

Particle Swarm Optimization and Kalman Filtering for Demand Prediction of Commercial Buildings

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Abstract:

The integration of weather forecasts and demand prediction into the energy management system of buildings is usually achieved using a model-based predictive control. The performance of such control techniques strongly depends on the accuracy of the thermal model which describes the building behavior. However, increasing the model complexity results in a reduced computational efficiency of the optimization problem which is an intrinsic part of the model predictive control.

In this paper, a linear control-oriented thermal model of a commercial building is considered as the base model. Using the Particle Swarm Optimization technique, the parameters of the model are identified and the performance of the improved model is compared with the actual measurements. Afterwards, the improved model is used by a Kalman filter to predict the temperature and the heating/cooling demand of the building.

The investigations are based on a commercial building located in the campus of ETH Zurich in Switzerland. Long-term measurements of temperature and power flows are used for the parameter identification. Initial parameter values are provided by the building manufacturing datasheet. The results of the case-study show that a very accurate temperature prediction can be achieved even for a four-day horizon, with a maximum absolute error of one degree Celsius.

Keywords:

Simulation and optimization; Building energy system; Thermal analysis; Demand prediction; Parameter identification; Operation and control.

1. Introduction

According to a review [1] published in 2008, the building sector accounts for about 40% of final energy demand. A big part of this demand belongs to commercial and office buildings, which are usually equipped with heating, ventilation, and air-conditioning (HVAC) systems.

Since as early as 1970s, researchers [2] have tried to improve the operation strategy of such HVAC components to reduce the required energy demand, shift the time-of-use, and increase the efficiency of the overall system. In recent years, heuristic control approaches have been replaced by model-based predictive control (MPC) as an optimal operation strategy. These novel methods enable the energy management system to calculate the thermal and electrical demand of the building within foreseeable future using weather and occupancy forecasts, building thermal model, and statistics from previous measurements. As a result, periods with overheating or overcooling are avoided, resulting in lower energy costs and higher comfort for the occupants [3]. In many studies, authors have demonstrated the potential of MPC for operation of HVAC system [4] as well as designing the building components [5, 6].

A requirement for MPC is an availability of predictions. Usually a forecast of external data such as temperature and solar irradiations is available via the closest weather station. However, MPC also

requires a relatively accurate model to predict the thermal behavior of the building and the energy demand. Contrary to weather forecasts, the parameters of such thermal model have to be known beforehand or need to be identified by the energy management system. This is especially important since specific parameters such as the thermal mass and thermal heat transmittance are not constant during the operation life of the building.

Generally there are two approaches for the parameter identification of already existing models. On the one hand, an offline identification technique incorporates a set of previously measured data from the internal and external signals in order to tune the parameters such that the simulated output of the model fits the actual measurements in the best possible way. This method can be computationally sophisticated, since the offline identification can take place well before the actual energy management system will need the calibrated model; hence computation time not being an issue. On the other hand, an online identification technique is an algorithm which runs in parallel to the actual building operation and tries to recalibrate the model parameters at each time step, using the most up-to-date measurements and the current states of the system. The online identification needs to be computationally more efficient compared to the offline approach, since it is often placed on the less powerful but more compact processing units which are available onsite.

In this paper, first the proposed thermal model for a test commercial building is provided. Then in section 3, firstly an offline identification algorithm based on particle swarm optimization (PSO) [7] is presented, aiming at finding a first set of acceptable model parameters. Then an extended Kalman filter (EKF) [3] is used for online improvement of parameters while a prediction of internal building temperature is generated. Finally, the results of the identification and prediction phases are shown and the performance of different setups are discussed and brought to a conclusion.

2. Thermal Model for Commercial Buildings

Complexity of the thermal model directly affects the computational effort of both the parameter identification and the state prediction processes. Therefore, it is crucial to find a compromise between the model accuracy and simplicity. A thermal model with a single temperature zone, also known as the 1R1C model, is discussed by the authors in [3]. The 1R1C model is not capable of capturing the temperature development in different zones or rooms in a building, but when a study of the total HVAC demand is intended, it can be sufficient. In other words, the model is simple enough for the parameter identification stage and still accurate enough for the temperature prediction process.

