# Computational Intelligence based Anomaly Detection for Building Energy Management Systems

Ondrej Linda, Dumidu Wijayasekara, Milos Manic
University of Idaho
Idaho Falls, ID, USA
olinda@uidaho.edu,wija2589@vandals.uidaho.edu,
misko@ieee.org

Craig Rieger
Idaho National Laboratory
Idaho Falls, ID, USA
craig.rieger@inl.gov

***Abstract*— In the past several decades Building Energy Management Systems (BEMSs) have become vital components of most modern buildings. BEMSs utilize advanced microprocessor technology combined with extensive sensor data collection and communication to minimize energy consumption while maintaining high human comfort levels. When properly tuned and operated, BEMSs can provide significant energy savings. However, the complexity of the acquired sensory data and the overwhelming amount of presented information renders them difficult to adjust or even understand by responsible building managers. This inevitably results in suboptimal BEMS operation and performance. To address this issue, this paper reports on a research effort that utilizes Computational Intelligence techniques to fuse multiple heterogeneous sources of BEMS data and to extract relevant actionable information. This actionable information can then be easily understood and acted upon by responsible building managers. In particular, this paper describes the use of anomaly detection algorithms for improving the understandability of BEMS data and for increasing the state-awareness of building managers. The developed system utilizes modified nearest neighbor clustering algorithm and fuzzy logic rule extraction technique to automatically build a model of normal BEMS operations and detect possible anomalous behavior. In addition, linguistic summaries based on fuzzy set representation of the input values are generated for the detected anomalies which increase the understandability of the presented results.**

***Keywords—Anomaly Detection; Building Energy Management Systems; Computational Intelligence;***

## I. INTRODUCTION

Building Energy Management Systems (BEMSs) have evolved into highly complex information gathering and control systems. When properly tuned, BEMS enable significant energy savings in buildings [1]-[3]. According to the Department of Energy (DOE) over 50% of energy used in buildings is consumed by Heating Ventilation and Air Conditioning (HVAC) units and lighting systems [4]. However, research has shown that up to 40% of this energy can be saved by closely monitoring the state of the building and applying advanced control strategies [5], [6].

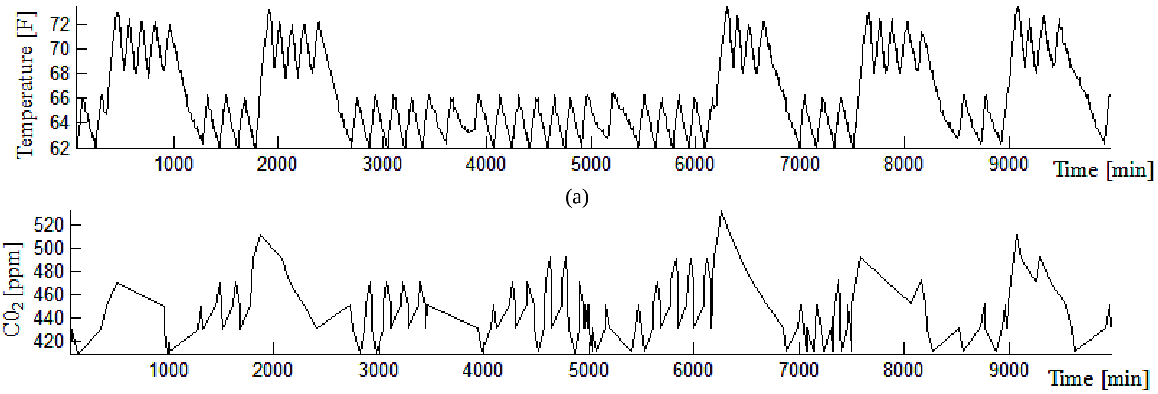
Advanced BEMS uses a large array of sensors placed within the building, outside the building and throughout the Air Handling Units (AHUs) to gather information about temperature, air quality, lighting or occupancy [3], [7], [8]. BEMS use this information to control the heating, cooling and lighting of the building [2], [3]. This type of control has the potential of large energy savings when compared to conventional systems, without sacrificing occupant comfort [1], [9]-[11]. Furthermore, gathering and analyzing sensor data allows the identification of previously unknown building performance characteristics [1].

BEMS also provide data about the current state of the system to building managers. Building managers are responsible for maintaining uninterrupted safe operation of the HVAC and lighting systems without compromising the comfort level of the building. The information provided by the BEMS should allow the building managers to gain understanding of the current state of the building and to quickly focus on inefficiencies and anomalous behavior [10], [12], [13].

