < \mu_{A^k_{f(j)}}(x_{f(j)}), \quad i,j=1,\dots,n \qquad (11)$$

### B. Linguistic Label Assignment

The range of the input attributes can be described using a group of fuzzy sets with assigned linguistic meaning. Note, that various fuzzy partitions of the respective domains are possible. The actual fuzzy representation of each input variable should be manually designed based on the context, domain and linguistic terms commonly used by the end users, i.e. building managers [45].

The linguistic description $B_i$ for the $i^{th}$ attribute of the feature vector $X(t)$ denoted in (10) can be obtained by selecting the $k^{th}$ linguistic label $D_i^k$ with the highest fuzzy membership degree according to:

$$k = \arg\max_{j=1\dots K} \mu_{D_i^j}(X_i(t)) \qquad (12)$$

Here, $K$ denotes the number of fuzzy sets used to describe the domain of the $i^{th}$ attribute. Identical approach can be applied to select the linguistic label $C_i$ for the anomaly confidence.

The anomaly detection algorithm evaluates the presence of an anomaly at each time sample. However, an anomalous event in a particular building zone can last multiple consecutive time samples. In order to achieve increased state awareness, it is important to avoid overloading the building manager with anomaly alarms with associated linguistic label for each time instant. Instead, the presented method computes a simple meaningful linguistic description, which characterizes the entire anomalous event. For an anomaly occurring at time $t_1$ and lasting $\Delta$ time steps the linguistic label $B_i$ for a given input feature $i$ is selected as the $k^{th}$ linguistic label $D_i^k$ according to:

$$k = \arg\max_{j=1..K} \sum_{t=t_1}^{t_1+\Delta} \mu_{D_i^j}(X_i(t)) \qquad (13)$$

## V. Mining BEMS Data via Anomaly Detection and Linguistic Descriptions

The presented Fuzzy-ADLD method was implemented in a software prototype that focuses on increasing the state-awareness of building managers and on automatically identifying anomalous behaviors without the need to tediously scan through the large data set.

TABLE I
List of Extracted Attributes and Their Scope

| Attribute | Scope |
|---|---|
| Zone Temperature | Zone |
| Time | Building |
| Outside Air Temperature | Building |
| Chiller Temperature | Floor |
| Mixed Air Temperature | Floor |
| Return Air Temperature | Floor |
| Damper Position | Floor |
| Exhaust Fan Load | Floor |
| Exhaust Fan Current | Floor |
| Supply Fan Load | Floor |
| Supply Fan Current | Floor |

### A. Implementation Parameters

The presented Fuzzy-ADLD method was applied to real-world BEMS data recorded from an office building in the Pacific Northwest part of the U.S. The building consists of 11 floors, where each floor has between 10 and 60 different measured thermal zones. Various sensors are available throughout the building measuring attributes related to individual thermal zones, entire floors or the entire building.

For the purpose of experimental demonstration, 11 attributes were identified. These attributes together with their scope are listed in Table I. The data is collected by the system at 45 minute intervals. All attribute values were first normalized into a unit interval between 0 and 1. Next the domain of the input attributes was represented using 5 triangular and trapezoidal fuzzy sets as denoted in Fig. 3(a) with the exception of the time attribute, which was represented using 6 fuzzy sets as denoted in Fig. 3(b). Finally, the confidence of the anomaly detection algorithm was represented using 5 fuzzy sets as depicted in Fig. 3(c). These fuzzy partitions represent a suitable decomposition of the respective domains established with respect to the targeted application.

The anomaly detection algorithm was implemented with the following parameter values. The maximum cluster radius for the nearest neighbor clustering method was set to 0.1. The $\alpha$ parameter for the fuzzy rule extraction based on the identified clusters was set to 2.0 and the sensitivity threshold for detecting anomalous events was set to 0.8. Note, these parameter values were selected based on extensive experimental testing. However, the values can be modified by the user. For example, the building manager can lower the sensitivity threshold, which would result in detecting more anomalies in the observed building behavior.