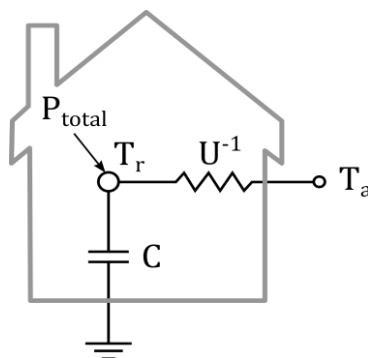


Fig. 1. The 1R1C thermal model of the building.

Figure 1 shows the control-oriented 1R1C model in the form of a lumped-parameter equivalent using electrical elements. The voltages T_a and T_r represent the ambient and room temperatures, respectively. The total heat capacity of the building is shown as the capacitor C . The total heat transmittance through the walls and windows is lumped into the resistance U^{-1} , which is the equivalent of a conductance U . Finally, the heat-gain powers are lumped into a current source shown as P_{total} . In order to obtain the thermal equation, Kirchhoff's current law is applied to the node in the middle. The

law states that the summation of currents flowing out of a node is equal to zero. This will result in the following equation:

$$C \frac{dT_r}{dt} + U(T_r - T_a) - P_{total} = 0 \quad (1)$$

In (1), the first term shows to the current of the capacitor in the form of a derivation of the voltage multiplied by the capacitance. The second term is the current flowing in the resistor, calculated as the conductance multiplied by the voltage difference. The last term is the current flow representing the total heat-gain power entering the building envelop. The elements of the total heat-gain power are shown below.

$$P_{total} = P_{sun} + P_{int} + P_{hvac} \quad (2.1)$$

$$P_{hvac} = P_{heat} - P_{cool} + P_{ven} \quad (2.2)$$

In (2.1), P_{sun} is the heat-gain power from solar irradiations which is calculated from raw solar irradiation using the Perez's model [1]. The second term, P_{int} , includes the internal heat-gain power from the electrical devices, such as lights and computers, as well as the heat introduced by the presence of people in the building. The last term, P_{hvac} , represents the power from heating, ventilation, and air-conditioning system, which can be subdivided into the heating power P_{heat} , cooling power P_{cool} , and ventilation power P_{ven} , as shown in (2.2).

Next, the thermal model is discretized to be used in a computer-based simulation. For this, an exact discretization, also known as a zero-order hold discretization, is applied to (1). The result is shown in (3), where t_s is the sample time.

$$T_r[k] = e^{\left(\frac{-U}{C}t_s\right)}T_r[k-1] + \left(1 - e^{\left(\frac{-U}{C}t_s\right)}\right)T_a[k-1] + \frac{1}{U}\left(1 - e^{\left(\frac{-U}{C}t_s\right)}\right)P_{total}[k-1] \quad (3)$$

Introducing two new parameters α and β results in a simplified vectorized form, as shown below.

$$T_r[k] = (1 - \alpha)T_r[k-1] + (\alpha \quad \beta) \begin{pmatrix} T_a[k-1] \\ P_{total}[k-1] \end{pmatrix} \quad (4.1)$$

$$\alpha = 1 - e^{\left(\frac{-U}{C}t_s\right)}, \quad \beta = \frac{1}{U}\left(1 - e^{\left(\frac{-U}{C}t_s\right)}\right). \quad (4.2)$$

In case of a commercial building, the heat-gain powers are usually in the order of 10^5 [W] while temperatures are in the order of 10^2 [K]. However, typical values for α and β are in the orders of 10^{-4} [-] and 10^{-7} [K/J], respectively. These differences in the orders of magnitude is disadvantageous for numerical computations such as kalman filtering. Therefore, the temperatures are calculated in [kK] and the powers in [MW]. This change of units will normalize the problem. Hence, (4) is re-written as

$$T_r[k] = (1 - 10^{-3}\alpha)T_r[k-1] + 10^{-3}(\alpha \quad \beta) \begin{pmatrix} T_a[k-1] \\ P_{total}[k-1] \end{pmatrix} \quad (5.1)$$

$$\alpha = 10^3 \left(1 - e^{\left(\frac{-U}{C}t_s\right)}\right), \quad \beta = 10^6 \frac{1}{U}\left(1 - e^{\left(\frac{-U}{C}t_s\right)}\right). \quad (5.2)$$