However, due to the complexity and overwhelming amount of the acquired data it is difficult to identify the anomalous behaviors and resolve them accordingly [12]-[14]. Current BEMS tools also lack the capability of providing actionable information by processing and integrating gathered data [1]. Some advanced tools specifically created for monitoring and analyzing BEMS data exist in the industry [15]-[19]. However, these tools commonly require extensive training and understanding of the system in order for it to be utilized effectively [6], [20].

In order to improve the understandability of the BEMS and the state-awareness of the building managers this paper reports on a research effort that utilizes Computational Intelligence (CI) techniques for extracting relevant actionable information via fusing multiple heterogeneous sources of BEMS data. This actionable information is then presented to the responsible building managers in order for them to better understand the building system and to be able to make correct decisions regarding tuning the performance of the system. Advanced CI based techniques have been previously used for improving BEMS [21]-[24].

More specifically, this paper describes the use of anomaly detection algorithms for improving the understandability of BEMS and enhancing the state awareness of the building managers [25]. The developed system utilizes modified nearest neighbor clustering algorithm and a fuzzy logic rule extraction technique to build a model of normal BEMS operations based on provided normal behavior training data set [26]. The developed method can then be used to detect anomalous BEMS operation. Furthermore, linguistic




(b)

Fig. 1 Building zone measurements of temperature (a) and $CO_2$ (b).

summaries based on fuzzy set representation of the input values are generated for the detected anomalies which increase the understandability of the presented results.

The rest of the paper is structured as follows. Section II elaborates on the developed anomaly detection algorithm for BEMS. The implementation and experimental results are presented in section III and the paper is concluded in section IV.

## II. Anomaly Detection for BEMS

This section first describes the algorithm for normal behavior modeling and anomaly detection using online clustering and fuzzy logic system. Next, the linguistic description of identified anomalies is described.

### A. Feature Extraction

Typical BEMS provides measurements from multiple sensors throughout the building, e.g. temperature, $CO_2$ or occupancy sensing. These measurements can be associated with different spatial zones in the building, for example with individual rooms. The sensor measurements collected over time constitute a time-series data describing the behavior of each zone. Different patterns of zone behaviors can be experienced in a typical building, for instance, pre-heating of the rooms in the morning, maintaining human comfortable temperatures during a day, cooling of the zones in the evening or maintaining lower temperatures at night. An example of real world temperature and $CO_2$ data for a building zone recorded over a one week period is depicted in Fig. 1. The alternations between working hours (increased temperature and $CO_2$) and night time hours is clearly visible.

Specific features can be extracted from the sensor measurements that can describe the different behavioral patterns. For simplicity sake, only the temperature sensor data are used in the presented initial design of the anomaly detection method for BEMS. Two descriptive features are extracted from the input data at each sampled time instant: the temperature amplitude and the gradient of the temperature. Hence, a 2-dimensional feature vector $X(t)$ at time $t$ can be computed as:

$$X(t) = \{T(t), T(t) - T(t-1)\} \tag{1}$$

Here, $T(t)$ denotes the temperature measurement at time $t$. Including additional sensor measurements, such as $CO_2$, occupancy or user comfort level into the feature vector is scope of future work.

### B. Rule Extraction via Online Clustering

The behavioral patterns in a specific building zone can be extracted using a previously proposed online fuzzy rule extraction technique [26]. This algorithm is capable of online learning, which means that the model can be updated without the need to re-learn the entire training data set. The obtained model of normal zone behavior is composed of a set of fuzzy rules. Each rule is extracted using a modified Nearest Neighbor Clustering (NNC) algorithm [26]. 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.

Initially, the algorithm starts with a single cluster $P_1$ positioned at the first supplied training data point $X(0)$. Upon acquiring a new data point $X(t)$ the set of clusters is updated according to the NNC algorithm. First, the Euclidean distance to all available clusters with respect to the new input feature vector $X(t)$ is calculated. The nearest cluster $P_a$ is identified. 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:

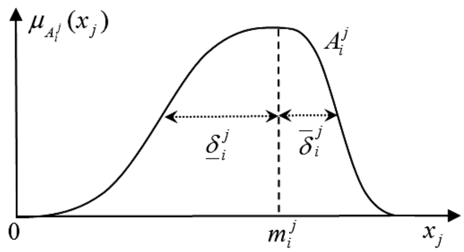



Fig. 2 Illustration of the non-symmetric input Gaussian Fuzzy Set $A_i^j$.

