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Power disaggregation of combined HVAC loads using supervised machine learning algorithms

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ABSTRACT

Power disaggregation algorithms are used to decompose building level power consumption data into individual equipment level power information. In order to ensure energy efficient operation of complex systems, such as commercial buildings, a continuous and detailed energy monitoring system is essential. In this paper a novel power disaggregation technique is presented, in which a single set of aggregated power usage data of multiple HVACs from a single power meter is disaggregated to identify the operations of individual HVAC units. Parameters, including the combined real and reactive power of compressors and air handlers, are used in addition to the phase currents of both, as well as the true index values representing the combination of active compressors at any given time. Four different supervised machine learning algorithms – Decision Trees (DT), Discriminant Analysis (DA), Support Vector Machine (SVM) and *k*-Nearest Neighbors (*k*-NN) were tested. According to results, the *k*-Nearest Neighbors model was found to be most efficient in solving the problem of aggregated power disaggregation.

1. Introduction

Continuous and detailed energy monitoring is essential to ensure the energy efficient operation of complex systems, such as homes and office buildings, and also to ensure economic preservation. This information can also be used locally to analyze the usage and power consumption of devices/appliances. This will provide information for energy counseling, energy management applications, and increasing energy awareness of users by providing detailed device-level feedback. While it is expected that the number of smart appliances will increase significantly in the future, a considerable number of household appliances will be legacy devices, which are not able to directly report their operational data regarding time and consumption. Most of reported techniques for appliance's load monitoring can be classified under two categories: (1) distributed direct sensing (or submetering); and (2) single-point power profile disaggregation. Distributed direct sensing requires the monitoring of each appliance using submetering sensors (current, voltage, power, etc.). While this technique can provide accurate measurements, using a high number of dedicated meters to monitor these devices will be neither cost nor energy-effective. In principle, it requires a complex and costly power sensor system. An alternative approach motivated by the increasing deployment of smart meters and the awareness of promoting energy savings measured in the residential sector is the so-called non-intrusive load monitoring system (NILMS) that provides device level information while requiring a relatively simple installation. NILMS monitors the voltage and the overall electrical current entering the system, and infers the contribution of different energy consuming devices by looking at the time evolution of the monitored signals. Smart meters can transmit detailed energy consumption information back to the utility on a more frequent schedule than classical meters. However, still more detailed information on individual appliance consumption is required to direct the attention to actions that carry high energy savings.

There have been a number of state of the art approaches that have been taken to solve the problem of power disaggregation. In the context of data centers [1], non-intrusive power disaggregation (NIPD) establishes power mapping functions (PMFs), between the states of the data center servers and their power consumption. PMFs are used to infer the power consumption of each server with the aggregated power of the entire datacenter. Sparse approximations [2] have been tested for load disaggregation of home appliances from aggregate power measurements using sparse data models (data dependent dictionaries) learnt from individual appliances. A block sparse approximation was solved using an aggregated power signal to estimate the representational coefficients of each appliance. An analysis sparse optimization problem was then solved using the estimated coefficients, to estimate the power profile features of each appliance. Appliances have also been modeled by multi-state finite state machines [3]. Each state of an appliance

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is described by exactly one vector of power consumptions, measured at subsequent time instants, rather than a single measurement.

Electrical signatures [4] based on transients (Root Mean Square (RMS) Increment, Settle Time, Peak to Trough) and current-voltage phase shift during steady-state conditions have been used as features for the small power load disaggregation. Decision Tree classification incorporating tree pruning has been used for disaggregation using the aforementioned features. Discrete events, including switching ON/OFF of appliances, appliance operational time and some portion of the raw signal, are considered for achieving load disaggregation [5]. A method for residential appliances based on uncorrelated spectral components of an active power consumption signal [6] is presented. Karhunen Loeve expansion is used to breakdown the active power signal into subspace components (SCs) in order to construct a unique information rich appliance signature, used for disaggregation.

Event detection of appliances based on power edges is also used in [7] where subtractive clustering is used instead of K-Means clustering, in this case prior knowledge of the number of devices is not known. A dynamic fuzzy C-Means clustering algorithm is used to build appliance signature data based on active and reactive power in [8]. Two different clustering techniques, i.e., K-Means and Gaussian Mixture Models (GMM), are used and compared in [9]. GMM is a probabilistic approach whereas K-Means is not, however both rely on Expectation Maximization algorithm to iteratively determine cluster centers.

Using Artificial Neural Networks (ANN) [10], a low sampling rate of monitored data was used to detect any change of power signal that obtained a 1 Hz sampling rate of active power from the energy meter. Neural networks have been used to disaggregate residential loads in a point-to-state energy disaggregation model based on Back Propagation Neural Network algorithm [11]. Deep learning methods [12] have also been used such as Factored Four-Way Conditional Restricted Boltzmann Machines (FFW-CRBM) and Disjunctive Factored Four-Way Conditional Restricted Boltzmann Machines (DFFW-CRBM). These are able to perform both, classification and prediction of different loads.

A generic algorithm has been used to extract the main power states of electrical appliances based on iterative K-Means clustering [13] that is applied on historical plug-level active power data. Similar states are merged together and Factorial Hidden Markov Modeling (FHMM) models appliances for power disaggregation purposes, and incorporates the extracted set of appliances states. Another approach examines both the modeling of home appliances as Hidden Markov models (HMMs) and the solving of non-intrusive load monitoring (NILM) based on segmented integer quadratic constraint programming (SIQCP) [14] to disaggregate a household power profile into the appliance level. FHMM in combination with Viterbi algorithm [15] using initial and final power states of devices and device interactions have also been used to disaggregate loads. The most probable interaction is calculated using the Viterbi algorithm to detect active devices. The main features and interactions of the devices as explained in [15] are adaptively estimated in [16], resulting in an improved accuracy of active device estimation. Graph signal processing using features, such as active power, ON and OFF status, ON time and portion of the raw power waveform, has been used to classify the loads [17]. The concept of current waveforms using features of a current wave derived by distributed wavelet transform (DWT) has been used for disaggregation [18].

