Improving Energy Efficiency of Buildings Using Data Mining Technologies

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***Abstract*—Building automation systems record operation data including physical values, system states and operation conditions. This data is stored, but commonly not automatically evaluated. This historic data is the key to efficient operation and to quick recognition of errors and inefficiencies, a potential that is not exploited today. Instead, today the evaluation during operation delivers only alarming in case of system failures. Analysis is commonly done by the facility manager, who uses his experience to interpret data. Methods from data mining and data analysis can contribute to a better understanding of building operation and provide the necessary information to optimize operation, especially in the area of Heating, Ventilation and Air Conditioning (HVAC) systems. Increases in energy efficiency and can be achieved by automated data analysis and by presenting the user energy performance indicators of all relevant HVAC components. The authors take a first step to examine operation data of adsorption chillers using the X-Means algorithm to automate the detection of system states.**

***Index Terms*—data mining, energy efficiency, building automation, HVAC, adsorption chiller**

I. Introduction

Data monitoring is the key to understanding complex systems as we find them today in building automation systems [1] [2]. Data recording is a function that is commonly provided by building management systems as well as in controllers for HVAC energy systems - it can be easily implemented, since the data is available anyway for the operation and requires only to be exported to some storage. Beyond the mere storage of data, there is today only little support for analysis. Trending is available, but usually only provides graphs of data points without the possibility of combining or correlating data points. Statistical analysis is also not commonly found when looking at historical monitoring data. Complex errors such as aging or structurally/temporally correlated errors can therefore not be detected.

Errors and inefficiencies often remain undiscovered, which may manifest in a significant increase in energy consumption, decrease of comfort, or reduced component life time. Simple approaches are the definition of hard lower and upper limits of process parameters that indicate erroneous operation. This allows coarse checking of the operation, but on the other hand requires deep knowledge on the process boundaries (e.g. optimal temperature range in heat rejection of water/silica gel based adsorption chiller). A preferable solution would be able to learn regular operation parameters based on training data and use the process boundaries taken from this learning process.

For conventional HVAC components such as compression refrigeration machines some approaches for automatic fault detection and fault diagnosis already exist, using algorithms from the field of data mining and artificial intelligence. For data analysis to be successful in HVAC systems it is necessary to find algorithms for automatic identification and classification e. g. to classify system states (on, off, heating, cooling) independent of the system specifications.

This paper describes approaches on data mining technologies that can support the optimization of building automation [2]. By analyzing operation data either online or in the aftermath errors and inefficiencies can be identified. Possible algorithms span over a broad spectrum ranging from simple plausibility checks of system parameters to inductive statistics. The main focus of the work in this paper is the automatic detection of duty cycles in adsorption chillers by using the X-Means algorithm. This approach is exemplary for automatic identification of many other process variables like temperatures or pressures and can easily be adapted. Given the page limitations the authors decided to provide an in-depth description of this duty cycle classification. The long term goal in data mining for building automation systems is the multiplicity of algorithms, meaning that they can detect the same category of errors independent of the actual installation in a similar fashion. This will dramatically reduce or even avoid the effort for continuous adaption of algorithms to new systems.

The rest of the paper is organized as follows: Section II gives an overview of the work that has been done so far, Section III details the methodology and the different approaches, Section IV shows the results of the analysis and Section V gives a conclusion and outlook.

II. Existing Approaches Today

Automated monitoring, fault detection and fault diagnosis have already been investigated and implemented in many areas of industry. For example, there are numerous methods for monitoring wind power plants [3]. Andrew Kusiak et al. [4] used data mining technologies to detect errors in wind turbine bearings. In the field of building automation and plant engineering there are already some approaches to optimize systems using data mining for error detection and classification. Ammar Ahmed et al. [5] built a model with the help of data mining technologies, which models the thermal comfort and the available daylight in rooms. They used the classification methods Naive Bayes, decision tree and Support Vector Machines on sample data sets and compared the methods with regard to accuracy and reliability. The work showed the high accuracy and reliability of the methods used in the prediction of comfort and energy efficiency.

In the area of HVAC systems there are already approaches to modeling and automatic information extraction by data mining. Like in this paper, the focus is more on individual HVAC components and less on overall HVAC systems.