### B. Implemented GUI

The GUI of the implemented prototype is depicted in Fig. 4. The GUI contains three main information views: the building view (Fig. 4(a)), the floor view (Fig. 4(b)) and the data view (Fig. 4(c)). The building view provides a summary view of all floors in the building, where color can be assigned to depict various information, such as average floor temperature or the

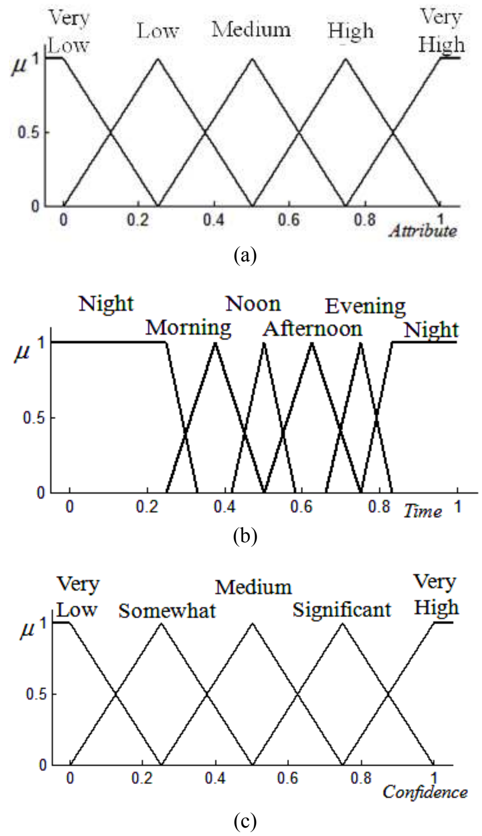


Fig. 3 Linguistic labels for sensor input (a), for time attribute (b), and for anomaly confidence (c).

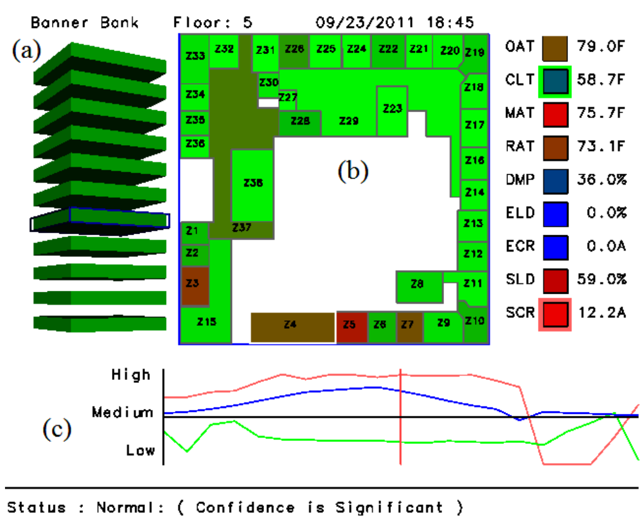


Fig. 4 User interface with the building (a), floor (b) and data view (c).

maximum anomaly level. In this figure, the floor view shows the floor plan of the selected floor, where the color of each zone depicts either the average temperature or the confidence that an anomalous behavior was identified for a given zone. Finally, the user can select a specific zone for the given floor and observe the source data plotted over time. The building manager can plot multiple sources of data in the data view.