A semi-supervised shift-invariant weighted non-negative matrix factorization method [19] has been simulated, with auxiliary feedback that records the ON or OFF status of each appliance. Another method is a three-stage process for energy usage analysis, based on pulse extraction [20], pulse clustering and classification, and pulse to appliance association. The smart meter data are decomposed into a discrete set of pulses, and each pulse is associated with the operation of the appliances. Sum-to-k constrained non-negative matrix factorization (S2K-NMF) has also been used for disaggregation [21]. By imposing the sum-to-k constraint and the non-negative constraint, S2K-NMF is able to effectively extract perceptually meaningful sources from complex mixtures. By performing matrix factorization, activation coefficients for each device are calculated. After calculating the activation coefficient for each device, estimated power signal for each particular device is calculated. Power signals combined with ultra-wideband (UWB) radar [22] used for occupancy detection has also been used for multiple load power disaggregation. Data gathered from UWB detects and identifies the movements of person(s) within an indoor environment. This feature improves accuracy of disaggregation. An unsupervised load disaggregation method for monitoring and supervision of the load profiles of individual equipment of a HVAC system has been carried out using features, such as state of compressors, impulsion temperature and return temperature [23].

There have also been a number of earlier methods of power disaggregation as well. Current waveforms [24] have been used as power signatures. A voltage monitoring method is discussed in [25] where voltage variations are mapped to power jumps or drops caused by different devices. Based on these transients, power is calculated and matched with the power of connected devices to see which are active. Many forms of clustering had also previously been used for power disaggregation. An unsupervised disaggregation approach is proposed in [26] where models are created using rising and falling power edges, and appliance features are extracted from these edges. Air Conditioning (AC) units are disaggregated using edge detection and K-Means clustering in [27]. Key parameters of AC units are detected, and then used to identify ON and OFF events. Two different methods of edge detection, i.e., the Sobel edge detector and Two-step change filter, are compared in [28]. Once edges have been detected, features are extracted in the form of real and reactive power surrounding the edges. Appliances are modeled as Gaussian distribution in [29]. Expectation–Maximization (EM) clustering algorithm is used to calculate the clusters of edges to obtain the number and type of appliances used.

Some of the earlier electrical features which were used to improve performance [30–33] of data segregation for loads. Some of these features are Real/Reactive Power, Harmonics, Electromagnetic Interference (EMI), Current Waveforms, Transient Waveforms, Instantaneous Admittance Waveforms, Voltage readings and Eigenvalues.

Fourier series models had also been used [34] to calculate the lighting-plug and power of submeters in a commercial building from aggregated submetering data. Motif mining techniques [35] had also been used where motifs are referred to primitive shapes and frequent patterns. Meaning recurring load curves of electrical appliances can be considered motifs. Based on motif statistics, load curves are reconstructed and matched with ground truth data to separate active appliances.

A probability based approach [36] was also used for disaggregation where the system has probabilities of loads which may be active at a given time. Aggregated power data is then matched with probability of device status, e.g., whether they are ON/OFF, based on probability maximization. Discrete Time Warping [37] is another method that was used for disaggregation instead of using clustering. It was seen to be more effective than K-Means clustering. Appliances had previously also been modeled as SISO (Single Input Single Output) devices [38] and instead of looking for outputs, disaggregation is done by looking at inputs to appliances. The output is the power consumed by the device and the input is the device's setting when it is ON.

There are many methods of power disaggregation mentioned above which are applied to aggregated signals of different appliances. However, the problem of disaggregating data from an aggregated power signal of multiple identical appliances or devices, in order to identify which devices are active at a particular moment in time, has not yet been fully addressed. Power disaggregation in the context of smart buildings is the process of separating the power data for a number of devices, which are monitored by a single power meter. For example, to implement a Demand Response (DR) algorithm to control HVAC unit, an energy management system would require power consumption data from each unit. However, it is not practically feasible to use separate meters to measure the power consumption of each individual HVAC unit. Therefore, data for a number of HVAC units may be collected using a single meter. This data must then be disaggregated to retrieve the individual power consumption data for each unit.

In this paper the performance of different supervised classifiers is simulated and compared. These include Decision Trees (DT), Discriminant Analysis (DA), Support Vector Machine (SVM) and *k*-Nearest Neighbors (*k*-NN). Our main contributions in this paper are as follows:

1. A novel approach is presented to solve a problem which has not been addressed fully – to disaggregate the power data from an aggregated power usage signal, of multiple identical devices. This will be done in order to identify which devices are in operation at any given moment in time, allowing the fine-grained monitoring of the individual devices whose data has been aggregated together, using only a single power meter. Therefore, this would significantly reduce the installation and maintenance costs of the entire system.
2. Only three components of smart meter data are used to achieve this objective – real power, reactive power and phase currents.
3. Using simple machine learning classification algorithms, the problem of aggregated power disaggregation can be solved with high accuracy.

The devices under consideration are five HVAC compressors installed on a particular floor in a commercial building. Real and reactive power, phase currents of each compressor and air handler unit, along with corresponding index values representing the combination of active compressors, are used to train classifier models. Each classifier then matches input data points to a particular index value based on the training data, therefore outputting which particular compressors are active at any given time instant. By incorporating these features it is possible to achieve a high degree of accuracy in detecting the device status, i.e. which compressors are active and inactive at any given point in time.

2. Supervised classifiers

In this section, a brief overview of the different supervised classifiers, which have been tested for data disaggregation, is given.

