Smart home management system with extensive disturbance predictions

M. ZAUNER, M. KILLIAN, L. BÖHLER, M. KOZEK
Vienna University of Technology, 1060 Vienna, Austria
A. LEITNER, R. GOLDGRUBER
evon GmbH, 8200 Gleisdorf, Austria
G. GÖRTLER
FH Burgenland, 7423 Pinkafeld, Austria

ABSTRACT: Minimizing the energy consumption of residential buildings while providing maximal thermal comfort is a current challenge. In this paper a smart home management system is proposed which is able to globally optimize the thermal and electrical systems of a modern smart home, instead of locally optimizing each subsystem alone. The used controller consists of a mixed-integer quadratic program (MIQP) implemented into a model predictive controller (MPC) scheme. The MIQP-MPC is capable of handling multiple energy sources, respecting external grid-based constraints, as well as handling the electrical heating systems. Furthermore, extensive disturbance prediction methods for the most influencing external and internal disturbances of a smart home are presented. Those disturbances are ambient temperature, solar irradiation and occupancy. With the predictions of the future occupancy, the MIQP-MPC is also able to heat the building only when needed. The MIQP-MPC can help future smart grids to reduce the peak loads and can act as an energy storage, if grid-side energy production is high. Another feature of the proposed controller is a simple-to-use interface for the end-user. This interface enables the end-user to tune the controller in an intuitive way to their individual demands. Therefore, the end-user is able to balance the partially conflicting goals of the MIQP-MPC. Those goals are the reduction of running costs, the maximal usage of renewable energy sources, and the minimization of the temperature deviation from the set point.

1. INTRODUCTION

The building sector accounts for 20 % to 40 % of the energy consumption, where one-third of this consumption attributes to heating and cooling. Model predictive control (MPC) can achieve considerable reductions in energy consumption while also enabling the integration of smart homes into future smart grids.

Smart grids are necessary, because residential loads are to scale responsible for seasonal and daily peak demands in power consumption. About 20 % of the power generation capacity is only used for meeting the peak demands that occur approximately 5 % of the time. With the usage of demand response schemes the peak power demand can be decreased and the energy consumption can be linked to the energy production capacities. The authors of (Haider et al., 2016) highlights the need for demand response schemes in the future. In general, two different approaches are considered: "incentive based" and "price based" demand responses. The first one is invasive as the utility company has direct access to customer appliances and controls them directly. The second approach offers the customers time-varying rates that reflect the abundance/scarcity of energy. This schedule shifts the decision-making power towards the consumer and rewards those who optimize their energy consumption according to the situation present in the grid.

Modern smart homes are more often equipped with photovoltaic (PV) systems and residential battery systems. Optimally managing those systems under the constraints imposed by the previously mentioned smart grids is difficult. Managing additional household appliances or scheduling the usage times of those appliances further adds complexity to the problem. As soon as discrete variables (ON/OFF states, discrete starting times, etc.) are present in the optimization criterion, a mixed-integer solver is needed. An advantage of MPC schemes, opposed to traditional control schemes, is that they can be used with mixed-integer problem statements.

Another advantage of MPC schemes is the ability to utilize predictions of the future conditions in the controller to pre-emptively react to these future conditions. This allows the MPC to look ahead and plan an optimal trajectory, instead of just reacting to the current conditions. The ability of the MPC to pre-emptively react is of course dependent on the quality of the available predictions. By improving the quality of these predictions, the overall performance of the MPC will also improve. The only major disadvantage of MPC are the relative high computational cost for calculating the future inputs. With the installation of more powerful hardware in home automation systems and the usage of more efficient algorithms for optimizations, the high computational cost for calculating the future inputs is not a limiting factor anymore. For even more computational expensive tasks, cloud solutions could be used, since literally all modern smart home systems are connected to the internet.

Traditionally, smart home controllers are also responsible for providing a comfortable indoor climate. Usually the end-user defines a static reference temperature according to their preferences. While holding the defined reference temperature during the whole day guarantees maximum user comfort, it is not necessary during the times the user is not at home. If the smart home controller would know when it is not going to be occupied, it could minimize the needed energy for heating/cooling while remaining near maximum user comfort. While assuming a price-based demand response scheme in the smart grid also adds a monetary aspect to the heating/cooling task. For example could it be beneficial to overheat the smart-home during the time the user is not at home if the energy-prices are low during that time. This, of course, is in direct conflict to the goal of minimizing the overall energy consumed. Therefore, the smart home managing system has to balance partially conflicting goals against each other.