The values of U and C can later be derived from α and β using

$$U = 10^3 \frac{\alpha}{\beta}, \quad C = \frac{-Ut_s}{\ln(1-10^{-3}\alpha)}. \quad (6)$$

While these equations are used for an offline identification of parameters U and C , it is crucial to perform a continuous online identification of them while operating the building. The reason is that the building occupants will constantly modify these parameters, for example by bringing in or removing some furniture, or by altering the state of windows and doors. Even more dramatic changes are applied when the building goes through a partial or total renovation. Hence, the online parameter

and state identification is added to the system to provide a persistent improvement of the thermal model. In addition to of U and C, there are uncertainties in the value of the heat-gains which eventually affect the temperature. For example, the Perez's model has only a rough approximation of how solar irradiations are distributed over the sky, close mountains, or nearby buildings. Therefore, the actual value of the solar heat-gain can be different from what is calculated. In order to include the uncertainty of the heat-gains, three new parameter are added to (5.1) as coefficients:

$$T_r[k] = (1 - 10^{-3}\alpha)T_r[k - 1] + 10^{-3} (\alpha \quad k_{sun}\beta \quad k_{int}\beta \quad k_{hvac}\beta) \begin{pmatrix} T_a[k - 1] \\ P_{sun}[k - 1] \\ P_{int}[k - 1] \\ P_{hvac}[k - 1] \end{pmatrix}. \quad (7)$$

In the next section, the structure of the parameter identification problem is explained.

3. Problem formulation

The goal is to find an optimal set of parameters shown in (7) which enables the output of the thermal model to follow the actual temperature of the building. This is not a modeling problem since the structure of the model is already defined. Instead, the interest is to calibrate the model to capture the behavior of the system.

3.1. Identification procedure

The recursive discrete model in (5) is used for parameter identification using two different algorithms for offline and online identification methods. Figure 2 depicts the structure of the whole procedure using a block diagram. The building block represents the actual plant, from which the measurements are obtained.

The particle swarm optimization (PSO) block is where the offline identification takes place. This process needs a thermal model of the building as well as a recorded set of measurements, which is provided by the data logger. The output of the PSO is a primary set of calibrated building parameters, described in (7).

Next, the online identification process using an extended Kalman filter (EKF) is started. The EKF requires a fresh set of measurements on the external and internal temperatures and the heat-gains. The EKF then produces a constantly improved version of building parameters together with an estimation of the internal temperature. The outputs of the EKF can then be used for demand estimation of the building.

3.2. Choice of parameters

Since the identification process is computationally very expensive, the parameters are divided into two group to be used in the offline or the online process, as shown below.

$$\theta_{off} = \begin{pmatrix} \alpha \\ \beta \\ k_{sun} \\ k_{int} \\ k_{hvac} \end{pmatrix}, \quad \theta_{on} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix}. \quad (8)$$