2.1. Decision Trees

Decision Trees (DT) are predictive models, in which tree like structures are generated. The branches of a tree represent the different features present in the data set, and the leaves represent the different output classes. The model moves from one branch to another by calculating entropy and then information gain to split classes based on a set of given features. There are mainly two types of Decision Trees – models where the outputs consist of a discrete set of values are called classification trees, whereas models with continuous valued outputs are called regression trees.

Entropy is defined as:

$$\sum_{i=1}^{J} p_i \log_2 p_i \tag{1}$$

where p_i are fractions that add up to 1 and represent the percentage of each class present in the child node that results from a split in the tree.

Information Gain = Entropy (parent) – Weighted Sum of Entropy (Children)

$$IG(T, a) = H(T) - H(T|a) \tag{2}$$

Information gain is used to decide which feature to split on at each step in building the tree. At each step a split is chosen that results in the purest daughter nodes, resulting in a small tree and low model complexity.

2.2. Discriminant Analysis

Discriminant Analysis (DA) is a classification problem where output classes are known a priori. New observations are then classified into one of the known outputs, based on the features that are present in the observations. It is a score based system, with each possible output having a score, generated from the features present in a particular observation. This makes DA effective in determining whether a particular group of features is effective in predicting output classes.

2.3. Support vector machine

Support vector machines (SVM) are supervised learning models that can be used for both classification and regression analysis. Using training data, a SVM algorithm creates a model that assigns output classes to new observations based on input features, making it a non-probabilistic binary linear classifier. An SVM model is based on the concept of hyperplanes, where the hyperplanes divide the space into different categories, so that data points of separate categories are divided by a clear gap that is as wide as possible. Data points are then mapped into that same space and predicted to belong to a category, based on which side of the hyperplane they fall. A hyperplane can be defined as,

$$f(x) = \beta_o + \beta^T x \tag{3}$$

where β is known as the *weight vector* and β_o as the *bias*.

The optimal hyperplane can be represented in an infinite number of different ways by scaling of β and β_o. The chosen representation is,

$$\left|\beta_o + \beta^T x\right| = 1 \tag{4}$$

where x symbolizes the training examples closest to the hyperplane. The training examples that are closest to the hyperplane are called support vectors. This representation is known as the canonical hyperplane.

The next step is to compute the distance between a point x and a hyperplane (β, β_o).

$$\text{distance} = \frac{\left|\beta_o + \beta^T x\right|}{\|\beta\|} \tag{5}$$

In the case of a canonical hyperplane, the numerator is equal to one and the distance to the support vectors is,

$$\text{distance}_{\text{support vectors}} = \frac{\left|\beta_o + \beta^T x\right|}{\|\beta\|} = \frac{1}{\|\beta\|} \tag{6}$$

M is a margin that is twice the distance to the closest examples,

$$M = \frac{2}{\|\beta\|} \tag{7}$$

Fig. 1. Location of the five thermostats on the second floor within the building from which the compressors are controlled.

Finally, the problem of maximizing M is equivalent to the problem of minimizing a function $L(\beta)$ subject to some constraints. The constraints model that classifies correctly all the training examples x_i is given below,

$$\min_{\beta,\beta_o.} L(\beta) = \frac{1}{2}\|\beta\|^2 \quad \text{subject to}\, y_i\left(\beta_o + \beta^T x_i\right) \geq 1 \text{ for all}\, i \tag{8}$$

Here y_i represents each of the labels of the training examples. This is a problem of Lagrangian optimization that can be solved using Lagrange multipliers to obtain the weight vector β and the bias β_o of the optimal hyperplane.

2.4. k-Nearest Neighbors

The k-Nearest Neighbors (k-NN) algorithm is a non-parametric supervised classifier, since the complexity of the model increases with the size of the training data. An observation is classified based on its input features in addition to the most common output classes of its neighboring data points. The output class for an observation is calculated, by taking the average of the outputs of its k nearest neighbors.

$$D = \{(x_1, y_1), \ldots, (x_n, y_n)\} \tag{9}$$

D is the set of training data consisting of objects (x_n) and their corresponding classes (y_n)

$$f(x) = y_k, \text{where}\, k = \text{argmin}_i d(x, x_i) \tag{10}$$

$f(x)$ is the output of the classifier, which computes the minimum difference between an input and objects in the training data and then assigns the class of that particular object to the output.

3. Data sets

3.1. Thermostats and compressors

Fig. 1 shows the floor plan of the second floor of the commercial building in Alexandria, VA from where the aggregated compressor power signal is collected. The position of each of the thermostats is labeled, each of which is used to control a single compressor. Thermostat 1 is inside an office room whereas thermostat 4 is inside a computer lab. The remaining three thermostats are placed in hallways on the second floor. It is not economically feasible to measure the power readings from each individual compressor and so a single power meter is used to measure the aggregated power consumption of five compressors.

3.2. Training data

The training data had been collected over a number of months, April through September of 2017 from a commercial building in Alexandria, VA. Data was collected at one-minute intervals and consists of both compressor and air handler unit data. The training data is composed of:

- Real power
- Reactive power
- Phase currents
- Compressor indexes

The values of real power for the compressors vary from 0 kW for when all the compressors are OFF, to a maximum of just under 14 kW for when all five compressors are ON, whereas the maximum reactive power is about 5 kVar. The combined phase currents of compressors vary from 0 A to a maximum of nearly 50 A. The real and reactive powers have similar values when a particular number of compressors are running, even if the combination of compressors are different. Hence it is difficult to distinguish which ones are actually active and so additional features were tested such as the phase voltages of both the compressors and air handlers. However, the phase voltages did not seem to vary significantly when combinations of compressors were changed and so the effect of phase currents was investigated. The phase currents were significantly different for each combination of compressors and were therefore included as a feature in the models for the process of data disaggregation. For example, when two different combinations of three active compressors are running, both have similar compressor power values – close to 8 kW real power and 2.5 kVar reactive power. However, they have different phase currents varying by 1 or 2 A in each case. Therefore, when real and reactive power are taken as the only features, they would not be enough to distinguish between the different indexes. The addition of phase currents as features, which are significantly different between indexes, improves the accuracy of disaggregation.