In this paper a smart home management system is presented that is capable of achieving globally optimal performance with respect to the electrical system and also the thermal system. The presented system also takes advantage of sophisticated self-learning occupancy predictions to minimize the energy consumption while providing full user comfort. The rest of the paper is structured as following: Section 2 gives an overview over the modelling processes. Section 3 illustrates the MPC scheme, used in the smart home management system and provides an example on how the user can balance the conflicting optimization goals. The 4th Section highlights the methods to gather the various predictions, which are necessary for the MPC. Section 5 concludes the paper and gives a brief outlook.

2. MODELLING

In this section the modelling process of the building is presented. Since the proposed smart home management system is not only responsible for the heating/cooling tasks in the building, but also responsible for the power management, the model has to incorporate both the thermal and electrical behaviour of the building. In this work an electrical heat pump was chosen as primary heating system for the building, which couples the thermal model to the electrical model. The user places constraints/demands on both the electrical and the thermal sub model (e.g. scheduling the household appliances or placing a constraint on the indoor temperature). Fig. 1 gives an overview of the modelled components and their interactions.

2.1 THERMAL SMART HOME MODEL

Creating a suitable model for a building automation is one of the most time-consuming parts (Privara, 2013). Deriving a first principle model is not only a time and cost intensive task, but also prune to errors since a completely new model has to be created for every individual building. A much faster and simpler approach is to model the characteristics with low order models and parametrize them via black-box methods (Killian et al., 2015). This also allows for automated adaption schemes for the smart home management system, which greatly simplifies the commissioning process and reduces potential errors (Killian et al., 2018a).

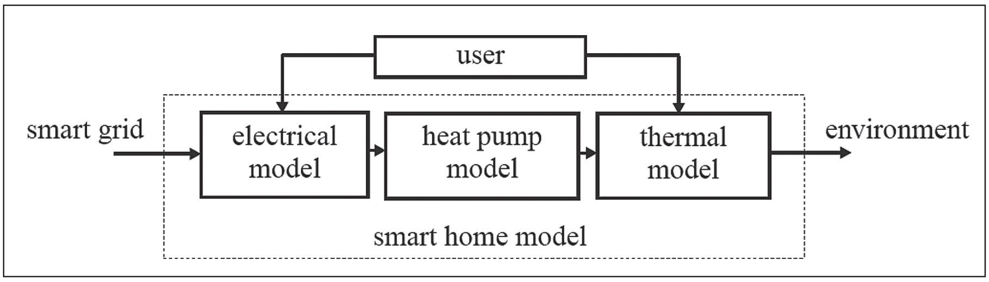

Fig. 1: Overview of the modelled components and their interactions.

The thermal model of the building is assumed to be an ordinary discrete-time linear time-invariant state-space system of second-order, as given by:

$$\boldsymbol{x}_{k+1} = \boldsymbol{A}\boldsymbol{x}_k + \boldsymbol{B}u_k + \boldsymbol{E}\boldsymbol{z}_k, \tag{1a}$$

$$y_k = \boldsymbol{C}\boldsymbol{x}_k. \tag{1b}$$

Note that u_k is the input or manipulated variable, in this work the supply temperature of the heating system, and $\boldsymbol{z}_k$ is the input disturbance vector. The considered disturbances are ambient temperature, solar irradiation and occupancy. Occupancy not only includes the emitted body-warmth of the users but also the heat emitted by the electrical appliances that they might operate. The output y_k is the indoor room temperature of the smart home. The matrices of the state-space system are given as the system matrix $\boldsymbol{A}$, the input matrix $\boldsymbol{B}$, the output matrix $\boldsymbol{C}$, and the disturbance matrix $\boldsymbol{E}$, while the state vector is given as $\boldsymbol{x}_k$. For a more in-depth description of the model and the modelling process, the reader is redirected to (Killian et al., 2018a).