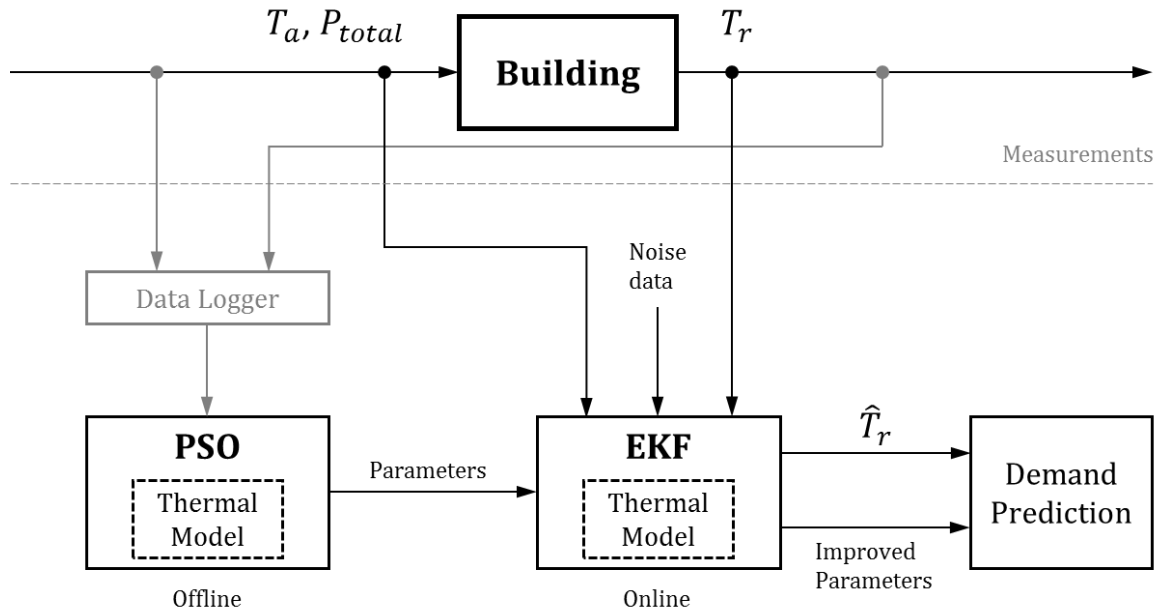


Fig. 2. The block diagram of the procedure. \hat{T}_r represents the estimation of T_r .

As shown in Fig. 2, the optimal parameters of the offline identification are passed to the online stage, which implies that the identification of θ_{on} is dependent on θ_{off} . The optimal values of parameters at the end of each stage are displayed in section 4.

3.3. Studied building

The studied building is a commercial building located in the campus of the ETH Zurich in Switzerland. The building was constructed in 2007, has 6 floors and is fully air-conditioned. Hundreds of sensors in various locations measure the temperature every 15 minutes. The exhaust air is blown from the occupied areas to the atrium. The temperature of the final exhaust air leaving the building is considered as the single zone temperature used in the 1R1C model.

Commercial and office buildings regularly have a very limited need of domestic hot water, hence neglected in this investigation. On the contrary, the electrical power of the lighting and computing services comprise a big portion of the internal heat-gains. Figure 3 demonstrates the measurements obtained from the building during 3 months in 2011. The external temperature and solar irradiations are measured in a weather station located on the roof of the building. The internal temperature is mostly kept within a range of 22 and 26 degrees Celsius. The internal heat-gains show a pattern which matches the building occupancy, while there is still considerable electricity demand during the weekend due to the existence of a server room.

It is also noticeable that the internal heat-gains are in the same level of magnitude as the solar and hvac powers. Looking at the hvac power measurements, the mostly negative values reveal that the building is in fact in the cooling season. However, at specific period it can occur that the ventilation becomes the dominant term in (2.2), resulting in a positive value (for example, during the third part of August).

4. Results

In order to provide a concrete evaluation of the suggested algorithm, the measurements are divided into two separate group. The first group, from August 1st to September 11th, are used for the offline

identification. The second group, from September 12th to October 31st, are used for the online identification as well as temperature prediction. Since the offline identification requires the whole set of data at once, the same data cannot be used for verification. Therefore, the performance of the online identification at the beginning of the second period is used to validate the correctness of the model. The second stage, i.e. the online identification, takes place at each time step, hence there is no need for a validation. In other words, at each step a new set of measurements is received, therefore an over-fitting of the model does not occur.

The simulations are implemented on MATLAB and the measurements are provided by the technical staff of ETH Zurich using a web portal.