Training data was collected by testing the 5 compressors in all the possible 32 different combinations, using BEMOSS™ (Building Energy Management Open Source Software) developed by Virginia Tech – Advanced Research Institute for small and medium-sized commercial buildings. An index was assigned to each possible combination and was then matched with the corresponding power and phase current data which had been recorded by BEMOSS. 30 min of training data for each index value was taken. The list of compressor indexes corresponding to the combination of active compressors is given in Table 1.

3.3. Test data

The test data consists of the same four features (real power, reactive power, phase currents and compressor indexes) for both compressors and air handlers that were included in the training data. However, the difference here is that the true value of compressor indexes is not an input to the model, is only used for validation of accuracy – to be compared with the compressor indexes that are predicted by the classifier models. The test data was collected by running each of the 32 combinations using BEMOSS, with each index being tested for 15 min. The testing schedule was recorded, and the data was later retrieved from the one-minute interval data recorded by BEMOSS.

Table 1
List of compressor indexes.

Index	Active compressor
0	**All are off**
1	1
2	2
3	3
4	4
5	5
6	1,2
7	1,3
8	1,4
9	1,5
10	2,3
11	2,4
12	2,5
13	3,4
14	3,5
15	4,5
16	1,2,3
17	1,3,4
18	1,4,5
19	1,2,4
20	1,3,5
21	1,2,5
22	2,3,4
23	2,4,5
24	2,3,5
25	3,4,5
26	1,2,3,4
27	1,3,4,5
28	1,2,4,5
29	1,2,3,5
30	2,3,4,5
31	1,2,3,4,5

4. Data analysis

4.1. Compressor models

The compressor models are trained using real and reactive powers as well as phase currents of only the compressors, in addition to the corresponding true values of the compressor indexes. Test data for all 32 indexes is collected over a period of 24 h, during the month of June 2017 when the temperature was among the highest during the entire month. Once trained, each of the four models – Decision Trees, Discriminant Analysis, SVM and *k*-NN use test data to predict the corresponding compressor indexes. The predicted compressor indexes, generated sequentially by the models for each of possible 32 combinations (starting from 0 to 31) is plotted along with true values of the compressor index at those time instances, for comparison purposes. In the figures given below, the power consumption is only used as a reference to show that power consumption increases as the number of active compressors increases.

Fig. 2 illustrates the pattern of the Decision Trees line which does not perform well at predicting the correct compressor indexes. This is represented by rapid changes in gradient and large deviations from the black true index value line.

Fig. 3 shows that the line for Discriminant Analysis only has a few large rises or drops when compared to the true index value.

Fig. 4 shows how the SVM model does have a few rises and drops however the magnitude of these compared to previous classifiers is less.

Fig. 5 illustrates the *k*-NN model which can be seen to most accurately follow the trend of true index value line, performing significantly more accurately than the other classifiers.

Figs. 2–5 show the pattern of the indexes predicted by the four different classification models, compared with the trend of the true index value at particular time instants for each of the possible 32 compressor indexes, ordered sequentially. The objective of these figures is to be able to visualize the results and determine which model is most accurately able to predict the indexes that follow the trend of the true index value line.

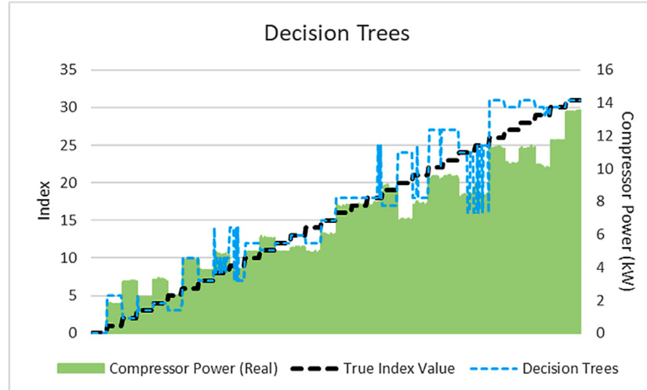

Fig. 2. Indexes generated by Decision Trees model plotted against the true index value of the compressors.

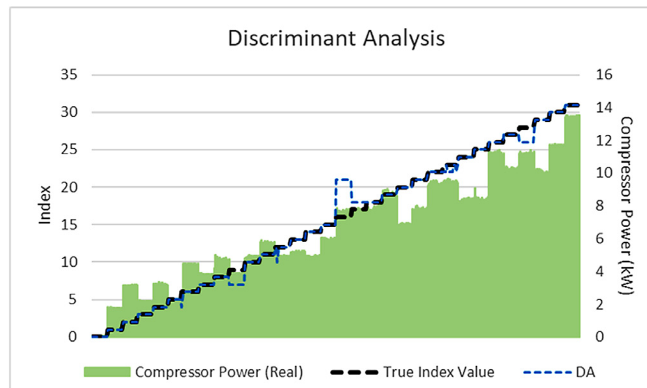

Fig. 3. Indexes generated by DA model plotted against the true index value of the compressors.

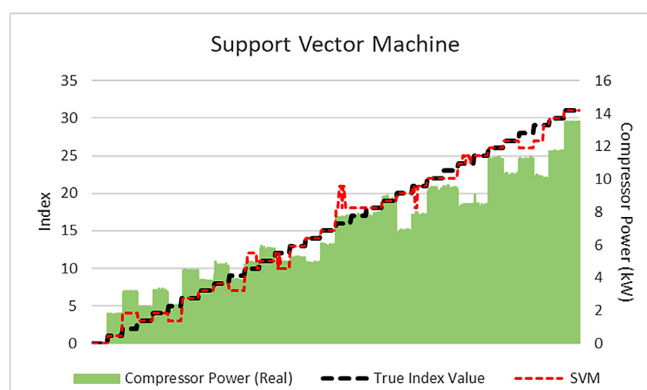

Fig. 4. Indexes generated by SVM model plotted against the true index value of the compressors.

