Data-based Predictions of Load Profiles for Buildings for Flexible Optimization

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ABSTRACT: The flexible usage of modern buildings results in varying load profiles. This means that internal loads, which are often critical for both energy consumption and the thermodynamics of the building, can be of the type of residential or commercial buildings, or a combination of both. Nevertheless, typical usage patterns arise in residential and non-residential buildings. These electric load profiles can be measured, and based on this measurement data, dynamic models can be designed that serve as a basis for prediction. Such predictions, which are adapted to the specific use case, can subsequently be used for optimized operation management (heating/air conditioning, storage management, sector coupling, etc.). In the present work, dynamic mode decomposition is used for data-driven modeling and predicting the load profiles of buildings with mixed usage. This enables adaptive yet reliable predictions in buildings with time-varying mixed usage. Utilizing the structure of a Takagi-Sugeno fuzzy system for energy management a seamless weighting between residential and commercial usage becomes possible.

1 INTRODUCTION

Since people generally spend a large part of their time indoors, the energy consumption of buildings is increasing rapidly. The same holds for production facilities. The amount of electricity fed into the power grid must always match the amount consumed so that frequency and voltage remain stable. Load data is, therefore critical for planning power distribution networks and optimal production capacity. Accurate knowledge of building load is equally crucial if small distributed energy technologies are to be optimally sized. As a result, policymakers are encouraging the development of effective approaches to quantify the load impacts of demand response programs. Modern model-predictive control needs predictions of all disturbances, like outdoor temperature, solar radiation, and electrical load profile for optimal system management. There are numerous methods for estimating energy use in buildings. The various methods can be broadly classified into three groups: statistical regression analysis, intelligent computer systems, and energy simulation. In this paper, an adaptive computer algorithm is presented that can flexibly predict electrical energy consumption in both residential and other buildings based on dynamic mode decomposition (DMD).

In a previous work (Killian & Kozek 2019), an electric load prediction method for a smart home was presented. It is based on the feature extraction from historic data, clustering of different load profiles, and a Kalman filter bank with a hypothesis test to select the currently valid profile. The load profile is consequently also used for determining the optimal heating strategy. The method is self-learning, i.e., after some time different features are detected in the data and can be successfully detected. The main disadvantage is the strictly switching behavior, meaning only a single specific load profile can be active. In the approach presented here, the case of mixed residential and non-residential usage of a building should be covered. This means that at the same time different proportions of the individual load profiles can add up to the effective total load profile. In order to cope with this problem, dynamic mode decomposition (DMD) is utilized here. DMD is a well-established method to 1) parametrize a linear dynamic model from on-line data and 2) use this model for predictions of future trajectories. If multiple models are identified, an internal multiple model (IMM) approach can be utilized to select the most probable model as the active one. Alternatively, using a Takagi-Sugeno fuzzy structure a continuous blending of the model outputs can be achieved, thus obtaining near-optimal control of non-linear systems (Böhler et al. 2020). This formulation allows for seamless superposition of residential and non-residential load profiles based on the evaluation of online data.

In Luo & Oyedele (2022), an artificial neural network is designed to predict the electric power consumption in buildings with a moving horizon. A number of 33 input variables is utilized to predict the load profile. The authors show that an R^2 of more than 97% can be consistently obtained. However, the large number of exogenous input variables requires extensive knowledge of all relevant influences. The same team has already proposed a feature extraction algorithm using neural networks to achieve the same goal (Luo et al. 2020). They also use a detailed set of variables for weather description plus information on the calendar, including holidays. R^2 values larger than 92% are reported. Again, the applicability of the algorithm critically depends on the availability of detailed data.

A different approach has been chosen in Luo et al. (2020): A thermodynamic reduced order model is derived to analytically describe the individual building zones. Equivalent-circuit models for each building zone are coupled to result in a linear 82-states states space model. An extended Kalman filter is employed to obtain the estimates. The authors concede that accurate knowledge of the model parameters and input variables is crucial for successful implementation. In Andersen et al. (2021), a tool for generating aggregated load forecasts only based on floor area and outdoor temperature is presented. A simple energy efficiency categorization is performed prior to the prediction. In winter time, the heating load could be predicted quite well, while consumption in summer time was not predicted accurately.

A simple method for load prediction is reported in Lemence & Tamayao (2021). For the purpose of power supply for healthcare units in rural areas, the electrical power consumers and converters of the specific premises were recorded. Based on that data and using historic measured consumptions a grid-connected and an off-grid scenario was considered. Using an existing simulation platform for buildings the load profiles for different scenarios were obtained. Obviously, this method requires high effort in gathering all the information necessary for setting up the central simulation. A good overview on load modeling technologies is given in Lindberg et al. (2019) and Ramokone et al. (2021). The authors propose an energy signature curve for each considered non-residential building, and the final model considers the complete calendar, the ambient temperature, and other explanatory variables. It is interesting that this model is intended for long term (e.g. 10-30 years ahead) studies. Accordingly, the accuracy over a 24-hour time span is limited.