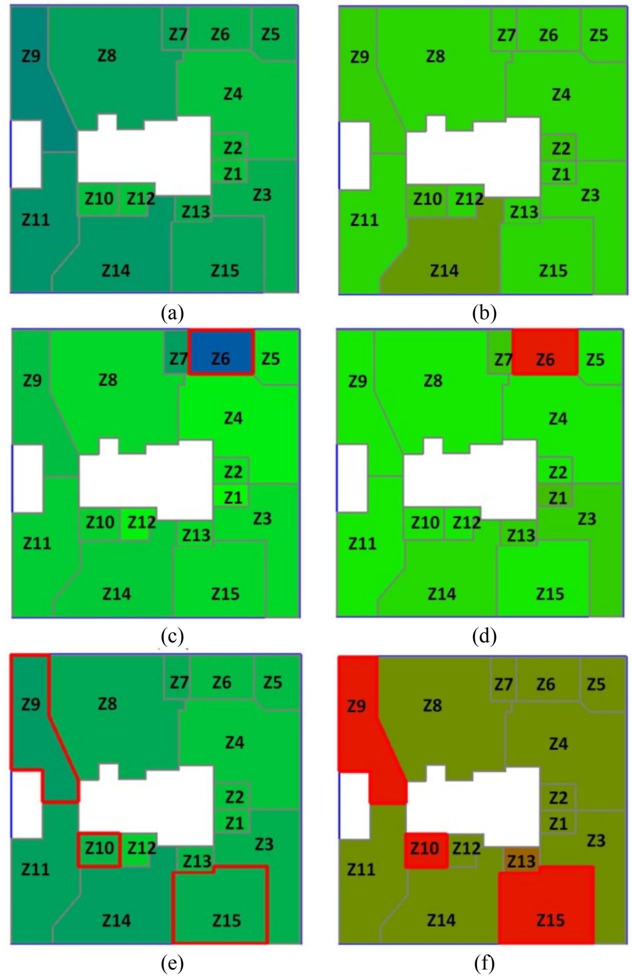


Fig. 5 Floor view depicting the zone temperature and the anomaly level in normal behavior (a), (b) and during an anomaly (b)-(f).

Upon selecting a specific building zone, the algorithm also linguistically expresses either the confidence level that a particular zone behaves according to the normal behavior model or the confidence level that an anomaly has been identified. Finally, the linguistic description of the identified anomaly is provided, where the complexity of the generated summaries can be interactively adjusted.

### C. *Anomaly Detection in BEMS Data*

The developed GUI can be used to explore the BEMS performance data. An example of the floor view showing the distribution of temperature in each zone is depicted in Fig. 5(a). The associated floor view, which depicts the level of anomaly of each building zone is depicted in Fig. 5(b), where it can be confirmed that all building zones are operating according to the normal behavior model. Note, that in the implemented visualization, low temperature values are depicted as blue color, while high temperature values are depicted as red. Similarly, low anomalous level (i.e. normal behavior) is depicted using green color, while high confidence in an anomaly is depicted using red color tones.

TABLE II
AUTOMATICALLY GENERATED BEMS PERFORMANCE REPORT

| Location | Time | Linguistic Description |
|---|---|---|
| Floor 7, Zone 6 | 9/16/2011, 3:45am – 6:00am | **Zone Temperature** is *Very Low* and **Chiller Temperature** is *High* ( **Confidence** is *Very High* ). |
| Floor 7, Zone 4 | 9/16/2011, 3:00pm – 6:00pm | **Exhaust Fan Load** is *High* and **Time** is *Afternoon* ( **Confidence** is *Very High* ) |
| Floor 7, Zone 15 | 9/16/2011, 6:45am – 7:30am | **Zone Temperature** is *Very Low* and **Mixed Air Temperature** is *Low* ( **Confidence** is *Significant* ) |
| Floor 7, Zone 10 | 9/26/2011, 11:15pm: | **Time** is *Night* and **Supply Fan Current** is *Very Low* ( **Confidence** is *Very High*) |
| Floor 5, Zone 21 | 9/27/2011, 9:00am | **Exhaust Fan Current** is *Very Low* and **Return Air Temperature** is *Low* ( **Confidence** is *Significant* ) |
| Floor 5, Zone 20 | 9/27/2011, 11:15pm | **Supply Fan Current** is *Very Low* and **Exhaust Fan Current** is *Low* (**Confidence** is *Very High*) |
| Floor 5, Zone 17 | 9/28/2011, 9:00am – 9:45am | **Damper Position** is *Medium* and **Return Air Temperature** is *Low* (**Confidence** is *Very High*) |
| Floor 5, Zone 9 | 9/28/2011, 9:45pm | **Zone Temperature** is *Very Low* and **Exhaust Fan Load** is *Medium* (**Confidence** is *Very High*) |
| Floor 5, Zone 17 | 9/30/2011, 1:30am | **Mixed Air Temperature** is *Medium* and **Damper Position** is *High* (**Confidence** is *Significant*) |

Next, instead of manually exploring the building data, the building manager can utilize the implemented anomaly detection engine to process the data and focus on the occurrence of the next anomaly. The floor view depicting the temperature of the particular time step is shown in Fig. 5(c), where it can be observed that zone 6 (Z6) features decreased temperature. The view of the anomaly indicator in Fig. 5(d) further confirms that the behavior of this particular zone does not comply with the established normal behavior model. Finally, upon selecting the anomalous zone a linguistic description is generated, which by default uses a single input antecedent and linguistically describes the anomalous event as:

**IF** Zone Temperature **IS** *Low* **THEN** Anomaly **WITH** Confidence **IS** *Very High*

Another example of identified anomalies is depicted in Fig. 5(e). Here, only reviewing the zone temperature does not indicate an anomaly. However, the anomaly indicator shown in Fig. 5(f) signalizes high confidence in detecting anomalies in zones 9, 10 and 15. The generated description of the anomaly detected in zone 9 is then:

**IF** Exhaust Fan Current **IS** *High* **THEN** Anomaly **WITH** Confidence **IS** *Very High*

### *D. Generation of Linguistic Descriptions*

As explained above, in order to increase the state-awareness of building managers and not to overwhelm them with additional sources of data, it is important to generate compact and informative linguistic descriptions. The actual level of complexity expressed as the number of antecedents in the linguistic description, can be interactively adjusted by the building manager.

