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A tool for automated detection of hidden operation modes in building energy systems

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Abstract. The integration of renewable energy sources into building energy systems and the progressive coupling between the thermal and electrical domains makes the analysis of these systems increasingly complex. At the same time, however, more and more building monitoring data is being collected. The manual evaluation of this data is time-consuming and requires expert knowledge. Hence, there is a strong need for tools that enable the automatic knowledge extraction from these huge data sets to support system integrators and favor the development of smart energy services, e.g., predictive maintenance. One crucial step in knowledge extraction is the detection of change points and hidden states in measurements. In this work, we present a tool for automated detection of hidden operation modes based on multivariate time series data deploying motif-aware state assignment (MASA). The tool is evaluated utilizing measurements of a heat pump and compared to two baseline algorithms, namely k -Means and k -Medoids. MASA performs particularly well on noisy data, where it shows only a small deviation in the number of detected change points compared to the ground truth with up to 77% accuracy. Furthermore, it almost always outperforms the baseline algorithms, which in turn require extensive preprocessing.

1. Introduction

Building energy systems (BES) hold great potential for reducing the primary energy demand and CO₂ emissions. Therefore, they are in the focus of energy policies in many countries [1]. Besides retrofitting, the efficient system operation is a key to leverage this potential. In fact, about 40 to 70 % of today's BESs operate inefficiently [2, 3]. Additionally, the integration of renewable energy sources and the coupling between the electrical and the thermal energy systems significantly increases the system complexity of BES. Hence, there is a strong need for methods to better understand this augmented complexity while making the commissioning procedure and management more efficient and reliable. As many modern non-residential buildings are already equipped with sophisticated building automation and monitoring systems (BAS) the availability of collected operation data increases significantly [4]. However, BAS are often implemented under high cost and time pressure and with missing naming standards, leading to errors and thus incoherent data sets, which inhibits potential for energy savings [5]. Therefore, the generation of valuable interpretable knowledge about the operational behavior of BES from this data is a challenging task. This motivates the application of machine learning for an automated computer-aided evaluation of monitoring data [6].



In the literature, authors broach the issue of structuring data sets by applying machine-learning algorithms to achieve automated classification and the assignment of data points to the corresponding physical data sources [6]. Furthermore, they try to automatically recognize the physical interaction between sensors and actuators in order to create a causal network of functional relationships for further analysis of the monitored data sources. The results of this research are already promising and may come close to its limits in the near future only lacking the ability for generalization. Nevertheless, the availability of structured data sets enables the application of further data-driven methods for the optimization of BES operation, such as data-driven model predictive control [7, 8] or fault detection [9]. However, although these methods show great potential and favor the mentioned applications, the energetic interpretation of building monitoring data sets still requires considerable expert knowledge of the BES and its individual subsystems in order to derive meaningful measures to improve the system performance. Therefore, we present a tool that enables the detection of meaningful patterns and state changes in multivariate time series data such as building monitoring data in order to support building operators to better understand behavior of individual subsystems.

2. Related Work

Identification of distinctive patterns and detection of change points (CP) in multivariate time series data has become a common task in signal processing for the identification and analysis of complex systems whose underlying states change [10–12]. Although most research is currently being conducted in the medical and financial fields, the topic is gaining attention for engineering applications, e.g., predictive maintenance. Truong et al. [10] give a comprehensive review of existing methods for offline CP detection, whereas offline CP detection is often referred to as *event* or *anomaly detection*. The methods presented typically focus on detecting specific points in time that indicate a change in system behavior, but do not classify the resulting time segments. Nevertheless, this is a crucial step in order to uncover hidden patterns in big data sets and thus support better interpretability. Here, classical distance-based clustering methods such as k -Means or k -Medoids are commonly used in the studies and, therefore, provide a benchmark for the evaluation process [13]. This means that CP detection and clustering are two sequential steps without interaction, whereas Hallac et al. [11] present the Toeplitz Inverse Covariance-Based Clustering (TICC) of multivariate time series. This method performs the segmentation and clustering simultaneously. Each cluster is defined by a correlation network that describes the interdependencies between observations over a short temporal window. Based on the network structure the clusters are calculated, which makes TICC more suitable for multivariate time series analysis. Also for applications in process engineering TICC returns better results as more traditional CP detection methods as demonstrated by Kapp et al. [14]. Based on TICC, Jain et al. [12] present the motif-aware state assignment (MASA) which extends TICC and makes it more robust when noise is present. Therefore, it seems particularly suitable for use in engineering applications.