4.2. Combined compressor and air handler models

The combined models are trained using real and reactive powers as well as phase currents of both the compressors and air handlers, and the corresponding true values of the compressor indexes. Using this updated test data, the predicted compressor indexes from each model are again plotted along with the true com-

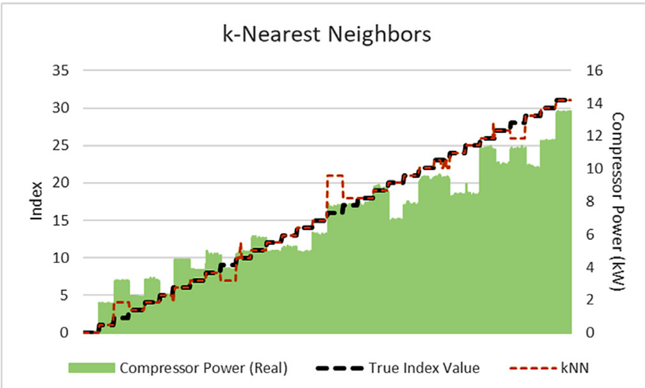

Fig. 5. Indexes generated by *k*-NN model plotted against the true index value of the compressors.

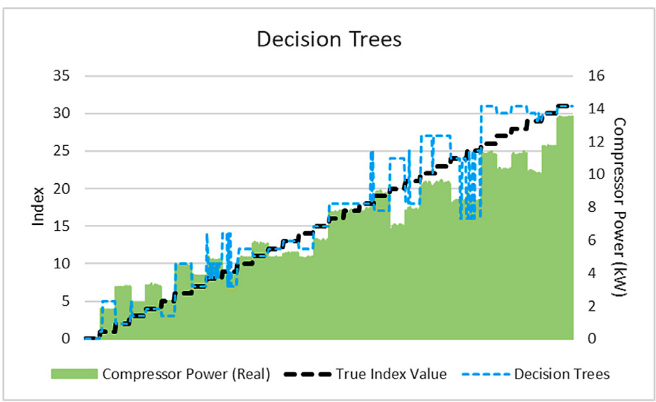

Fig. 6. Indexes generated by Decision Trees model plotted against the true index value of the compressors.

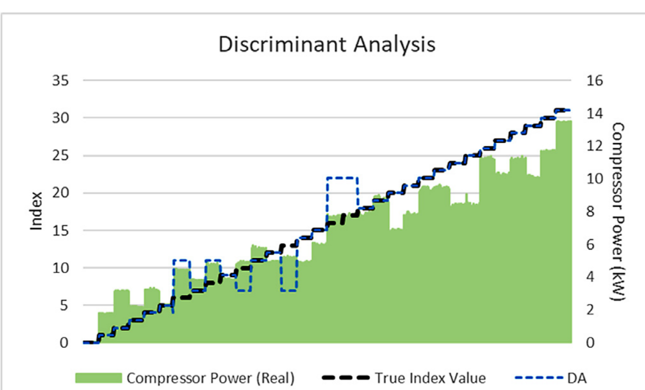

Fig. 7. Indexes generated by DA model plotted against the true index value of the compressors.

pressor index values at those time instances, for comparison purposes. Once again the power consumption is only used as a reference to show that power consumption increases as the number of active compressors increases.

Fig. 6 illustrates that the pattern of the Decision Trees line remains unchanged even for the combined model, meaning that the addition of the phase currents as features did not help to improve the accuracy of the results.

Fig. 7 shows how Discriminant Analysis performs better with fewer rises and drops resulting in a line that follows the true index value line more accurately.

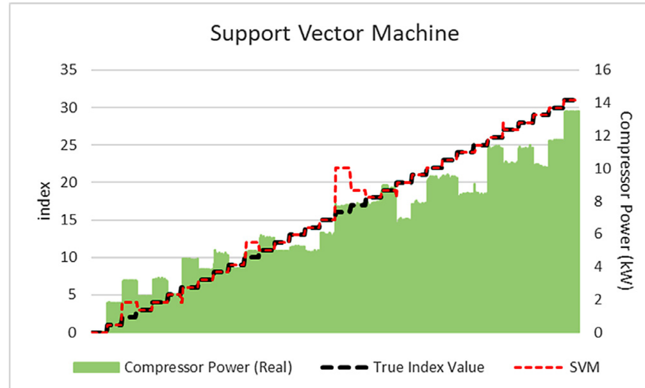

Fig. 8. Indexes generated by SVM model plotted against the true index value of the compressors.

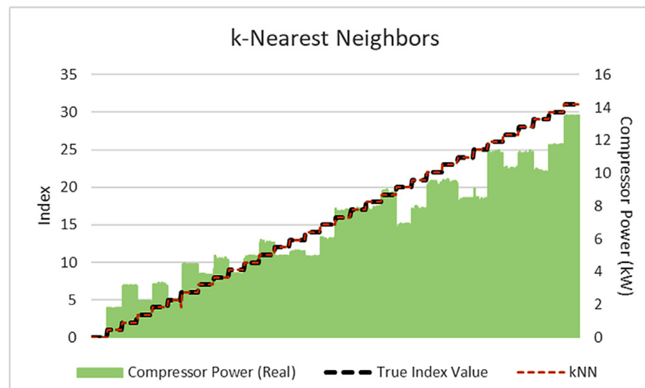

Fig. 9. Indexes generated by *k*-NN model plotted against the true index value of the compressors.

Fig. 8 illustrates how the accuracy of predicted indexes increases with the use of the SVM classifier with very few large rises and drops.

Fig. 9 shows that the line for *k*-NN is by far the most accurate. Small step rises from left to right correspond to accurately predicting the increasing value of the index, as this is consistent with the line of true index values.