Another paper dealing with the load prediction of non-residential buildings utilizes simple statistics Coughlin, et al. (2009). Although in this way a basis for clustering or data preprocessing is provided, it cannot be directly used for dynamic predictions. It is rather used for predicting the probability of e.g., load sheds to support planning and analysis of grid operators. A different approach is reported in Pedersen, et al. (2008). The authors use piecewise linear regressions for heat load models and probability distribution analyses for the electrical load profile. The background knowledge of generalized electricity load profiles is used to obtain a more robust result. The load prediction method presented can be used for the purpose of planning for mixed energy distribution systems. In Chuan & Ukil (2015), it is shown that residential buildings need to be modeled differently to non-residential buildings as the electrical load profiles differ considerably. Gathering extensive data of all household appliances a model is set up and validated, although no decisive Figures are given to evaluate the model quality.

In the remainder of this paper, we outline the approach to use linear dynamic models for adaptive prediction of load profiles. This feature can be combined with internal multiple model (IMM) observers for fast-tracking of current load profiles. Another application is to utilize the load predictions in a Takagi-Sugeno Fuzzy controller for adaptive-predictive energy management.

2 DATA-BASED MODEL EXTRACTION

This paper identifies the corresponding utilization profiles from historical data by using clustering methods like K-means, which is an unsupervised machine-learning algorithm. Additionally, the singular value decomposition (SVD) is used to reduce the dimension of the data prior to the learning process of the k-means Clustering. As shown in Fig. 1, the raw data is reduced offline into a finite number N of load profiles. The load profiles represent the significant features in a static model description.

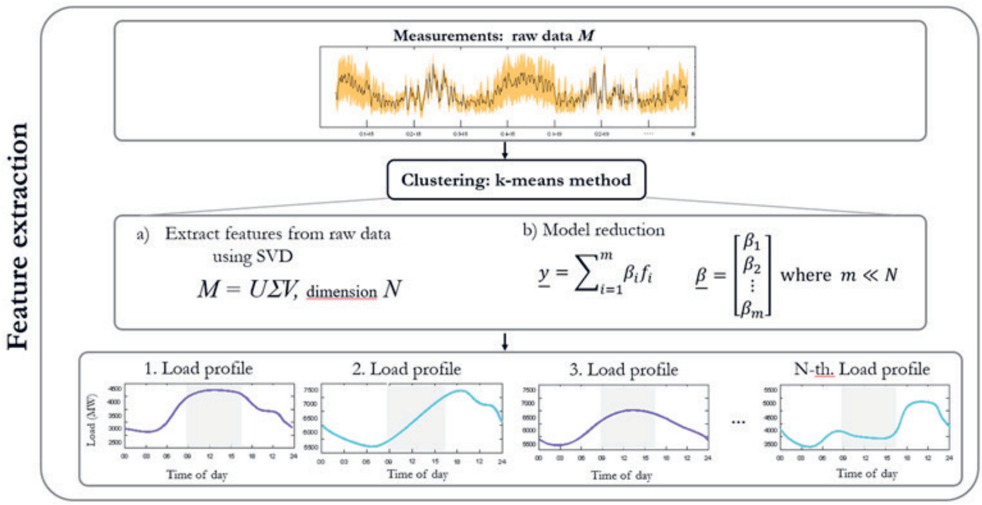

Fig. 1: Extraction of features (load profiles) from historic data using k-means clustering method with dimensional reduction

Based on the offline models and the clustered data, the online learning of the dynamic models is implemented. In online operations, these models are used to

1. Quickly determine which of the identified profiles is present.
2. Provide predictions for the future trend based on the identified models.
3. Superimpose valid models weighted by internal model models

For the online model learning progress, we apply the concepts of dynamic mode decomposition with control (DMDc) (see Narasingam & Kwon 2017; Proctor et al. 2016) to capture the local dynamics associated with the clustered load profiles and develop multiple models that describe the fully-resolved data. Fig. 2 illustrates the learning process where the clustered data is first collected and organized in corresponding snapshot matrices.

Following an approximation of the dynamic system matrices and resulting in a model, representing the dynamic properties of the used clustered data. Each cluster has to go through this learning process resulting in N linear dynamic models, which also can be updated online.