3. Methodology

In this work, we present a tool for automated detection of hidden operation modes based on multivariate time series data. Figure 1 gives an overview of the implemented tool chain starting from raw building monitoring data. When working with measurements, usually data cleaning and preprocessing is required. In the field of machine learning this usually comprises resampling, denoising and outlier removing, scaling and normalization and "Not a Number dealing" of measurements [4, 14]. Since CP detection strongly depends on discrete changes in data this becomes a challenging step. On the one hand, noise and outliers should be removed, on the other hand, meaningful peaks, which can indicate, e.g. hysteresis control, must be preserved. We accomplish this step by combining a multi step wavelet denoising with a low pass filter

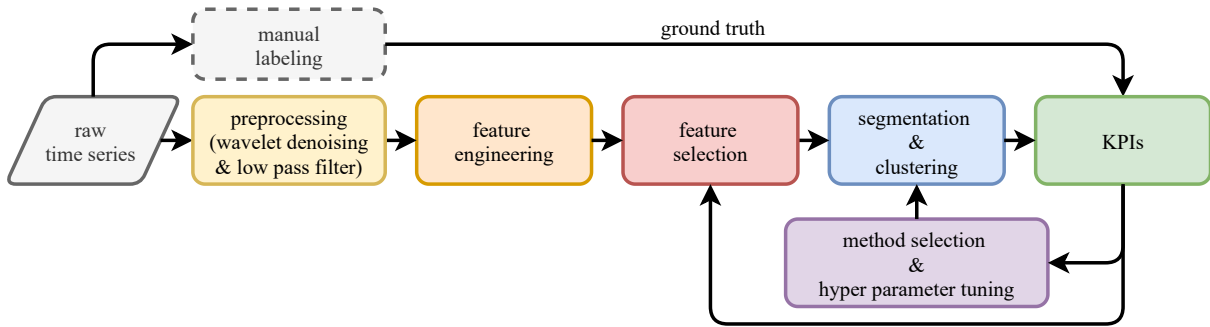


Figure 1: Workflow of the implemented tool chain for change point detection and pattern discovery in multivariate time series data

with high cut off frequency. Afterwards, we manually add features to the data set such as first and second derivative. In the long term, toolboxes such as *TSFEL* [15] or *TSFRESH* [16] may support the automatic extraction of additional meaningful features from time series. However, most of these auto generated features project the entire time series onto a single value. This is very useful when the length of each segment or window is known a priori and the individual segments have the same length, e.g. when clustering daily data in order to find representative days in a year. However, when detecting CPs, the selected segment length can be critical to accuracy because a CP can only be predicted between two windows unless a rolling window method is deployed. Therefore, we only consider continuously computed features. Subsequently, based on extracted features and their correlation we cluster the data set along the time axis resulting in a segmentation. Here each segment corresponds to a previously visible or hidden operation mode of the system.

Since the number of hidden states is unknown a priori, the procedure is repeated while the number of clusters k is increased successively. Furthermore, we vary the clustering method and the corresponding hyper parameters. The methods include k -Means, k -Medoids and MASA. The individual results are evaluated semi-automatically using a selection of well-known key performance indicators (KPI) for evaluating the segmentation process. The *Annotation Error* is the difference between the number of CPs, K^* , in a set of true CPs, $\mathcal{T}^* = \{t_1^*, \dots, t_{K^*}^*\}$, and the number of CPs, \hat{K} , in a set of predicted CPs, $\hat{\mathcal{T}} = \{\hat{t}_1, \dots, \hat{t}_{\hat{K}}\}$ [10]. Here t_i^* denotes the time of a true CP and \hat{t}_i denotes the time of a predicted CP, respectively. *Hausdorff* quantifies the robustness of the process describing the greatest temporal distance between a true CP and the closest predicted ones [10]. However, in order to use the *Annotation Error* and *Hausdorff* in combination with other KPIs, we scale them between 0 and 1 according to equations (1) to (4), where δ_{\max}^* is the maximum distance between two neighbored CPs in \mathcal{T}^* . Finally, for both KPIs, a value of 1 indicates the highest and a value of 0 the lowest score.

$$\text{Scaled Annotation Error} (K^*, \hat{K}) = \begin{cases} 1 - \frac{|\hat{K} - K^*|}{K^*}, & \text{if } K^* \geq |\hat{K} - K^*| \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

$$\text{Hausdorff} = \max\{\max_{\hat{t} \in \hat{\mathcal{T}}} \min_{t^* \in \mathcal{T}^*} |\hat{t} - t^*|, \max_{t^* \in \mathcal{T}^*} \min_{\hat{t} \in \hat{\mathcal{T}}} |t^* - \hat{t}|\} \quad (2)$$

$$\delta_{\max}^* = \max\{t_{i+1}^* - t_i^* \mid \forall i \in \{1, \dots, K^* - 1\}\} \quad (3)$$

$$\text{Scaled Hausdorff} (\mathcal{T}^*, \hat{\mathcal{T}}) = \begin{cases} 1 - \frac{\text{Hausdorff}}{\delta_{\max}^*}, & \text{if } \delta_{\max}^* \geq \text{Hausdorff} \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

Furthermore, we quantify the accuracy by the *F1-Score* ($F_{1,CP}$), which ranges as well between 0 (total disagreement) and 1 (total agreement) between the ground truth \mathcal{T}^* and the prediction $\hat{\mathcal{T}}$ [10]. $F_{1,CP}$ also allows for a user-defined error margin in order to adjust its tolerance. For further details on the KPIs we refer to the literature [10, 14].