2.2 ELECTRICAL SMART HOME MODEL

As mentioned before, not only the homes will become smarter in the future, but also the grids supplying those. Therefore, the grid was modelled with variable prices for buying/selling energy and limits for the amount of power the smart home is allowed to draw/sell. Furthermore, a battery storage is included in the model, as well as a renewable energy source in the shape of a PV system with a PV converter. The internal electric load of the smart home is separated in shift-able loads and non-shift-able loads. The shift-able loads are for example the power draw of the electrical heat pump, a smart freezer or a dishwasher. The dishwasher in this example represents a non-interruptible schedulable load for which the MIQP-MPC will optimize the starting time, subject to a user defined latest activation time. Fig. 2 shows the individual components of the electrical subsystem and their connections. Furthermore, Fig. 2 introduces the variables p_{out}^{grid} (power sold to the grid) and p_{in}^{grid} (power consumed from the grid), p_{out}^{bat} (power discharged from the battery) and p_{in}^{bat} (power charged into the battery) as well as p^{PV} (power generated by the PV system) and p^{house} (power consumed by the smart home).

For a more detailed description of the model and the modelling process, see (Killian et al., 2018a).

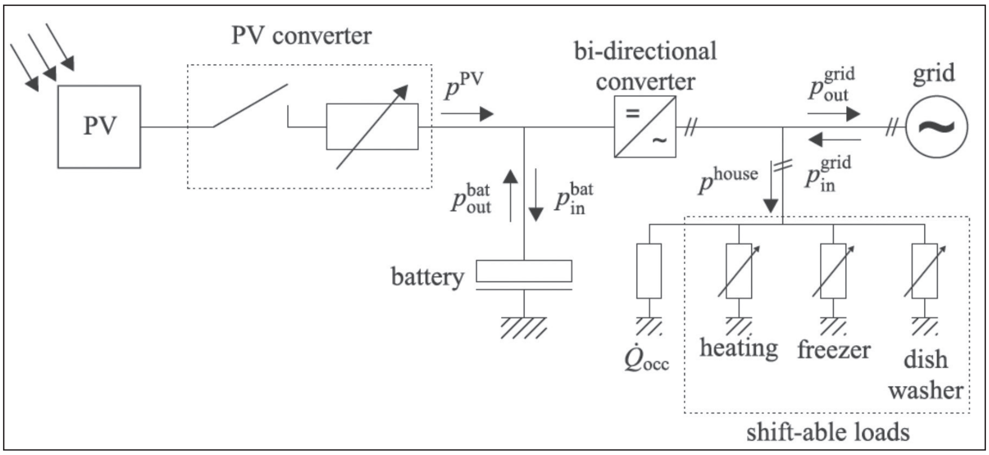

Fig. 2: Scheme of the electrical smart home model and its components.

3. MODEL PREDICTIVE CONTROL SCHEME

The MPC scheme in the smart home management system is formulated as a MIQP problem. This enables the management system to optimally manipulate and schedule continuous variables as well as discrete variables. The overall idea of the specific control structure is illustrated in Fig. 3. The plant has been discussed in detail in Section 2. In this work it is assumed that a PV system complements the electrical part of the plant.

The manipulated variables $\boldsymbol{u}^*$, generated by the MIQP-MPC, are the inputs for the electric plant as well as for the heat pump (heat supply temperature). The output of the plant is the indoor temperature ϑ^{act}, as well as the raw data for the occupancy prediction described in Section 4.2.

The inputs for the MIQP-MPC are the reference temperature set by the user ϑ^{ref}, the user weights, the energy prices g^{buy} and g^{sell} of the smart grid, various measurements from within the smart home, and the result of the occupancy prediction.