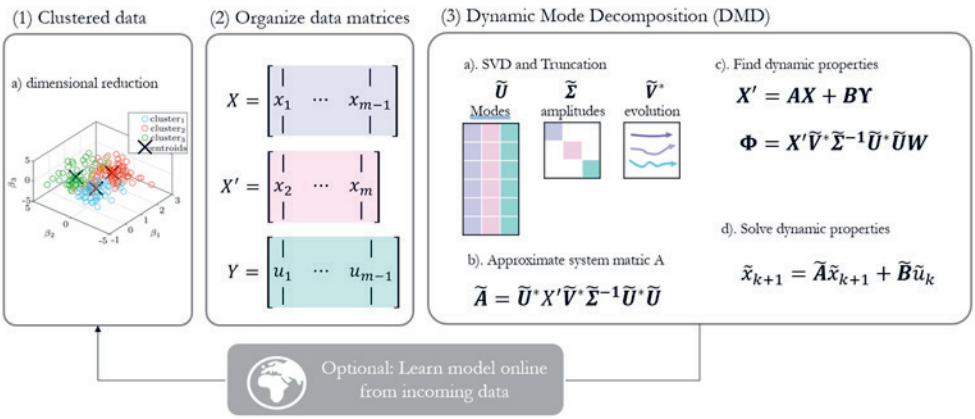

Fig. 2: Linear dynamic model identification based on clustered data

3 PREDICTION AND CONTROL

As shown in the previous section, we apply the DMDc and combine the learning model concept with the interacting multiple model approach (IMM), as shown in Fig. 3 (left). The IMM is utilized to improve the accuracy of the predictions. The IMM algorithm, proposed by Blom and Bar-Shalom (Kirubarajan & Bar-Shalom 2003; Blom & Bar-Shalom 1988), switches among the set of designed models. The final prediction is obtained by controlling a Markov chain and the estimations of a weighted sum of Kalman filters. Each Kalman Filter is designed by a model learned by the method described in this paper.

The presented concept is the basis for efficient modern optimization frameworks like the model predictive controller (MPC) (Killian & Kozek 2019) and delivers valuable information, especially for storage management systems, see Fig. 3 (right). In addition, the method can also be used for different energy sources regardless of pure electrical or thermal consumption. Also, mixed and coupled (thermal-energetic) building models can be mapped and optimized.

The proposed method is highly flexible, with no limitations on the number of usage patterns, building size, house type, or building location.

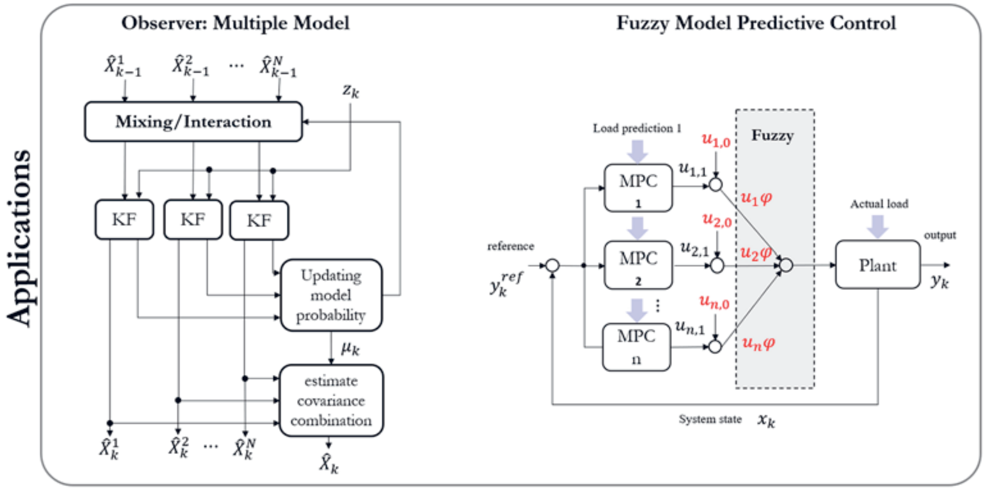

Fig. 3: Applications for dynamic mode decomposition in buildings. Left: Interacting multiple models (IMM) for prediction of future loads. Right: Fuzzy model predictive control for building energy management utilizing predictions from IMM

4 BUILDING APPLICATION ISSUES

Crucial for the implementation of this method is the availability of measurements. For the presented control application, a dynamic building model must be set up in addition. As shown in Killian & Kozek (2016), setting up building models can be challenging and needs expert knowledge and also more data.

A general challenge of data-based methods is ensuring that the data is representative and free of systematic errors or bias.

The computation of Singular Value Decompositions (SVDs) is also crucial for a successful application. The computation of the SVD can be intensive and may require significant processing power. However, using cloud computing, SVDs can be performed efficiently and effectively.

In summary, to use the presented method efficiently, it is necessary to set up a dynamic building model, compute SVDs, and ensure that the data used is representative and free from systematic errors. While these steps can be time-consuming and require specialized knowledge, they are essential for achieving accurate and effective control.

5 CONCLUSION

Overall, this method is an essential extension of monitoring and controlling through prediction. The proposed data-driven approach offers offline self-learning and online adaptation, which provides a flexible building management framework. An extension of this method to production facilities is straightforward.

Load profiles of modern buildings become increasingly more complex and difficult to categorize. The proposed solution offers a methodology to automatically identify the specific load profiles of a building even when mixed residential/commercial usage exists. The method can easily be extended to online adaptation, thus tracking the changing usage of a building over time.

For some years to come the limited computational resources of a building automation system will not allow the straightforward implementation of the method. Nevertheless, using cloud computing, the proposed method could even be offered as a commercial service.

LITERATURE

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