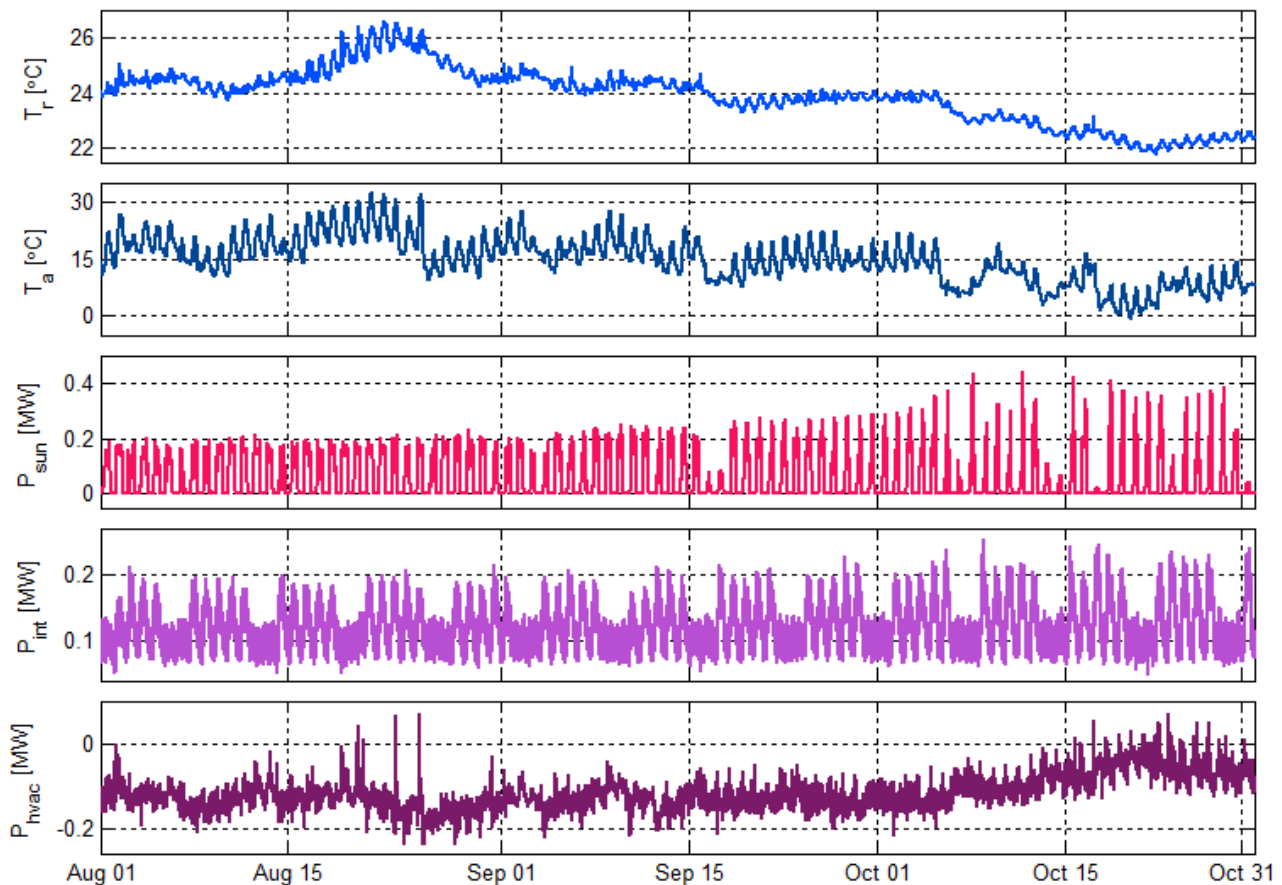


Fig. 3. Measurement from the building shown for the months of August, September, and October 2011.

4.1. Offline Identification using PSO

Particle swarm optimization is an evolutionary optimization technique and was introduced in 1995. The interested reader is referred to [8] for further study on PSO and resources available. In this paper, the PSO is used to calibrate the parameters of the pre-defined model using a stored set of measurement. Similar to other optimization algorithms, the PSO aims at minimizing a cost function while satisfying a set of constraints. Table 1 lists the constraints used for the offline identification.

Table 1. Settings for the PSO during offline identification

Parameter	Minimum	Maximum	Parameter	Minimum	Maximum
α	0.25	0.45	k_{int}	0.9	1.1
β	0.02	0.06	k_{hvac}	0.9	1.1
k_{sun}	0.9	1.1	PSO generations	1	500

For this study, the PSO has a population of 50. The boundaries for the parameters α and β are selected based on the values provided by the building datasheet. The cost function for the PSO is defined as the least absolute deviations (LAD), described as

$$cost_{PSO} = \sum_k |\hat{T}_r[k] - T_r[k]| \quad (9)$$

which penalizes a difference between the real and the estimated internal temperature. With the cost function in (9), the optimal offline parameters are found using

$$\theta_{off,opt} = \underset{\theta_{off}}{\operatorname{argmin}} cost_{PSO}(\theta_{off}). \quad (10)$$

For the given problem, the offline identification process is completed within 10 minutes on a typical personal computer with a CPU clocking at 2.2 GHz and 8 GB of memory. Table 2 shows the final values for the identified parameters.