The aforementioned user weights are used to tune the conflicting optimization goals in the global optimization criterion of the MIQP-MPC given by:

$$\min_{\Delta \boldsymbol{u}} J(\boldsymbol{u}) = \sum_{k=0}^{n_p} \Big[\big(\vartheta_k^{ref} - \vartheta_k^{act}\big)' \boldsymbol{Q}_k \big(\vartheta_k^{ref} - \vartheta_k^{act}\big) + \Delta \boldsymbol{u}_k' \boldsymbol{R}_k \Delta \boldsymbol{u}_k + \big(g_k^{buy} \boldsymbol{S}_k + \boldsymbol{P}_k\big) p_{in,k}^{grid} - g_k^{sell} \boldsymbol{S}_k p_{out,k}^{grid} \Big]. \quad (2)$$

The weighting matrices define a trade-off between comfort ***(Q)***, monetary cost ***(S)***, and energy efficiency ***(P)*** of the smart home. The constant value *R* is used to weight the rate of change of the manipulated variables.

This trade-off can also be visualized by a triangle as shown in Fig. 4. The end-user can select an interior point of the triangle. The closer the point is to one of the edges, the more this goal is prioritized. This selection process is simple and user-friendly, and no complicated or abstract numerical figures are needed.

If the user would select a point near the…

- 'eco' corner, the MPC would prioritize the usage of renewable energy (smart home PV system). This is done by penalizing the amount of power consumed from the grid.
- 'cost' corner, the MPC would try to minimize the monetary cost of operating the smart home. This is done by penalizing the cost of buying power from the grid, but also by rewarding selling power to the grid.
- 'comf' corner, the MPC would maximise the user comfort. This is done by penalizing the quadratic deviation from the reference temperature defined by the user.

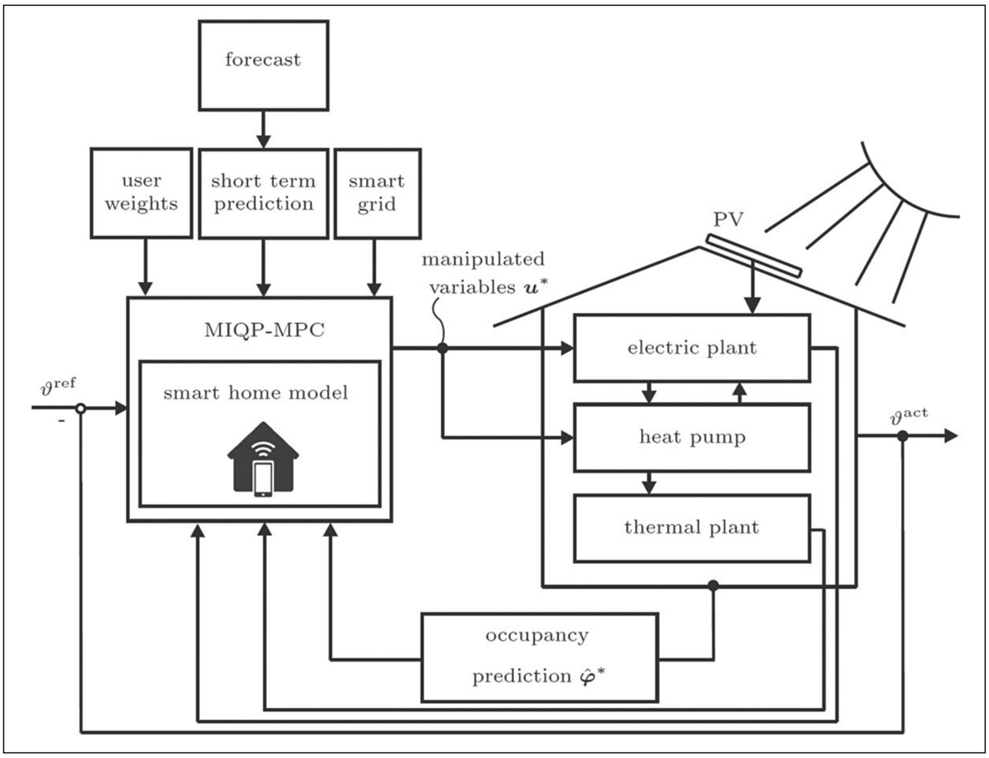

Fig. 3: Schematic control structure of the smart home MPC and the plant structure.