Zhun Yu et al. [6] used data mining technologies in their work, that is, Association Rule Mining to extract information from the recorded data. The goal was to correlate meaningful connections and derive measures to improve energy efficiency. The methods were applied to data of an air conditioning system and allowed the identification of inefficiencies and errors.

To specifically detect sensor failures in heating, ventilation and air conditioning systems, a combination of Rough Sets and artificial neural networks has been presented in [7]. Using only a few parameters they predict remaining sensor values during operation. If they deviate from measured values, this is rated as an indication for an error.

Setu Madhavi Namburu et al. [8] developed a generic scheme for fault detection and fault diagnosis for chillers. To minimize the complexity of the calculations and the cost of the required sensors, a genetic algorithm was used to support sensor selection. Additionally, an error classification based on previously trained faults and methods of Support Vector Machines, Principal Component Analysis and Partial Least Squares and an error weighting was implemented. The developed methods were then evaluated using a compressor chiller. Similar approaches were also used by Kihoon Choi et al. [9] and Hua Han et al. [10] for error detection and diagnosis in conventional chillers; the methods were developed further in [11] to detect multiple simultaneously occurring errors.

Andrew Kusiak et al. showed in [12] that data mining technologies can also be successfully used for the optimization of an HVAC system. Different methods for data-based modeling were used and evaluated. By means of a selected process and a set of measured data, a model was then generated. This model could be used for optimization of two setpoint values of the system. A similar approach to data-based modeling using multi-layer perceptrons, boosting Tree and the Random Forest method was successfully used also in [13] for the optimization of a ventilation system.

Bruckner et al. showed in [14] how to automatically detect the type of sensors that can increase the fault tolerance of different types of sensors. Machine Learning and scenarios detection were examined in [15] and [16], and were also part of the dissertation of Zucker [17]: based on the detection of temporal patterns in the sensor values, Hidden Markov Models were developed. In a hierarchical model structure Bruckner has shown that on the level of sensor values it is possible to use simple statistical models to describe parameters and their behavior, while on higher, more abstract levels model structures are required to describe behavior over time and to allow the model a certain capacity for abstraction [18].

Comprehensive information models for intelligent energy systems and related domains as well as efficient, innovative communication architectures for secure data transmission were investigated in [19] and [20].

In Austria 267 solar assisted cooling systems are currently installed [21]. The operation of some equipment was carried out in the project "Solar Cooling Monitor". The project aimed to provide an overview of design quality, energy efficiency and performance of solar cooling systems in Austria. By using dynamic simulation models of solar cooling systems it was possible to perform comparisons with measured data and to create real-world system behavior in simulated test runs. A system that has been studied in project "Solar Cooling Monitor" is air conditioning system of the Energy Base office building in Vienna, Austria. Brychta et al. [22] analyze the operation of the solid Desiccant Evaporative Cooling System (DEC) system and provide an overview of the optimization potential on plant and control level. Additional studies were performed at another facility operated by the City of Vienna, The results and experiences of the operation and optimization of the system are described in [23] and [24]. For both systems analysis had to be done without a full coverage of monitoring data, but improving the monitoring system was part of the authors' work, which is rated as an indicator of the importance of automated monitoring as well as automated fault and failure detection.

III. Methodology

A. Data Acquisition and Storage

The systems used in this paper are water/silica gel based adsorption chiller. The operation data were recorded and stored in a monitoring and analysis system, called JEVis [25]. The JEVis system is an open source data base and visualization system with the focus on data integrity and easy visualization. To acquire the data a driver for the JEVis system was written to import data from the chillers. Chiller systems are either connected with broadband connection that are continuously online, or use GSM/UMTS connections that require local buffering and storage. In the latter case data are only retrieved every few hours or once a day.