4. Application to building monitoring data

In order to evaluate the proposed tool chain and its potential for future application in building energy systems, we apply it to time series data gained from an hardware-in-the-loop (HiL) experiment of a real air-to-water heat pump (HP). The HP is part of a hybrid energy system, which also includes a heat storage and a condensing boiler. The data set \mathbf{X}_{raw} records about 20 h of data in 5 s samples, which in the field of building monitoring corresponds to a relatively high sample rate. It comprises measurements of the temperature at the inlet $T_{in,raw}$ and outlet $T_{out,raw}$ of the HP, as well as of the ambient air temperature $T_{amb,raw}$. Furthermore, it contains information about the electrical compressor power $P_{el,raw}$ and the volume flow \dot{V}_{raw} of the hydraulic connection to the other subsystems. For more details on the data set we refer to Storek et al. [17]. We neither have additional information about the operation states nor any other control signals. However, all of the presented KPIs require a previous knowledge of the true segmentation and its related CPs. Therefore, we manually label the CPs in our data set based on expert knowledge. First, we label CPs based on $T_{out,raw}$ to obtain $\mathcal{T}_{T_{out}}^*$, relying on abrupt changes in the signal, which is comparable with peak finding. Second, we use $P_{el,raw}$ to create $\mathcal{T}_{P_{el}}^*$, whereas also CPs are labeled that indicate smaller jumps. Since $P_{el,raw}$ contains significant noise the CPs cannot be clearly determined and may contain uncertainty. To account for this uncertainty in the labels and possible delays in the measurements, the time tolerance for the $F_{1,CP}$ is set to 30 s. This means that CPs predicted 30 s before and after a true CP will still be evaluated as correctly detected.

The preprocessed data set \mathbf{X}_{proc} is added to \mathbf{X}_{raw} as additional features. Furthermore, we add the temporal derivatives $\dot{\mathbf{X}}_{raw}$ and $\dot{\mathbf{X}}_{proc}$ to the feature set. This finally leads to the feature set shown in equation (5), where \vec{x}_t describes the samples of all features at time $t \in \{1, \dots, t_{end}\}$.

$$[\mathbf{X}_{raw}, \dot{\mathbf{X}}_{raw}, \mathbf{X}_{proc}, \dot{\mathbf{X}}_{proc}]^T = [\vec{x}_1 \quad \dots \quad \vec{x}_t \quad \dots \quad \vec{x}_{t_{end}}] \quad (5)$$

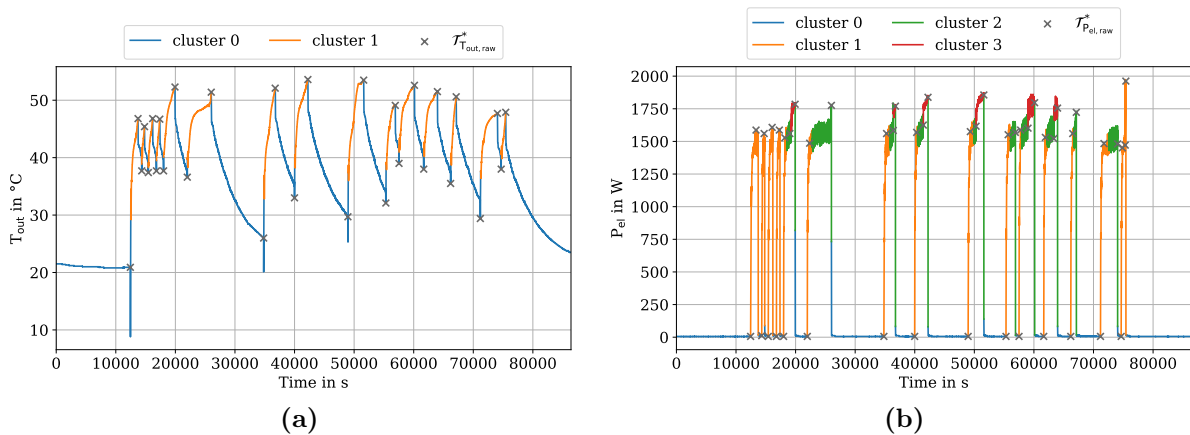


Figure 2: Best solution found for the segmentation of $T_{out,raw}$ compared to $\mathcal{T}_{T_{out,raw}}^*$ (a) and for $P_{el,raw}$ compared to $\mathcal{T}_{P_{el,raw}}^*$ (b). The changes between the clusters indicate $\hat{\mathcal{T}}_{T_{out,raw}}$ and $\hat{\mathcal{T}}_{P_{el,raw}}$, respectively.