As an example, consider the linguistic description generated in the previous section for zone 6. This linguistic description contains only single antecedent, which was identified as the most important antecedent from the available attributes. However, the building manager might request more information by increasing the complexity of the summary via the GUI. An example of a linguistic description with 4 antecedents would be as follows:

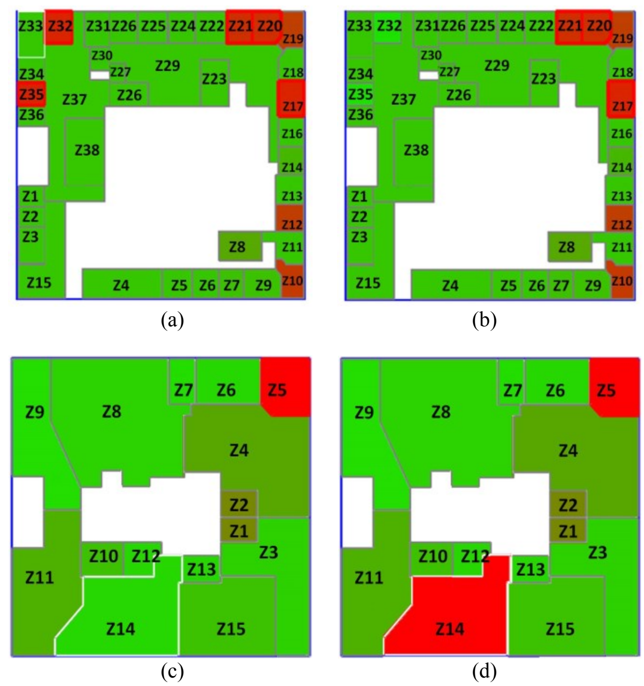


Fig. 6 Anomaly confidence level before and after the adjustment of the model. Including the behavior observed in zone 35 and 32 into the normal behavior model (a) before (b) after. Removing behavior in zone 14 from the normal behavior model (c) before (d) after

**IF** Zone Temperature **IS** *Very Low* **AND**
Return Air Temperature **IS** *Low* **AND**
Exhaust Fan Current **IS** *Low* **AND**
Mixed Air Temperature **IS** *Medium* **THEN**
Anomaly **WITH** Confidence **IS** *Very High*

Note that the antecedents are automatically ordered according to their importance.

TABLE III
BUILDING ANOMALIES TESTED

| Case | Type | Fault | Start Time | End Time | Duration |
|---|---|---|---|---|---|
| Case 1 | Sensor Fault | Constant default sensor value | 09/16/2013 22:30 | 09/17/2013 10:30 | 12 Hours |
| Case 2 | | Constant previous sensor value | 09/01/2013 20:00 | 09/01/2013 08:00 | 12 Hours |
| Case 3 | | Constant degradation of sensor value | 09/16/2013 21:00 | 09/17/2013 12:00 | 15 Hours |
| Case 4 | Physical Ab-normality | Open window | 09/02/2013 21:00 | 09/03/2013 09:00 | 12 Hours |
| Case 5 | | External heat source | 09/18/2013 21:00 | 09/19/2013 09:00 | 12 Hours |
| Case 6 | | Closed air supply vent | 09/19/2013 09:00 | 09/19/2013 21:00 | 12 Hours |

### E. Automatic Report Generation

Automatic report generation for a given period of time is also implemented in the proposed system. Assume a scenario in which the building manager needs to inspect several weeks of collected BEMS data in an attempt to identify anomalous behaviors and other indications of possible building energy management inefficiencies. Manual step-by-step inspection of the large dataset can be considered an overwhelming and infeasible task.

The report generation sequentially processes a given time interval and applies the anomaly detection method for each time step. For anomalies lasting a single time step, the generated report contains the time, location and the linguistic description of the anomaly, which is calculated according to (12). For anomalous events spanning multiple consecutive time steps, the generated report contains a summary of that anomaly with start and end times of the event, location and the representative linguistic description computed according to (13). An example of the generated descriptions is given in Table II.