B. Algorithms for Monitoring Data Analysis

X-Means Algorithm

The X-Means clustering algorithm introduced by the team of Dan Pelleg of the Auton Lab [26] is an offshoot to the well-known K-Means algorithm. The former provides a solution to the latter's problems on complexity and sensitivity to outliers in forming cluster models of some data. X-Means determines optimal clustering based on the computed values of the Bayesian Information Criterion (BIC) obtained in every iteration of the algorithm. These values determine when to make a sound local decision wherefore certain subsets of a group of observations are retained as one cluster or is split to form two in an iteration to better fit the inherent structure of the data. Furthermore, the algorithm will likely avoid being trapped in a worse local optima for a cluster model as it dynamically approximates optimal values of k (i.e. the number of clusters) of the data set.

X-Means is comprised of the following steps:

1) **Improve-Params.** This step executes the conventional K-Means until convergence.
2) **Improve-Structure.** This step determines when and where new centroids will appear. Such appearance is determined by computing the BIC of the clusters formed.
3) If the number of clusters formed in an iteration exceeds k_{max}, the algorithm stops and reports the best-scoring model (i.e. the cluster model where the BIC is maximized) found throughout the search. Otherwise, proceed to the first step. Note that k_{max} can be set to at most the number of points in the data set.

Non-Metric Multidimensional Scaling

Non-metric Multidimensional Scaling (nMDS) is a dimensionality reduction algorithm that maps multidimensional vectors of data into a 2D space [28]. Let P be an $n \times m$ data matrix that we wish to project into a lower dimension p, i.e. $p < m$. Generate a dissimilarity matrix D from P by computing the distances of each pair of points in P. Distance of two points can be computed by using either Euclidean Distance, Correlation, Mahalanobis, Manhattan, etc. computations depending on the type of the data set being analyzed. Using the dissimilarity matrix D, determine the values for $B = X^T X$, where X consists of the coordinates of the points of P in lower-dimensional Euclidean space. Spectral decomposition of B allows for the computation of X by computing the eigenvalues and eigenvectors of B. Since B is a positive-definite matrix with rank p, there are p non-zero eigenvalues and $n-p$ zero eigenvalues from B which may be obtained. This property of the matrix B allows for X with a dimension of $n \times p$ to be calculated. The resulting matrix X is projected in a p Euclidean space.

Confidence Intervals

- Confidence Bands.
  A confidence interval is a random interval whose endpoints are known as confidence limits. It is associated with a confidence coefficient $(1-\alpha)$, where $0 \leq \alpha \leq 1$. A $100(1-\alpha)\%$ confidence interval is given $100(1-\alpha)\%$ confidence to contain the true value of the parameter being estimated such as the mean μ.
  We can extend the concepts of confidence intervals to estimating best-fit curves where confidence limits are derived for all the values in a data set and are plotted along the estimated curve. A constructed confidence band will enclose an area where there is a $100(1-\alpha)\%$ confidence given to say that it contains the true curve. A confidence band is constructed as follows,
  1) Generate the best-fit curve for a chosen set of points.
  2) Project the band above and below the curve by
  $$\sqrt{c}\sqrt{\frac{SS}{DF}}t_\alpha(DF)$$
  where $c = G|x \times \Sigma \times G'|x$, $G|x$ is the gradient vector of the parameters at a particular value of x, $G'|x$ is the transposed gradient vector, Σ is the variance-covariance matrix, SS is the sum of the squares for the fit, DF is the degrees of freedom, and $t_\alpha(DF)$ is the Student's t critical value based on the confidence α and the degrees of freedom DF.
- Confidence Ellipse.
  Confidence ellipses are generated for a set of points in the 2D space by using intervals for both coordinate axes X and Y, i.e. the intervals are projected horizontally and vertically, respectively. An ellipse is derived by computing
  $$\overline{Z} \pm R \times I$$
  where $\overline{Z}$ is the mean of either X or Y, R is the range of either X or Y, and I is the confidence level $1-\alpha$. These form the minor and major axes of the ellipse. The ellipse is given a $100(1-\alpha)\%$ confidence to contain the data points it encloses inside its boundaries.

IV. Results

A. Preprocessing and Duty Cycle Extraction from Data

The monitoring data retrieved from JEVis is collected from an adsorption chiller [27] that uses water as refrigerant. Water is heated in the evaporator, then adsorbed and desorbed through the aid of the silica gel as sorption material found in the main chambers of the chiller, transformed back to liquid in the condenser, and goes back to the evaporator to complete a cycle. This cycle is mainly powered by heat supplied to the chiller to produce cooling to various spaces.