Table 2. Results of the offline identification stage.

Parameter	Value	Parameter	Value
α	0.3000	k_{hvac}	1.0772
β	5.6865×10^{-2}	C	1.5825×10^{10}
k_{sun}	0.9256	U	5275.7
k_{int}	0.9691	Final generation	146

Figure 4 shows the performance of the model after the offline identification has optimized the parameter values. The model is accurate enough to capture the main dynamic of the building thermal behavior which is rather slow. However, it fails to follow the faster dynamics, resulting in a damped response when sharp peaks and valleys occur (e.g. between August 15 and August 21).

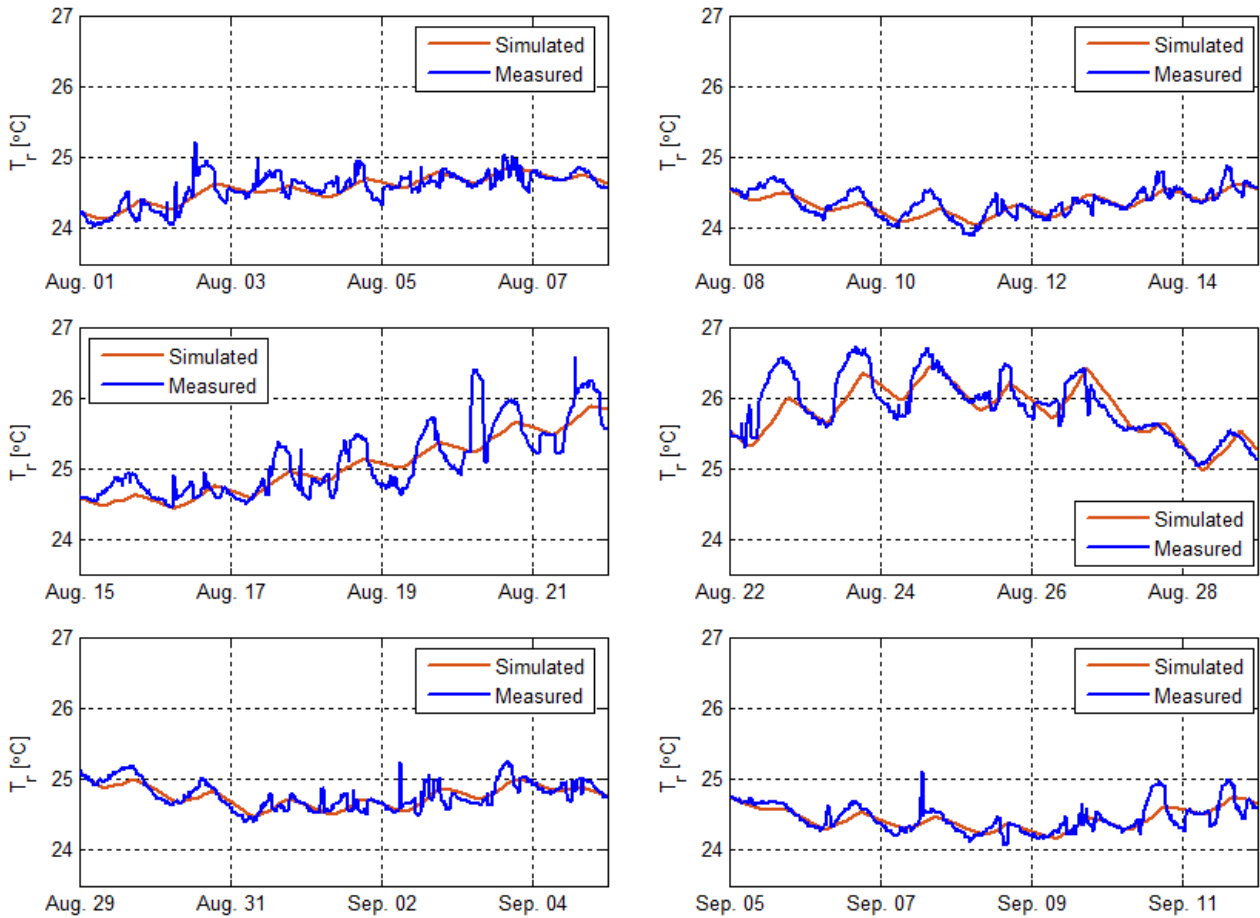


Fig. 4. Performance of the model with parameters identified offline with PSO.