Figs. 6–9 illustrate the pattern of the indexes predicted by the combined compressor and air handler classification models, plotted against the line of true compressor indexes at given time instances. These figures are again used to select which model yields the best results, when incorporating the air handler data in addition to the aggregated compressor data.

4.3. Compressor models throughout a 24-h period

Each of the four models were tested using only compressor data over a period of 24 h during August 4th 2017, when the average temperature was among the highest for the entire month. This test was carried out to see if the predicted indexes were consistent with the pattern of aggregated real power consumption for the compressors. The indexes will not equal the power consumption values as they are two different quantities on two different scales. However, it is expected to see similar trends in rises and falls for both. The true value of the compressor indexes is not known in this case, as the goal is to predict the indexes given power and phase current data. The figures showing the indexes generated by each model against the real power consumption of the compressors are given below:

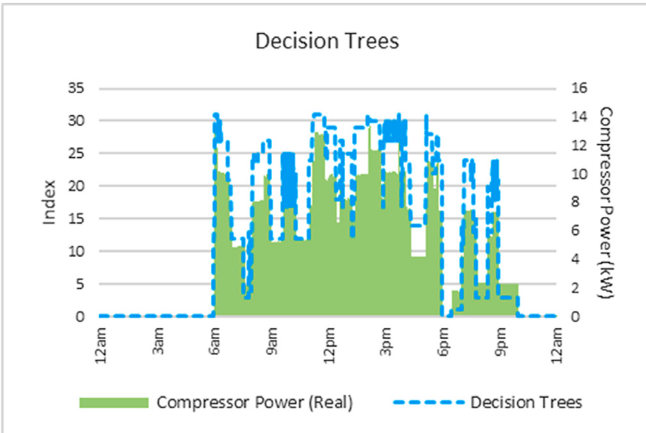

Fig. 10. Indexes generated by Decision Trees model plotted against the aggregated power consumption of the compressors.

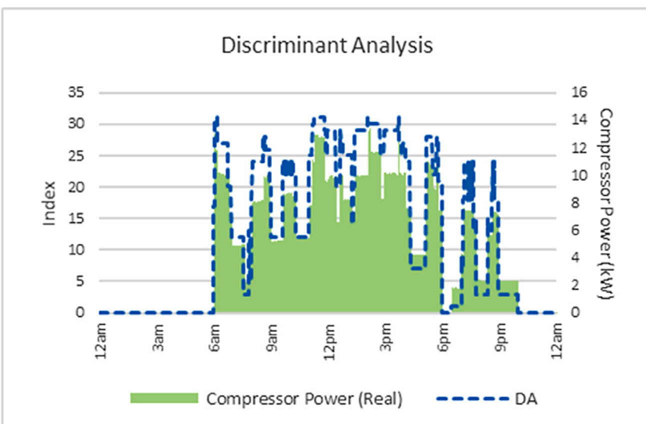

Fig. 11. Indexes generated by DA model plotted against the aggregated power consumption of the compressors.

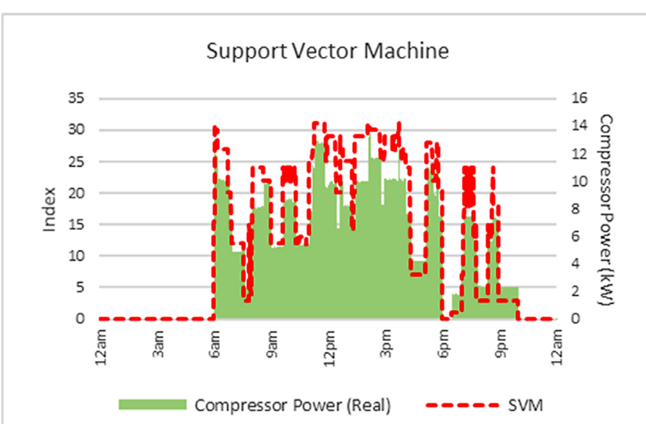

Fig. 12. Indexes generated by SVM model plotted against the aggregated power consumption of the compressors.

Fig. 10 illustrates the pattern of the Decision Trees line which does not accurately predict the indexes and does not follow the pattern of real compressor power consumption well.

Fig. 11 shows how Discriminant Analysis is able to predict indexes more accurately but still has a number of errors.

Fig. 12 illustrates how SVM performs better than the previous classifiers and follows the trend of real power consumption more accurately.

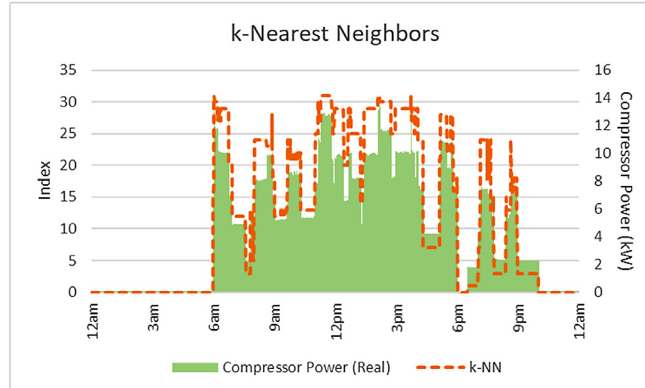

Fig. 13. Indexes generated by *k*-NN model plotted against the aggregated power consumption of the compressors.