Table 1: Calculated KPIs for the two best solution using $\mathcal{T}_{\text{Tout,raw}}^*$ and $\mathcal{T}_{\text{Pel,raw}}^*$ as ground truth, respectively

ground truth ranking	$\mathcal{T}_{\text{Tout,raw}}^*$ 1 st	$\mathcal{T}_{\text{Tout,raw}}^*$ 2 nd	$\mathcal{T}_{\text{Pel,raw}}^*$ 1 st	$\mathcal{T}_{\text{Pel,raw}}^*$ 2 nd
Annotation Score	1.0	0.967	0.917	1.0
Hausdorff Score	0.991	0.994	0.934	0.876
$F_{1,\text{CP}}$ -Score	0.767	0.721	0.580	0.542
Average Score	0.919	0.894	0.810	0.806
number of states	2	4	4	3
clustering method	k -Means	MASA	MASA	MASA
selected features	$\dot{T}_{\text{out,proc}}, P_{\text{el,proc}}$	$\dot{T}_{\text{out,raw}}, \dot{P}_{\text{el,raw}}$	$T_{\text{out,raw}}, \dot{P}_{\text{el,raw}}$	$T_{\text{out,raw}}, P_{\text{el,raw}}$

Figure 2 illustrates the results for the best solutions obtained for $\mathcal{T}_{\text{Tout,raw}}^*$ and $\mathcal{T}_{\text{Pel,raw}}^*$ by using a naive brute force approach for feature and method selection as well as the hyper parameter tuning. Furthermore, table 1 contains the calculated KPIs of the best and the second best solution, where the solutions are selected by means of the highest average score of all KPIs. For $\mathcal{T}_{\text{Tout,raw}}^*$, clustering with k -Means obtains the best average score using the preprocessed data $P_{\text{el,proc}}$, and the derivative of $T_{\text{out,proc}}$ as features. It detects two clusters which aligns with the expected number of clusters. Figure 2a shows that the segmentation matches $\mathcal{T}_{\text{Tout,raw}}^*$ very well. The second best solution obtained using MASA holds similar results although four clusters are detected. However, in this study we do not evaluate the segment allocation. More importantly it selects features directly derived from raw data, which indicates that MASA is more robust to noise in the signals. This assumption is also confirmed by the results of the experiments based on $\mathcal{T}_{\text{Pel,raw}}^*$. Here, MASA even detects complex patterns and the corresponding CPs. Overall MASA seems to be superior to the k -Means and k -Medoids for real world applications with noisy data sets. Considering that the selection of the best solution strongly depends on $F_{1,\text{CP}}$, this also results in a dependence on the selected tolerance threshold. Hence, this parameter needs to be chosen very carefully depending on the expected concurrency of measurements in the analysed system. In fact, raising the tolerance to e.g. 60s raises the $F_{1,\text{CP}}$ significantly for all solutions. However, the best found solutions in this scenario are all obtained by clustering with MASA based on the raw data. This not only indicates that MASA generally shows better performance but also that the results do not depend on the extensive preprocessing of the features. Nevertheless, the simple analytic feature engineering steps conducted in this work already lead to satisfying results and give valuable insides to the inner system control strategy.

5. Conclusion

In this work we present a tool chain for unsupervised detecting of change points in building monitoring data. Initially, the chain comprises the typical process steps of a machine learning pipeline. In order to evaluate the overall process, we conduct a case study based on measurements of a air-to-water heat pump, where we neither have knowledge about the true change points nor the internal control signals. Therefore, the data is labeled based on expert knowledge in order to calculate meaningful KPIs. Executing the pipeline using naive brute-force, varying the provided features, the detection algorithm and the corresponding hyper parameters, we find that the motif-aware state assignment (MASA) algorithm shows the overall best performance. Furthermore, we observe that the best solutions are not only found by MASA, but also that the selected features are based on the noisy raw data. This indicated that MASA is well suited for

real world applications and that complex preprocessing is not always mandatory. Nevertheless, future work will introduce primary component analysis (PCA) to investigate whether it favors the results. In addition, a comparison with supervised methods, e.g., Long Short Term Memory (LSTM) networks, is desirable. Finally, we draw the conclusion to provide a valuable tool chain for change point detection that will support the understanding of building energy systems and favor the development of smart energy services.

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