In such kind of an adsorption system, the duration of operation, also known as a duty cycle, is mainly detectable when pumps are turned from OFF to ON, and from ON to OFF, wherefore meters register the energy supplied for the operation. Different types of behaviour during duty cycles are expected with varying conditions for ambient temperature, cooling demand, etc., and states of the chiller, i.e. normal operation, malfunctioning, inefficient due to component or system ageing, etc.

In this study, we use the data collected from the meters associated to the chiller where we obtained 4-minute interval and hourly temperature and energy values, respectively. We extract duty cycles of variant lengths by segmenting the monitoring data from year 2011 by one of the chiller's energy variable, i.e. $Q7$, where $Q7$ is the chiller's values for its cooling load. A segment's initial point is determined by checking when the chiller is turned on, i.e. $Q7$'s value is positive, at some time t. Whenever we find another value that is within 60 minutes from the last value of the segment, we append it to the segment and mark it as the segment's last value, otherwise it will become a start value of the next segment. We use the same initial and terminal timestamps of the $Q7$ segments to form the segments of the chiller's return temperature values, i.e. T_LTre, which were collected from the low temperature circuit of the chiller.

B. X-Means Model for Chiller System Monitoring Data

Shown in Figure 1 is the X-Means cluster model of the T_LTre 30-dimensional segments (corresponding to 2-hour temperature values with 4-minute intervals) of year 2011 collected from JEVis. Extraction and processing of data from this year yielded duty cycles from the month of May to September when the chiller was in operational mode. A row of pixels correspond to a duty cycle (or segment) of data corresponding to this variable. The timestamp for the start period of the duty cycle is provided at the left side of visualization. A pixel's color is mapped to a value of the variable in some unit of time within the segment.

Note that clusters are shown in the figure as a set of segments appearing contiguously in a vertical arrangement and is bounded by the black lines separating them from other clusters.

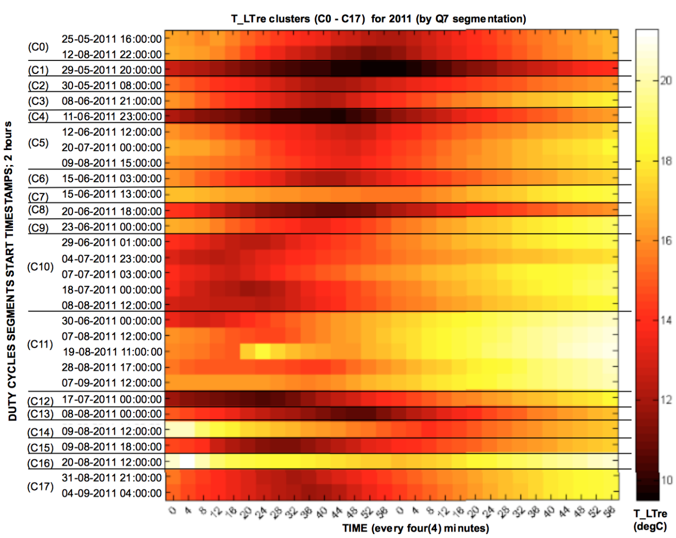

Figure 1. T_LTre Monitoring Data of 2011 X-Means Cluster Model

From Figure 1, we were able to detect different types of chiller behaviour in terms of the chiller's temperature variable under study. Two of its major clusters, i.e. Cluster 10 and Cluster 11, shows a pattern of gradual progression of the temperature that reaches their lowest points within 12 to 20 minutes of the first hour of the segments and then increases over time until the last time point of the second hour. The only difference from among the two is the range of values they take for their members, where Cluster 10's members have the lower set of values in general compared to Cluster 11's. Note that there are also clusters and outliers that have similar behaviour to them, however, their is a relative delay or earlier onset of the troughs for the values. Hence, having them separated as another cluster or outlier is justifiable in this case. Clearly, the use of the BIC parameter of X-Means helps us in distinguishing these dissimilar behaviours though they may first seem to be not apparent at the onset. Some outliers that are easily identifiable are in (the singleton) clusters 1, 3,12, and 16. Another interesting outlier is in cluster 7 where the range of the segment's values is very small and exhibits that the temperature is almost invariant throughout the two-hour period. Such sets of outlier behaviour are indicative of faults and malfunctions in the operations of energy systems.