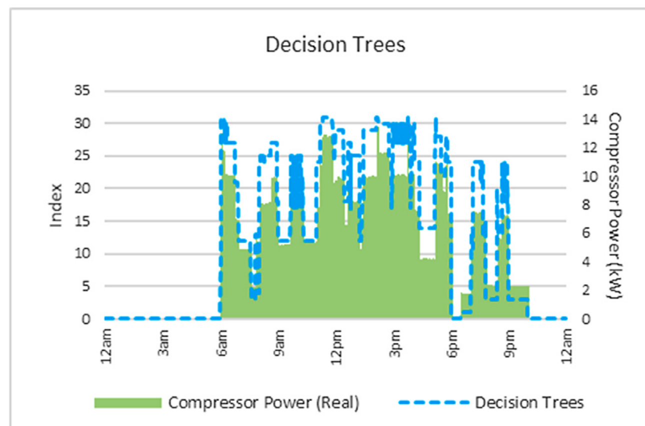

Fig. 14. Indexes generated by Decision Trees model plotted against the aggregated power consumption of the compressors and air handlers.

Fig. 13 shows that *k*-NN performs the most accurately among all the classifiers at predicting indexes and following the pattern of real power consumption.

Figs. 10–13 show the pattern of the indexes generated by the four different classifiers against the real power consumption of the compressors when they use compressor data only, for the entire summer day of August 4th 2017.

4.4. Combined models throughout a 24-h period

The four classifier models were also tested using both compressor and air handler data over the same period of 24 h on August 4th 2017. Figures showing the indexes generated by each of the combined models when plotted against the aggregated real power consumption of the compressors are given below:

Fig. 14 illustrates the pattern of the Decision Trees line has not changed from the line generated by the compressor model, there is no improvement from the combined model.

Fig. 15 shows how the Discriminant Analysis model performs significantly better than Decision Trees and also predicts the indexes more accurately than the previous compressor DA model.

Fig. 16 illustrates that the combined SVM model performs only slightly better than the compressor model, and Fig. 17 shows that combined *k*-NN model is the most accurate model among all at predicting indexes and following the pattern of real power consumption.

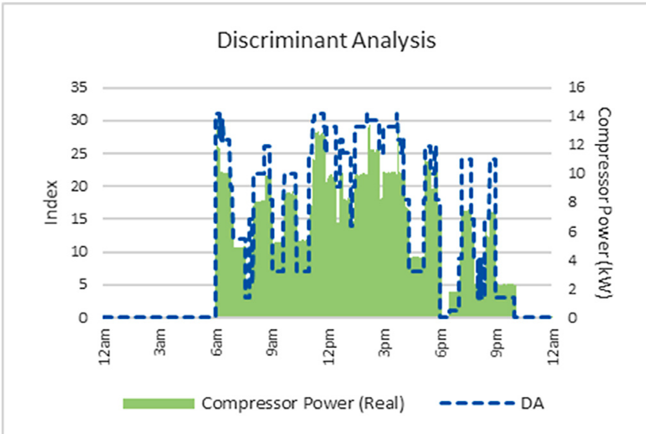

Fig. 15. Indexes generated by DA model plotted against the aggregated power consumption of the compressors and air handlers.

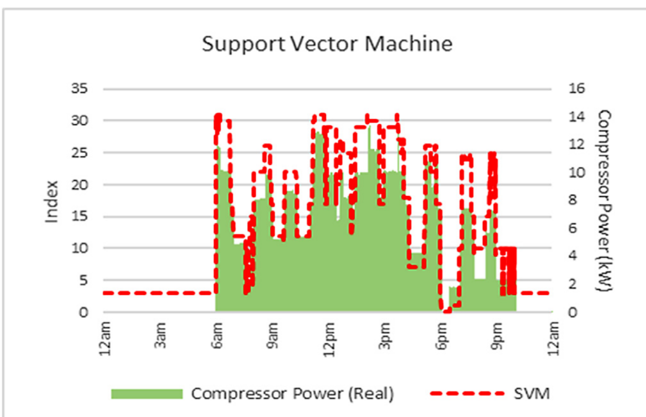

Fig. 16. Indexes generated by SVM model plotted against the aggregated power consumption of the compressors and air handlers.

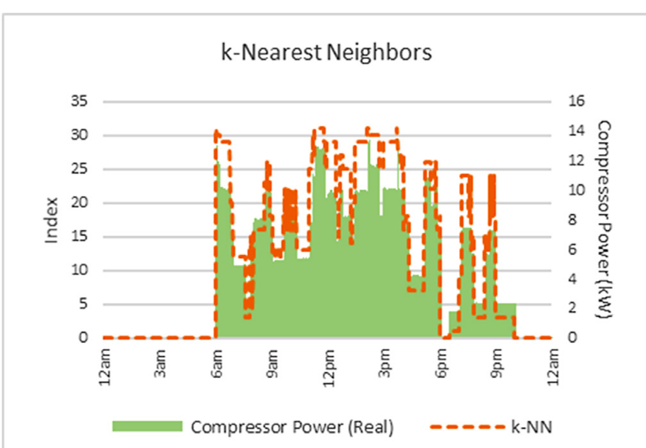

Fig. 17. Indexes generated by *k*-NN model plotted against the aggregated power consumption of the compressors and air handlers.

Fig. 17 shows that combined *k*-NN model is the most accurate model among all at predicting indexes and following the pattern of real power consumption.

Figs. 14–17 illustrate the pattern of the indexes generated by the four different classifiers against the real power consumption of the compressors when they use both the compressor data and air handler data, for a 24-h period during the summer day of August 4th 2017.

Table 2
The accuracy of tested classifiers.

Model	Decision Trees (%)	DA (%)	SVM (%)	*k*-NN (%)
Compressor model	60	81	89	96
Combined model	60	96	90	99

5. Results and discussion

Training data for the four supervised classifier models was collected over a period of several months and then used to evaluate the performance of the models in different scenarios. There were two groups of models simulated: (1) the compressor model and (2) the combined compressor and air handler model. At first each of the four models – Decision Trees, Discriminant Analysis, SVM and *k*-NN were tested to predict all possible 32 indexes consecutively over a period of a day, during the month of June 2017. The figures for each of the models were used to visualize the accuracy of the predicted indexes generated by the classifiers, against the line of true compressor index values. Going from one classifier model to the other starting with Decision Trees and eventually reaching the *k*-NN model, it can be observed that for both the compressor and combined models the accuracy of the models at predicting indexes which are consistent with the pattern of the true index values, steadily increases. The same trend in accuracy can been seen when the models are applied to a given day using the same training data as before. Table 2 shows the comparison in average accuracy between the compressor models and combined models, when predicting each of the 32 indexes consecutively.