### F. Normal Behavior Model Adjustments

It is important to emphasize that the notion of an anomaly here refers to an event that is sufficiently different from the set of previously collected and approved normal data used for the training of the algorithm. Hence, events which might be considered normal from a building operation point of view might also be labeled as anomalous if they were not included in the normal training dataset. Similarly, anomalous behavior existing in the initial training data will be identified as normal behavior. To address these issues, the developed anomaly detection system allows for incremental learning of new behavior patterns.

In this scenario, upon inspection of the identified anomalous event, the building manager can decide that an anomaly should be included in the normal behavior model. The algorithm then extracts the relevant input feature vector and updates the set of relevant clusters. According to the NNC algorithm, either a new cluster will be created or an already existing cluster will be updated to account for the new data pattern. Next, the set of fuzzy rules for particular zone is updated to reflect the recent update (see section III.B). Similarly, if the building manager decides that a given normal behavior is actually an anomaly the cluster related to the behavior, along with the generated fuzzy rules will be deleted from the model.

In this manner the performance of the anomaly detection algorithm can be interactively and incrementally tuned by the building manager to focus only on relevant anomalies. An example of this behavior is shown in Fig. 6. The anomaly confidence level for the 5th floor is depicted in Fig. 6(a). The anomaly detection algorithm clearly marks zones 17, 20, 21, 32 and 35 as anomalous. Fig. 6(b) then shows the anomaly confidence level after the observed behavior in zones 32 and 35 was included in the model. Similarly, Fig. 6(c) shows the anomaly confidence level for floor 7. The behavior of zone 14 is then removed from the normal behavior and the anomaly confidence after removal is shown in Fig. 6(d), where zone 14 is identified as an anomaly.

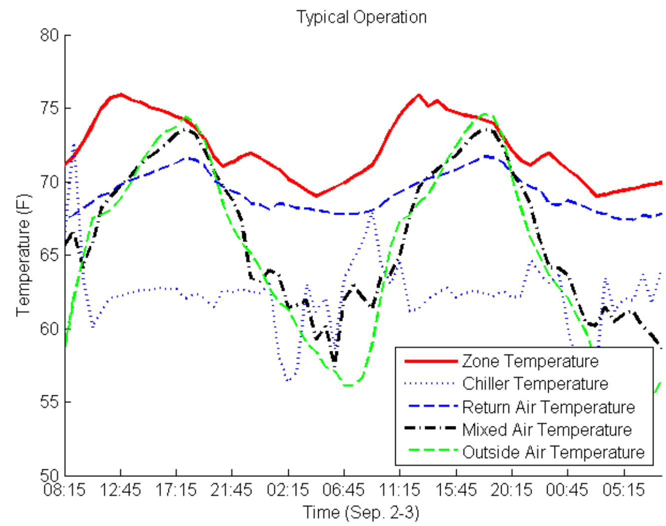


Fig. 7 Typical operation characteristics of the selected office room for a 48 hour period

## VI. EXPERIMENTAL RESULTS

The presented Fuzzy-ADLD method was compared with the existing traditional alarm based system in the afore-mentioned building. Six different abnormal scenarios were tested and the time each method identified the anomalous behavior was recorded for comparison.

The six cases were divided into sensor faults and physical abnormalities (see Table III). The sensor faults (Case 1, 2 and 3) were simulated by injecting artificial values to the system via the installed communication infrastructure. The physical abnormalities were simulated by actual physical changes to the environment (Case 4: by opening a window, Case 5: using a small portable heater, and Case 6: by closing an air supply vent). All six cases were performed in a small enclosed office room during non-occupied hours.