As a supplement to the intercluster analysis above, we also show the box-plot visualisations of the same set of segments of the data set as shown in Figure 2. The values of each segment are collected and the temporal information, i.e. sequencing of the values within the segment, is discarded. These collected values are then projected as a boxplot - represented by a rectangle with dotted vertical lines (called whiskers) on its top and bottom edges. The ends of these whiskers correspond to the extreme values of the segment, i.e. largest and smallest as referenced by the values of the y-axis. The red line at the middle of the rectangle corresponds to the value of the median. The top and bottom edges of the rectangle correspond to the first and third quartiles, respectively.

There are also values in a segment that is an outlier amongst its group. Such an outlier is projected as points beyond the ends of the whiskers of each group's boxplot.

The boxplots are arranged from left to right on the x-axis by the ordering of their segments in the cluster model as seen on the data image in Figure 1. For example, the first 2 boxplots, labeled along the x-axis as 0.1 and 0.2 are the segments of Cluster 0 where 0.1 and 0.2 are the segments with the timestamps [25-05-2011 16:00:00] and [12-08-2011 22:00:00], respectively.

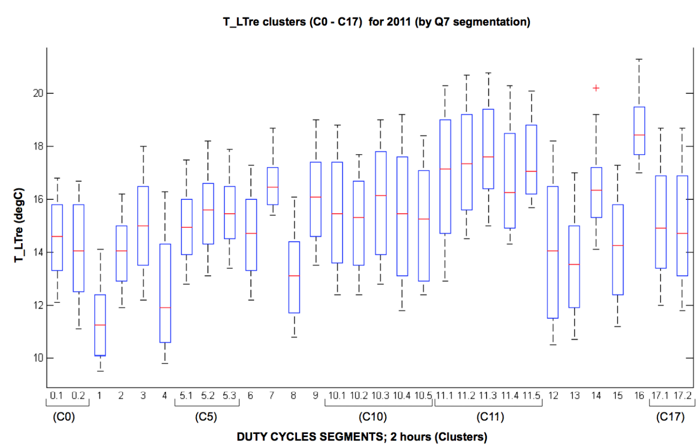

Figure 2. T_LTre Monitoring Data of 2011 Box Plot Visualization

To provide a simplistic, yet powerful intracluster analysis to reinforce what we were able to derive from the data image visualisation of the 2011 T_LTre values and cluster model, the nMDS 2D visualisation of this data set is provided in Figure 3. This visualization shows the mapped 2D points of each

30-dimensional segment of a duty cycle of the temperature variable with the same labelling provided in Figure 2.

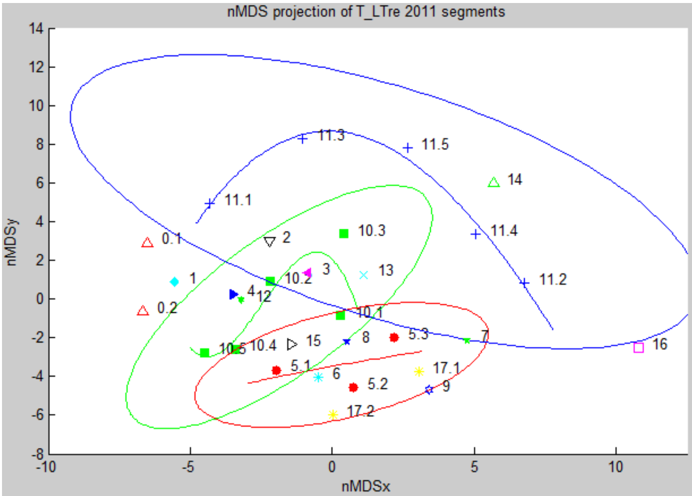

Figure 3. Non-Metric Multidimensional Scaling Visualization of the T_LTre Monitoring Data of 2011 with confidence intervals at 95% confidence