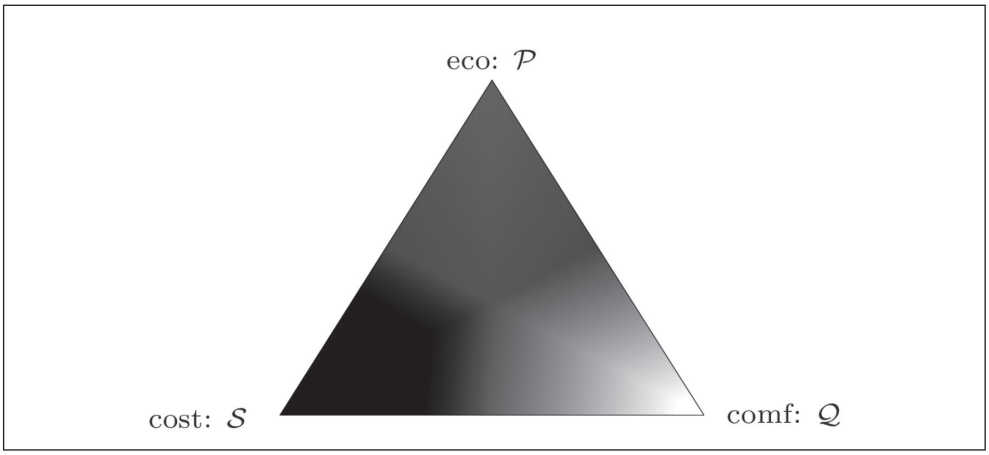

Fig. 4: Graphical end-user interface for selecting the individual weights.

Another advantage of using the proposed control scheme is that lower and upper boundaries for the indoor temperature can be defined as constraints for the MIQP problem. Those bounds for the admissible indoor temperature could depend on the predicted occupancy of the smart home, allowing larger deviations from the reference temperature if nobody is/will be at home. This anticipatory heating behaviour can yield large potential energy savings without any impact on user comfort.

4. DISTURBANCE PREDICTIONS

A major influencing factor for the performance of a MPC are the quality of the available predictions. In this section only the predictions for the disturbance vector z_k from (1a) are considered. Other predictions, like grid-prices or grid-side constraints, are assumed to be known and not discussed further in this paper. In the following subsections methods for acquiring those disturbance predictions are presented.

4.1 WEATHER PREDICTIONS

As mentioned in the introduction, the major influencing factors for the thermal model are ambient temperature and solar irradiation. Long-time forecasts of both are easily accessible and widely available, but those forecasts do not account for local conditions. For example, a house could be in the shade of large trees most of the day and only be subjected to a fraction of the solar irradiation predicted by external weather forecasting services.

Local sensors for capturing the weather are already standard in today's smart homes. Combining those local sensors with the external weather forecasts can lead to an improved localized prediction (Zauner et al., 2018).

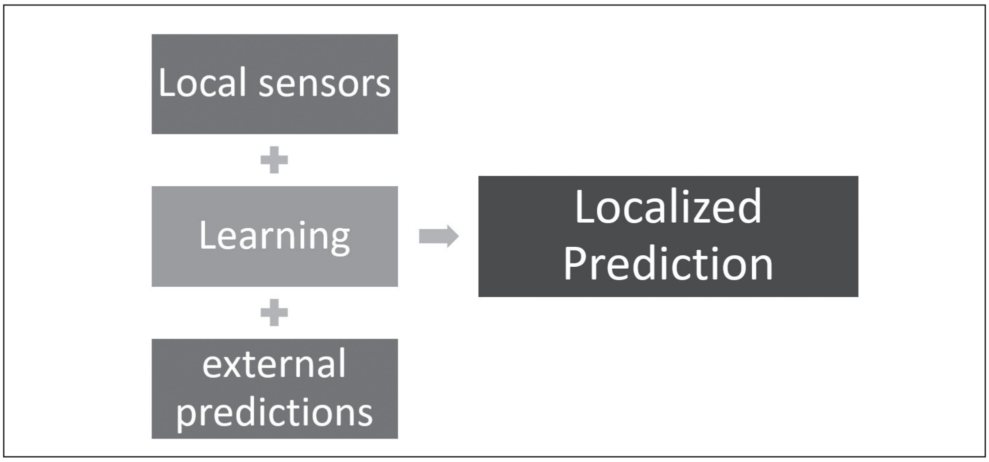

Fig. 5: Overview of the work for generating the localized predictions.