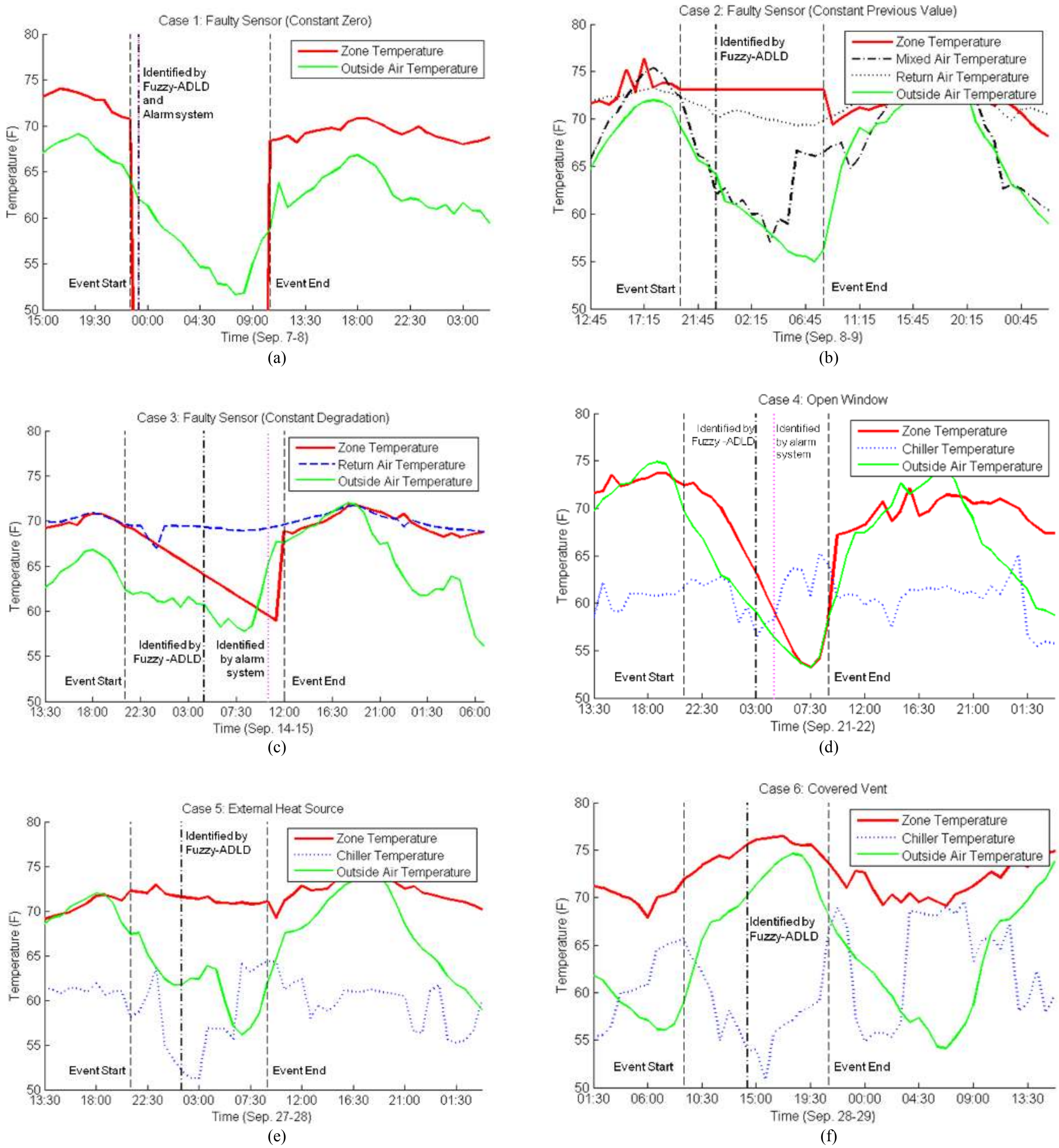


Fig. 8 Abnormal building behavior scenarios tested. (a) – (c) sensor based anomalies, (d) – (f) physical anomalies

Fig. 7 depicts typical operation of the selected zone for a 48 hour period. Fig. 8a to 8f show each test case and the time each method was able to identify the abnormal behavior. Note that the sensor values plotted in each figure are the ones that were identified by the Fuzzy-ADLD method as relevant for that scenario. Table IV shows the time when each of the methods identified the abnormal behavior along with linguistic descriptions provided by the Fuzzy-ADLD method.

Case 1 [Fig. 8(a)] where the sensor faults to the default value (in this case 0ºF) was immediately identified by both methods.

Case 2 [Fig. 8(b)] was not identified by the alarm based system since the sensor value does not go outside the preset bounds. However, the anomaly detection system was able to identify the abnormal behavior by identifying that the return air and mixed air temperatures were lower compared to the zone temperature.