From Figure 3, we could check the degree of similarity a point is to its comembers of its clusters. Notice the third member of cluster 10, i.e. point 10.3, where it is the farthest from its comembers in terms of its distance from the centre of the cluster's mass as well as its perpendicular distance from its cluster's best fit curve. Furthermore, it can already be seen inside Cluster 11's confidence ellipse. When we look at the data image and the box plot visualizations, it can be noted that 11.3 indeed has a set of large temperature values consistent from the start to the end of the segment with duty cycle [07-07-2011 03:00:00] just like the members of Cluster 11. However, it is very noticeable that majority of the members of Cluster 11 already has temperature values mapped to the white shade of color corresponding to the highest values in the data set. The number of high values required for point 11.3 was not enough, hence, it was clustered to Cluster 10. Accordingly, we can also do the same characterization of point 5.1 enclosed in the ellipse of Cluster 10 for having relatively lower values compared to its comembers in Cluster 5 and is similar to Cluster 10's set of low values. These instances provide us an immediate 2D reference when there are segments with transient behaviour inside one full operation of the chiller, yet this transient behaviour was weighted less by the BIC hence the segment was placed onto some (non singleton) cluster in the model. Note that we could use these transient behaviour to check for possibilities of faults and diagnosis. For this study, we can narrow down fault diagnosis on the main chambers of the chiller where the meter collecting T_LTre were obtained, and which timestamps these transient behaviour occurred during the chiller's operation.

C. Implications to Energy Efficiency and FDD

With the different sets of behaviours described by individual clusters, detected outliers with deviant behaviour, and identified segments containing transient behaviour, the following are derivable when we extend our methodologies to examining values of the variables of the different circuits (i.e. high temperature, low temperature, heat rejection) within the chiller,

1) energy consumption trend of each cluster. This can be used to profile which set of days within a year which has low, medium, and high energy consumption. Even with the sparsity of the hourly $Q7$ data collection, we can use the finer 4-minute interval temperature values and the flow rate q of the refrigerant to derive approximate values for $Q7$ in through time t computed for every 4 minutes inside some circuit C of the chiller, i.e.

$$Q7(t, C) = \Delta T * cp * q(t),$$

where ΔT is the absolute value of the difference in the return and supply temperatures of c, and cp is the specific heat of water.

2) determine acceptable values of all the variables in all circuits of the chiller, by way of establishing lower and upper bounds of each individual (cluster) behaviour, whether these bounds are the set points for normal or erroneous operation of the chiller.

3) since timestamps of comembers in all clusters are known, we can correlate the observed ambient temperature during these time points and check whether the newly observed behaviour of the chiller conforms with the general behaviour of the cluster itself, otherwise, faults may exist for further investigation. Matching of the behaviour with the singleton clusters (i.e. outliers) could then proceed to check if those types of newly observed behaviour is within the list of known errors in the cluster model.

4) diagnosis may be carried out to determine where faults are about to happen or have happened by checking which circuit possesses the temperature or energy variable whose values had deviated from the set points or are consistent with outlier behaviour as derived from the computed trends of each cluster and outlier in the X-Means model. Once these circuits are identified, we could then check their associated components to verify causes of its inefficiency and malfunction in its operation.

V. Conclusion and Outlook

In this paper we have shown the applicability of data mining approaches in the analysis of operation data of HVAC components in building automation. We focused on the X-Means algorithm used for clustering duty cycles for adsorption chiller. It was shown that it is possible to automate considerable parts of the configuration and commissioning efforts that are commonly needed before a specific system can be analyzed. Both the detection of system states as well as the automatic allocation of duty cycle periods can be done with a minimum of pre-configuration. The next steps now are the definition of abstraction layers and the assignment of error scenarios on each level. This will allow to make statements about systems on abstract levels (e.g. cooling cycle operates while heat rejection does not work) or, if more information about the system is available, also on very specific level (e.g. upper temperature limit for ammonium driven absorption compression chiller of Type X exceeded).

More work is also needed on automating data acquisition from different data sources. The effort of importing data from different formats, including all dialects of CSV, and then assigning correct units, offsets and multiplication factors are considerable and any support will greatly speed up data analysis.

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