The model is capable of simulating the development of internal temperature by a maximum absolute error of 0.5 degrees Celsius. Introducing a more complex thermal model which integrates the dynamics of the internal air, the internal and external walls, and furniture inside the building separately will improve the simulation results [3]. However, such precision is unnecessary for the target of this study.

4.2. Online Identification using EKF

The standard Kalman filter is an algorithm mainly used for estimation of system states. This filter is the optimal approach if measurement noise and plant disturbances are present. When the problem of parameter identification is added, an extended Kalman filter (EKF) is needed to provide the so-called dual-estimation. The reason is the introduction of an augmented state vector, which results in non-linear state-space equations. The system is described using the following discrete-time formulation

$$\begin{cases} \begin{bmatrix} x[k] \\ \theta_{on}[k] \end{bmatrix} = \begin{bmatrix} F(\theta_{on}[k-1])x[k-1] + G(\theta_{on}[k-1])u[k-1] \\ \theta_{on}[k-1] \end{bmatrix} + \begin{bmatrix} G_x \\ G_\theta \end{bmatrix} \omega[k-1] \\ y[k] = H(\theta_{on}[k])x[k] + v[k] \end{cases} \quad (11)$$

where θ_{on} , x , u , and y represent the vectors for parameters, state, input, and output, respectively. The variables ω and v denote the plant disturbances and measurement noise, respectively. The matrices G_x and G_θ depend on the plant and in this study they are found using the measurement data. The variables x and u , as well as the matrices F , G , and H are defined as

$$\begin{cases} x = T_r, & u = [T_a \ P_{sun} \ P_{int} \ P_{hvac}]^T \\ F = 1 - 10^{-3}\alpha, & G = 10^{-3}[\alpha \ k_{sun}\beta \ k_{int}\beta \ k_{hvac}\beta], \quad H = 1 \end{cases} \quad (12)$$

which is consistent with (7). More detailed equations on implementation of EKF are found in [9].