The aforementioned paper proposed an autoregressive model with exogenous inputs for combining external predictions with local sensor readings. The model employs a weighted recursive least-squares algorithm to adapt the model-parameters online. This allows the model to adaptively capture the statistically differences between the local conditions on-site and external predictions.

It has been shown that this algorithm can be used for creating a localized prediction for ambient temperature and (with minor adaptions) for solar irradiation, see Fig. 5.

4.2 OCCUPANCY PREDICTIONS

In Section 3 the potential advantages of having predictions about the future occupancy have been highlighted. Assigning the end-user to manually define the times where the smart-home will be occupied is an annoying and time-consuming task. Killian & Kozek (2018b) proposed an algorithm for semi-automated extraction of occupancy profiles based on internal sensor measurements in the smart home.

In a first step the daily occupancy probability of the end-users are recorded over a certain period of time. In a second step the most significant "features" (best describing occupancy profiles) are extracted offline. This feature extraction is done by performing a proper orthogonal decomposition (POD) and subsequently clustering the data. Performing the POD and clustering is computationally challenging, but it is sufficient to carry out these calculations only once every few months. Therefore, this task can be easily outsourced to cloud-computational services.

In a third step the extracted occupancy profiles are compared online to the current occupancy conditions via a robust statistical measure. The best fitting pre-extracted occupancy profile is chosen for predicting the future occupancy.

For a more in-depth description of the algorithm and additional figures, the reader is redirected to (Killian & Kozek, 2018b).

5. CONCLUSION AND OUTLOOK

A smart home management system is presented in this work. The management system does not only include the thermal subsystem of the smart home, to be able to provide a comfortable climate, but also the electrical subsystems to optimize the usage of battery-systems and grid-based power with respect to the power demand of the heating systems. This optimization problem is solved via computing a mixed-integer quadratic-programming problem.

The proposed MPC scheme is able to optimally help future smart grids with tasks like load scheduling and reducing peak loads, while also providing the user full comfort during those tasks. Furthermore, more sophisticated methods for gathering necessary predictions are presented. Those predictions include localized weather forecasts and occupancy predictions. The occupancy profiles are generated semi-automated via means of datamining and efficient feature extraction from big data.

The proposed algorithms and methods are in the progress of being implemented into real building for testing purposes. Future updates on the results including performance figures will be provided by the authors. For numerical simulation results and proof-of-concept results, see (Killian, 2018a; Killian & Kozek, 2018b; and Zauner et al., 2018).

LITERATURE

EAE- European Association for external thermal insulation composite systems, European energy saving guide. (2016): <http://www.ea-etics.eu> [cited 07. November. 2017].

Haider, Tarish Haider & Ong Hang See & Wilfried Elmenreich. (2016): A review of residential demand response of smart grid. In: Renewable and Sustainable Energy Reviews, 59:166–178.

Killian, M. & Mayer, B. & Kozek, M. (2015): Effective fuzzy black-box modelling for building heating dynamics. In: Energy Build 2015;96;175-86.

Killian, M. & Zauner, M. & Kozek, M. (2018a): Comprehensive smart home energy management system using mixed-integer quadratic-programming. In: Applied Energy 222 (2018) pp.662-672.

Killian, M. & Kozek, M. (2018b): Short-term occupancy prediction and occupancy based constraints for MPC of prosumers in smart homes. In Proceedings of the IFAC Workshop on Control of Smart Grid and Renewable Energy Systems (CSGRES 2019), June 10-12, 2019, Jeju Island, Korea, submitted.

Privara, S. & Cigler, J. & Vana, Z. & Oldewurtel F. & Sagerschnig, C. & Zacekova E. (2013): Building modeling as a crucial part for building predictive control. In: Energy Build 2013;56;8-22.

Zauner, M. & Killian, M. & Kozek, M. (2018): Localized Online Weather Predictions with Overnight Adaption. In: Proceedings of International conference on Time Series and Forecasting 2018, pp. 250-259.

Kontaktdaten Autor(en):
Michael ZAUNER
Getreidemarkt 9
1060 Wien, Österreich
Email: michael.zauner@tuwien.ac.at