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

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

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. If the nearest cluster is further away than the established maximum cluster radius, a new cluster is created according to the standard NNC algorithm.

### C. Fuzzy Rule Based Behavior Modeling

Each of the extracted clusters can be converted into a fuzzy rule [26]. 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.

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, which is defined by three parameters, mean $m_i^j$ and the left and the right standard deviations $\bar{\delta}_i^j$, $\underline{\delta}_i^j$, as shown in Fig. 2. The parameter values are extracted based on the computed cluster $P_i$ as follows:

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

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

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

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:

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

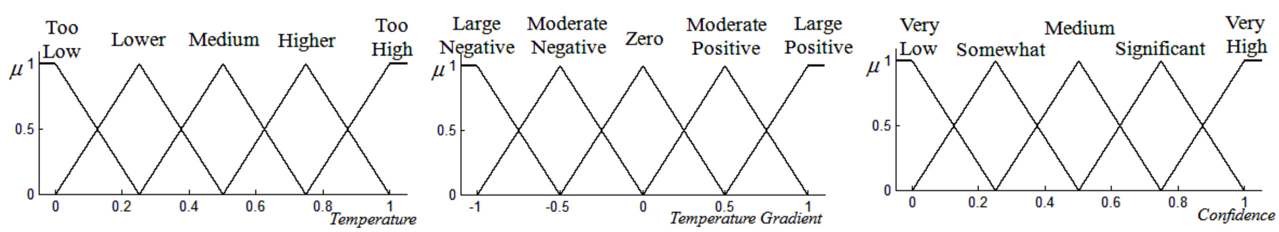
Here, $C$ denotes the number of extracted fuzzy rules, which is equal to the number of clusters. The value of the output $y$ denotes the degree of belonging of input pattern $X(t)$ to the class of normal behavior. In other words, the output value $y$ expresses the confidence of the algorithm in how likely 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.

### D. Linguistic Description of Anomalies

In order to further improve the state-awareness of the building managers, it is important that the anomaly detection system can provide easy to understand linguistic description of the identified anomalies. This description linguistically characterizes both the input features as well as the confidence of the anomaly detection algorithm in classifying the anomaly.

Assume that the 2-dimensional feature vector composed of temperature amplitude and temperature change is used. The range of these attributes can be described using a group of fuzzy sets with assigned linguistic meaning. In this work, five fuzzy triangular and trapezoidal fuzzy sets as depicted in Fig. 3(a) and Fig. 3(b) were used. Note, that the range of all input attributes has been normalized into a unit interval between 0 and 1. In addition the range of the output value $y$ of the anomaly detection algorithm which expresses the confidence of the algorithm can also be modeled using 5 fuzzy sets as




(a) (b) (c)

Fig. 3 Linguistic labels for input features Temperature (a), Temperature Gradient (b) and Confidence (c).

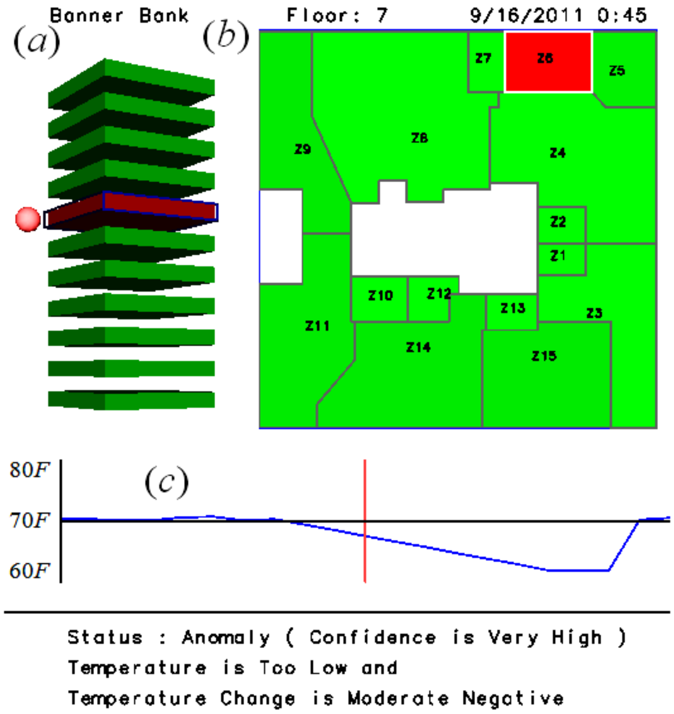



Fig. 4 User interface with the building (a), floor (b) and data view (c).

shown in Fig. 3(c). Note, that other fuzzy partitions of the respective domains are possible. The actual fuzzy representation of each input variable should be manually designed based on the language terms commonly used by the building managers.