TABLE IV
ANOMALY DETECTION AND THERE LINGUISTIC DESCRIPTIONS

| Case | Linguistic Description | Time Detected | | Difference |
|---|---|---|---|---|
| | | Fuzzy-ADLD Method | Alarm Based System | |
| Case 1 | Zone Temperature is Very Low | 09/16/2013 23:15 | 09/16/2013 23:15 | 0 |
| Case 2 | Return Air Temperature is Medium<br>Mixed Air Temperature is Low<br>Zone Temperature is Very High | 09/01/2013 23:15 | Not Detected | NA |
| Case 3 | Return Air Temperature is High<br>Zone Temperature is Very Low | 09/17/2013 04:30 | 09/17/2013 10:15 | 5 Hours 45 Minutes |
| Case 4 | Chiller Temperature is High<br>Zone Temperature is Very Low | 09/03/2013 03:00 | 09/03/2013 04:15 | 1 Hour 15 Minutes |
| Case 5 | Chiller Temperature is Very Low<br>Zone Temperature is Very High | 09/19/2013 01:15 | Not Detected | NA |
| Case 6 | Chiller Temperature is Very Low<br>Zone Temperature is Very High | 09/19/2013 14:15 | Not Detected | NA |

Case 3 [Fig. 8(c)] was identified by both methods, however, the alarm based system only identified the anomaly after the temperature reached the lower threshold set by the system (which was 60ºF). The anomaly detection system was able to identify the behavior since the return air temperature was much higher compared to the zone temperature.

Case 4 [Fig. 8(d)] where a window was opened during the night was identified by the anomaly detection system because of the discrepancy between the supply air temperature and the zone temperature. Again the alarm based system only identified the anomaly after the zone temperature reached the low alarm threshold.

Case 5 [Fig. 8(e)] was identified by the anomaly detection system because of the high zone temperature while the chiller temperature is very low. The alarm based system was unable to identify the anomaly.

Case 6 [Fig. 8(f)], similar to Case 5 was identified by the anomaly detection system due to the difference in the chiller temperature and the zone temperature. Again, the alarm based system failed to identify the anomaly.

Cases 2, 5 and 6 were not identified by the traditional alarm based system because all the sensor values were inside the preset bounds during the anomalous event. However, because the presented Fuzzy-ADLD method identifies anomalies based on the combination of interrelationships of the sensors, these cases were identified by the Fuzzy-ADLD method (see Table IV).

Similarly, cases 3 and 4 were identified by the Fuzzy-ADLD method before the alarm based system, because of the combined states of the sensors were anomalous. These cases were identified by the alarm based system only after certain sensor values exceeded the preset bounds.

Case 1 was immediately identified by both methods because the sensor value immediately exceeded present bounds.

Identifying such anomalous building behavior faster enables building mangers to react to the situation more quickly and more effectively. This may lead to energy savings, higher level of comfort for occupants, as well as mitigate equipment failure due to prolonged exposure to abnormal operation conditions. Furthermore, the presented Fuzzy-ADLD method provided linguistic descriptions for each of the identified anomalous event enabling the user to make more informed decisions.

## VII. CONCLUSION

Fuzzy Anomaly Detection and Linguistic Description (Fuzzy-ADLD) method is presented in this paper for improved state-awareness of buildings. The Fuzzy-ADLD method is composed of two main parts performing anomaly detection and generating linguistic descriptions of the identified anomalies. The generated linguistic descriptions are further enhanced by ranking the antecedents in order of importance. Furthermore, the complexity of linguistic descriptions as well as the performance of the anomaly detection can be adjusted for additional control. The presented Fuzzy-ADLD method was integrated with a graphical user interface and applied to real-world BEMS data collected from an office building in the Pacific Northwest part of the U.S. demonstrating potential for increased state-awareness for building managers.

The presented Fuzzy-ADLD method was compared to a traditional alarm based system using six abnormal building behavior cases. In each case the presented anomaly detection method was able to identify the abnormal behavior as least fast as or faster than (over an hour or more) the traditional alarm based system. Furthermore, the Fuzzy-ADLD method identified 3 of the cases that were not identified by the alarm based system. The linguistic description provided by the Fuzzy-ADLD method provides insight into the identified behavior.

Future work entails implementing the developed software prototype on a mobile device such as tablet, which would constitute a portable touch-screen controlled tool. Furthermore, possibility of classifying anomalous behavior using expert knowledge in the form of fuzzy rules will be investigated. Such classification can be used to provide more detailed descriptions of building behavior and possible solutions.

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