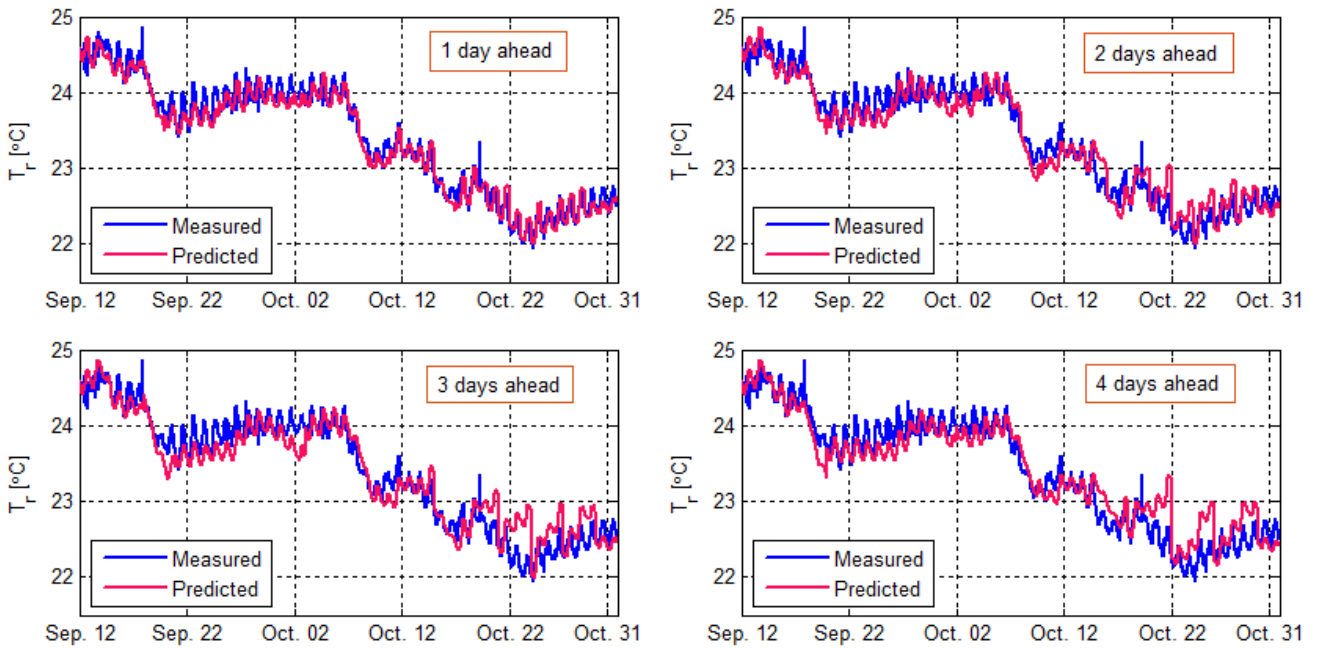


Fig. 5. The predicted internal temperature using the model with parameters identified online with EKF.

The EKF is initialized using the set of offline identified parameters from PSO, as shown in Table 2. Next, the new estimation of parameters and the predicted internal temperature are found. Figure 5 shows the prediction of temperature for prediction horizons between 1 day and 4 days ahead.

The errors corresponding to Fig. 5 are shown in Table 3. It proves that a prediction of internal temperature for 4 days ahead is possible with a maximum absolute error of almost 1 degree Celsius. The final step is to calculate a prediction of the demand for heating or cooling.

Table 3. Maximum and mean absolute errors for different prediction horizons.

Prediction horizon	Maximum absolute error [K]	Mean absolute error [K]
1 day	0.64806	0.10171
2 days	0.71679	0.14776
3 days	0.85049	0.18029
4 days	1.00910	0.17898

4.3. Demand Prediction

Once a prediction of internal temperature is available, the HVAC demand can be calculated using (7). This lead to

$$\hat{P}_{hvac}[k] = f(\hat{T}_r[k+1], \hat{T}_r[k], \hat{T}_a[k], \hat{P}_{sun}[k], \hat{P}_{int}[k]). \quad (13)$$

The predicted internal temperature, \hat{T}_r , is the output of the EKF stage. Furthermore, it is not possible to assume a perfect knowledge of the future external temperature, \hat{T}_a , and future solar heat-gain, \hat{P}_{sun} . Therefore, the predictions should, for example, be acquired from a local weather station. Finally, a prediction of internal heat-gains, \hat{P}_{int} , is required. This is especially a very complicated task since the signal is very stochastic. There are several machine learning methods which can be used to provide an estimate of such uncertain signals using pattern recognition techniques, for example the artificial neural networks (ANN) [10] and the support vector machine (SVM) [11].

5. Conclusions

In this paper, an algorithm for parameter identification of a commercial building is presented. First, a set of parameters related to the building mass and thermal transmittance, as well as coefficients corresponding to the effect of heat-gains on the internal temperature are identified. This stage is performed offline with a particle swarm optimization method, while previously stored measurements are used. Afterwards, an extended Kalman filter enables a continuous improvement of parameters using an online identification. At the same time, the EKF provides a prediction of the state, i.e. the internal temperature, for the upcoming time steps. The results suggest that the algorithm is accurate enough for predictions as far as 4 days ahead, with a maximum error of 1 degree Celsius. However, at this stage the future boundary conditions such as weather forecast including the external temperature and solar irradiations as well as internal electricity demand is assumed to be known within the prediction horizon. In reality, such assumption is not correct. Various pattern recognition and machine learning methods can be used to create statistical models and to provide such predictions. Finally, a prediction of heating or cooling demand can be achieved using the obtained prediction of internal temperature. The authors will focus the future research on statistical modeling of the boundary conditions in order to improve the demand predictions.

Acknowledgments

The authors would like to thank Mr. Damian Suski for his contributions to this work. Furthermore, this research has been partly funded by the Board of the Swiss Federal Institutes of Technology through the CTI project No. 12122.1. The authors gratefully acknowledge this support.

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