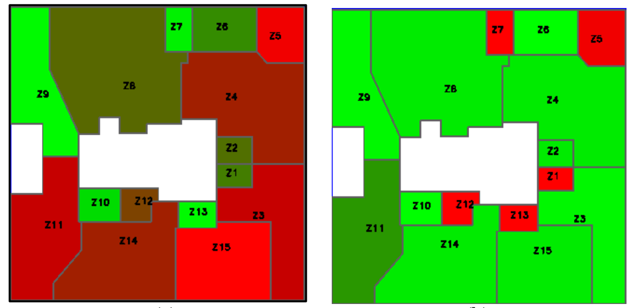
The linguistic description $B_i^*$ for the $i^{th}$ attribute of the feature vector $X(t)$ can be obtained by selecting the $k^{th}$ linguistic label $B_i^k$ with the highest fuzzy membership degree according to:

$$k = \arg\max_{j=1..K} \mu_{B_i^j}(X_i(t)) \qquad (10)$$

Here, $K$ denotes the number of fuzzy sets used to describe the domain of the $i^{th}$ attribute.

The anomaly detection algorithm evaluates the presence of an anomaly at each time sample. However, an anomalous event in 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 proposed 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 $B_i^*(t, t+\Delta)$ for a given input feature $i$ is selected as the $k^{th}$ linguistic label $B_i^k$ according to:

$$k = \arg\max_{j=1..K} \sum_{t=t_1}^{t_1+\Delta} \mu_{B_i^j}(X_i(t)) \qquad (11)$$




(a) (b)

Fig. 5 Visualization of temperature (a) and anomaly confidence level (b).

## III. Implementation and Experimental Results

The proposed anomaly detection method for BEMS was applied to the Banner Bank building in Boise, Idaho. This section describes the implementation and user interface of the developed tool and summarizes the provided novel capabilities of the system.

### A. *Enhanced BEMS Implementation and User Interface*

The enhanced BEMS system with the implemented anomaly detection algorithm was applied to the real-world data recorded from the Banner Bank building in Boise, Idaho. The building consists of 11 floors, where each floor has between 10 and 60 different measured zones. In each zone, multiple sensor measurements are be available. However, for simplicity sake, the initial design presented in this paper considers only the temperature sensors. Including additional sensor measurements is the scope of future work.

The presented algorithm was implemented with the following parameter values. The maximum cluster radius for the nearest neighbor clustering for was set to 0.1. The $\alpha$ parameter for the fuzzy rules extraction based on the identified clusters was set to 2.0 and the sensitivity threshold for detecting anomalous events was set to 0.8.

The inspection of the reported data and the identification of anomalous behaviors and inefficiencies in such a complex system is a daunting task for the building manager. The developed software prototype of the enhanced BEMS is focused on increasing the state-awareness of the building managers and on automatically identifying anomalous behaviors without the need to tediously scan through the large data set.

Fig. 4 depicts the user interface of the developed tool. The user interface contains three 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 the color of each floor can depict the average temperature or the maximum confidence that an anomaly is present on the floor. 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, as shown in Fig. 5. Finally, the user can select a specific zone for the given floor and observe the source data plotted over time. Upon selecting a specific building zone, the algorithm also