The average accuracy of the Decision Trees classifier is the least with no change in accuracy between the compressor models and combined models. All the other classifiers perform significantly better when they use the combined compressor and air handler data compared to just the compressor data. A reason for inaccuracies maybe that air handler units sometimes continue to stay active for a few minutes, even after the compressors have turned OFF. Therefore, this does hamper the accuracy of the combined models by a small amount. After testing each of the indexes, with the exception of the *k*-NN models, the other classifiers each have trouble accurately predicting the following set of five of indexes 9, 16, 17, 23, 28. The accuracy of each of these indexes is less than 50%, which may be due to the limitations of each of the classifiers. Index 9 has compressor power and phase current values which are very close the values for those of index 7. Therefore, classifiers are unable to accurately distinguish between the two indexes. In the case of indexes 16 and 17, combined phase current values for the active compressors are almost identical to that of index 21, and are also close to the values for index 18 and 22, leading to errors in predicted indexes. The compressor and air handler data for index 23 is also almost identical to index 22, and bares some similarity with the compressor power values of index 27, which also results in errors in predicted index. Finally, for index 28, the compressor data is comparable to that of index 26 and the air handler data for index 28 also follows a similar trend to that of index 31. Due to the similarity in data with other indexes, the classifiers are unable to accurately predict the correct index. The results show that among all of the classifier models, the Decision Trees classifier performs least accurately. There is also no improvement in the accuracy of this classifier between the compressor model and the combined model. Decision Trees are based on the concept of Entropy and Information Gain to split different classes (indexes) based on features. In the case of power disaggregation of compressors, many of the features for the compressors are very close to

Table 3
Active compressor time.

Compressor	% of time active
1	32.7
2	33.2
3	52.9
4	26.6
5	36.1

each other. Therefore, the Decision Trees classifier is unable to split indexes efficiently, as many of the indexes have similar and almost identical features. Discriminant Analysis uses the concept of scores which is generated based on the different features that are present. This method results in greater accuracy than calculating probability and has the second highest accuracy for the combined model. SVM is based on the concept of hyperplanes which divide a set of points into different categories based on the spacing between them. Depending on which side of a hyperplane the point falls within, an index is assigned. This method has quite high and comparable accuracies for both the compressor and combined models. Some errors are present as it can sometimes be difficult to separate points which are closely associated with each other. Finally, the *k*-NN models have the greatest accuracy with a peak of 96% for the compressor model and 99% for the combined model. *k*-NN is based on the concept of nearest neighbors. This means that the index value predicted by the model is based on the set of features that are present in a particular data point, in addition to the indexes that have been assigned to neighboring data points with similar features. Therefore, in this study this method seems to work the best because of some indexes having some similar features. As the *k*-NN model has the greatest accuracy when predicting each of the 32 compressor indexes, the *k*-NN model is used as a reference to compare the performance of the other three classifiers when applied to the 24-h test data of August 4th 2017. For the combined models, the indexes predicted by the SVM classifier are accurate to within 78% of the indexes predicted by the *k*-NN model, the DA classifier is accurate to within 75% and the Decision Trees classifier is accurate to within 62%. This follows the same pattern of accuracy as the results for when the models are used to predict each of the 32 indexes individually, further validating the results.

Results from the combined *k*-NN model for the 24-h period of August 4th 2017, show that the third compressor was the most active, as it was in operation for 52.9% of the time. This is consistent with our expectations due to the fact that third thermostat is placed in a long hallway on the second floor, where significant heat is generated due to the movement of people. Hence the thermostat is more active in order to maintain the set point temperature. Table 3 shows the predicted combined *k*-NN results of how long each of the compressors were active.

This pattern of results is also true for when each of the other classifiers is used to predict the indexes for a 24-h period, with the *k*-NN classifier following the trend of power consumption most accurately and further validating the results.

6. Conclusion

Power disaggregation algorithms decompose building level power data into device level power information, enabling the monitoring of individual devices and ensuring efficient energy usage. In this paper a novel power disaggregation technique was presented, in which a single set of aggregated power usage data of multiple HVACs from a single power meter, was disaggregated to identify the state of activity of individual HVAC compressors. This was done by using parameters, such as the one-minute interval real and reactive power of the compressors and air handlers, in addition to phase currents of both. Four different supervised machine learning algorithms – Decision Trees (DT), Discriminant Analysis (DA), Support Vector Machine (SVM) and *k*-Nearest Neighbors (*k*-NN) were tested, using just compressor data and then also using a combination of compressor and air handler data. The results show that in the majority of models, the combined compressor and air handler model is able to predict indexes more accurately than the compressor model. Based on this, the *k*-NN algorithm was found to be the most efficient model in solving the problem of aggregated power disaggregation.

Some limitations of our work presented in this paper include-

1. Loads need to constantly be monitored and have their data recorded by an Energy Management System (EMS).
2. Some combinations of active loads have almost identical power and current readings which leads to a small error in identifying which devices are active.
3. At times air handler units continue to operate for a few minutes, even after the compressors have turned OFF. This gives rise to small errors.
4. When testing the models on a random given day, accuracy of the models cannot be measured, as the true index values are not known beforehand.

The method of power disaggregation that has been explained in this paper can be used by researchers, to solve the problem of disaggregation/classification of similar or identical devices other than HVAC compressors. This is important as the usage characteristics of a number of devices which may be running simultaneously can be distinguished, even when data from these devices is only available in an aggregated form.

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