TABLE I
AUTOMATICALLY GENERATED BEMS PERFORMANCE REPORT

| Location | Time | Linguistic Description |
|---|---|---|
| Floor 7, Zone 7 | 9/16/2011, 3:45am – 6:45am | **Temperature** is *Too Low* and **Temperature Change** is *Large Negative* ( **Confidence** is *Very High* ). |
| Floor 7, Zone 6 | 9/16/2011, 0:45am – 7:30am | **Temperature** is *Too Low* and **Temperature Change** is *Moderate Negative* ( **Confidence** is *Very High* ) |
| Floor 7, Zone 11 | 9/16/2011, 9:00pm | **Temperature** is *Medium* and **Temperature Change** is *Large Negative* ( **Confidence** is *Very High* ) |
| Floor 7, Zone 2 | 9/19/2011, 12:45pm: | **Temperature** is *Too High* and **Temperature Change** is *Large Positive* ( **Confidence** is *Significant* ) |
| Floor 7, Zone 7 | 9/22/2011, 7:30am – 8:15am | **Temperature** is *Too Low* and **Temperature Change** is *Large Positive* ( **Confidence** is *Very High* ) |
| Floor 5, Zone 37 | 9/23/2011, 8:15pm | **Temperature** is *Lower* and **Temperature Change** is *Large Negative* (**Confidence** is *Very High*) |
| Floor 5, Zone 2 | 9/24/2011, 7:30pm – 8:15pm | **Temperature** is *Medium* and **Temperature Change** is *Large Negative* (**Confidence** is *Very High*) |
| Floor 5, Zone 23 | 9/25/2011, 11:15am – 12:00pm | **Temperature** is *Higher* and **Temperature Change** is *Moderate Negative* (**Confidence** is *Very High*) |
| Floor 5, Zone 17 | 9/26/2011, 9:00am | **Temperature** is *Too High* and **Temperature Change** is *Moderate Positive* (**Confidence** is *Significant*) |

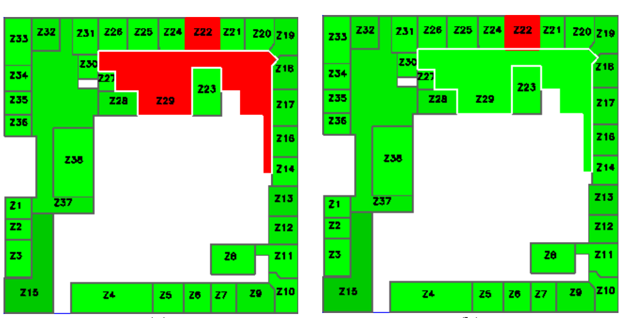
linguistically expresses either the confidence level that particular zone behaves normal or the confidence level that an anomaly has been identified and also provides a linguistic description of this anomaly.

The future work will be focused on implementing the developed software tool on a mobile device such as tablet, which would constitute a portable touch-screen controlled tool for building managers.

### B. Automatic Report Generation

One of the possible applications of the developed enhanced BEMS system is automatic report generation for the building managers. 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 is rather an infeasible task.

The anomaly detection method presented in this paper can be applied to achieve this task via generating an automatic report. The report generation method sequentially processes the selected time interval and applies the anomaly detection method at every time step. For anomalies lasting just a single time step the generated report contains the time, location and the linguistic description of the anomaly, which is calculated according to (10). For anomalous events spanning multiple consecutive time steps, the generated report contains a summary of that anomaly with the start and end time of the event, location and the representative linguistic description computed according to (11). An example of the generated summaries is given in Table I.




(a) (b)

Fig. 6 Anomaly confidence level before (a) and after (b) including the behavior observed in zone 29 into the normal behavior model.

### C. Performance Tuning

Apart from automatically generating the summary reports, the developed method also allows the building manager to step by step inspect the historical data. When interested in only inspecting the identified anomalous behavior, the building manager can rapidly step through the detected anomalies, rather than stepping through every single time sample. The developed user interface highlights the location of the anomaly and also provides the relevant linguistic description.

It is important to note that the notion of an anomaly refers here 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. To address this issue, the developed anomaly detection system allows for incrementally learning new patterns of normal behavior.

In this scenario, upon inspection of the identified anomalous event, the building manager can decide that this anomaly should be included in the normal behavior model. The algorithm then extracts the relevant input feature vector and updates the set of clusters of particular zone. According to the used 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.

In this manner the performance of the anomaly detection algorithm can be interactively 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 5$^{th}$ floor is depicted in Fig. 6(a). The anomaly detection algorithm clearly marks zones 22 and 29 as anomalous. Fig. 6(b) then shows the anomaly confidence level after the observed behavior in zone 29 was included in the model.

## IV. CONCLUSION

This paper reported on a research effort, which focuses on using Computational Intelligence techniques to automatically process complex sources of Building Energy Management Systems data and to extract relevant actionable information for responsible building managers. More specifically, this paper described the use of anomaly detection algorithms for improving the understandability of BEMS. The developed system utilized a modified nearest neighbor clustering algorithm and fuzzy logic rule extraction technique to automatically build a model of normal behavior for individual building zones. In addition, a fuzzy set representation of each input attribute was used to generate meaningful linguistic description of the identified anomalies. The implemented system can automatically notify the building manager when an anomalous behavior is encountered or the system can be used to generate automatic reports from a set of collected historical data. The proposed method was demonstrated on a set of real-world experimental data collected from the Banner Bank building in Boise, Idaho.

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