FHP

Flexible Heat and Power, connecting heat and power networks by harnessing the complexity in distributed thermal flexibility

Newsletter July 2019

Using Building Thermal Models for Determination of Energy Demand Side Flexibility

Introduction

In recent years, the capacity of power generation of wind farms and solar PV plants has increased and may even exceed the capacity of power transmission lines. This raises the question of how to make the most of these generators while not overloading the grid. The problem may also be the volatility of renewable sources – their power generation may fluctuate in a very troublesome way. Thus, we need to be able to reasonably consume excess electricity close to the generators and not to try to transfer it further on along transmission lines.

Another bad situation can occur, when the *consumption* is so high that the grid cannot satisfy electricity demand. Here, a temporary decrease of electricity demand is needed.

These situations, called grid congestion, can be mitigated on demand-side by appropriately shaping consumption profiles of relevant cluster of consumers. For that, thermal capacity of buildings with electric heating and cooling offers an attractive source of flexibility in power demand. It relates both to smart increase of consumption in periods of peak *generation* and to decrease of demand in periods of peak *consumption*.

Electricity load shaping

In the following paragraphs, we describe shaping of electricity consumption by suitable control of electrical heating and cooling in buildings.

Changing temperature setpoints of heating and cooling control results in changes of electricity consumption. However, manipulating indoor temperatures to accumulate heat must not be done arbitrarily - there is a strict requirement to maintain adequate indoor comfort. Therefore, to find thermal capacity that can absorb surplus energy from renewable sources, it is necessary to be able to predict zone temperatures in the building related to various ambient conditions and various control actions. Further, calculation of costs is important when evaluating various control strategies. Here, mathematical models can help.

To decrease considerable total effort of deploying qualitatively new controllers, models that minimize human labour have been developed.

Complex modelling software

Simulation models of various complexity are used to predict how temperatures inside heated or cooled zones are related to consumed electricity. *EnergyPlus* or *DOE2* software systems are building simulators that are best known in this field. They are based on detailed knowledge of the building – its topology, materials of all construction elements, technical description of heating, ventilation and air conditioning systems. These models process influences like weather, occupancy and heating or cooling time courses and respond with time series describing building thermal conditions.

Advantages and disadvantages of complex models

Accurate models like *EnergyPlus* are very useful for the solution of specific tasks. Civil engineers or architects can effectively verify thermal properties of their building designs. These models are on the other hand much less applicable, when one needs to implement model predictive control of heating or cooling subsystems. One of the reasons is, that these intricate models are highly computationally demanding – the complexity of resulting optimal control problem prevents their employment. Furthermore, relevant model can be assembled mainly for new buildings, where all details of the construction are available, while these models of old existing buildings are mostly not used, as identification of their parameters would be very expensive.

Models appropriate to reveal flexibility

For predicting electricity consumption flexibility, not too complicated building models, which can still satisfactorily characterize building thermal behaviour in real conditions, are needed. Two types of such models - grey-box and black box models – are described below.

Grey-box models originate in significantly simplified first principle state space simulation model. Each of their basic components represents whole cluster of building elements. In one such model, complex building dynamics is represented by three thermal inertia: By virtual mass of indoor air, mass of external walls and by integrated indoor solid masses. This model may be further extended or even simplified. Influencing inputs are weather, occupancy and supplied or removed heat. Outputs are states - generalized temperatures of all modelled virtual masses.

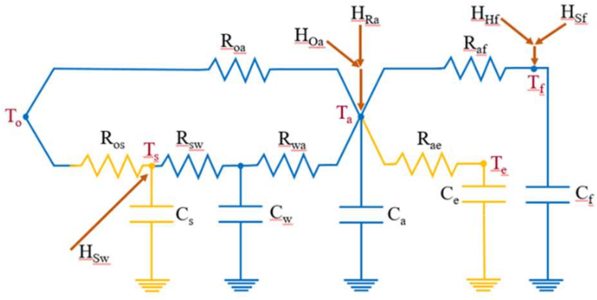

Figure 1. RC schema of the gray-box model with five temperatures as state variables T. Basic blue model is extended by two additional states in yellow.

Black box models on the other hand have no relation to physical structure of the modelled system. They are often based on machine learning and can learn relations between indoor temperatures and heating or cooling power under various influencing factors. These models can usually well characterize steady states conditions of the building, but their training needs quite a long monitoring history and their response on changes of building parameters is slow.

For determination of flexibility in *electricity* consumption, described thermal models must be extended by conversion of electricity to heat. Here, we do not consider dynamics, only static relation is used, potentially with a conversion factor depending on ambient conditions. For heat pumps, it may be their COP parameter.

Comparison of the used models

We tested described approaches in the FHP project. Two used *black-box models* are quite simple – classical time series ARIMAX N-lagged autoregressive model and self-learning regression model using random forest.

The first is a classical *ARIMAX* method, often used to compute responses of dynamic systems. Its disadvantage is that model parameters do not correspond to real physical properties of the building.

The simple regression model, as it is implemented, lacks dynamics and therefore it cannot grasp heat accumulation well. Revealed flexibility is thus lower than that available. This is the major weakness of this approach, when used for flexibility forecasting.

Grey-box linear state space models are systems of linear ordinary differential or difference equations. They are often called RC models due to their similarity to electric circuits with resistors and capacitors. The model approximates basic building *dynamics* by thermal capacities of perimeter walls, building envelope layer absorbing solar irradiation, indoor air masses, inner solid masses like inner walls and furniture and heating system thermal capacity. Model parameters representing *conductive* heat flows are thermal conductivity of perimeter walls, conductivity of inner walls and that of heating or cooling system. The manipulated variable is heating or cooling power. The disturbances are internal heat gains, solar irradiation, ambient temperature, occupancy and ventilation intensity. The model computes time courses of state variables, but only time course of virtual indoor air temperature is employed in flexibility estimation. Using only one virtual temperature instead of temperatures of all zones is the shortcoming of this approach; single variable cannot well represent all temperatures in all zones in the building. However, this simplification is a necessary compromise between model complexity and usability. The mitigation of this compromise is described later.

Another uncertainty of the result is due to the input uncertainties. While inputs like future profiles of heating and cooling are deterministic user-controlled manipulation variables, other disturbing inputs cannot be reliably forecasted. Thus, any computed time profile of temperatures is burdened with an error. This must be accounted for, e.g. by accepting some solution safety margin.

Model calibration methods

The last step of the model creation is iterative calibration, which has to determine parameters of the model equations as well as values of initial system state. After each calibration step, simulation results are compared to time series of historical measurements. Model parameters are then updated to minimize the difference between model outputs and measured data. This process repeats until some stopping criterion, like e.g. small progress of several steps, is satisfied. However, an absolute match of simulations and measurements is not expected.

The calibrations use historical building measurements from time periods with diverse influences, like e.g. seasonal data. Input data are pre-processed and outliers and noise are filtered out. Then the calibration iterations start with an Initial estimate of the model parameters. Initial guess of capacities and resistances of substitute electric circuits may be based on analogy with physical building properties.

Nonlinear unconstrained or constrained optimization method is then used, where the minimized objective function is a sum of squared differences between simulated and measured variables. This approach is known in statistics as method of least squares. Constraint optimization procedure must be used if the iterations tend to converge to odd, unrealistic values. For the sake of simplicity derivatives of the objective function are approximated by numerical differences.

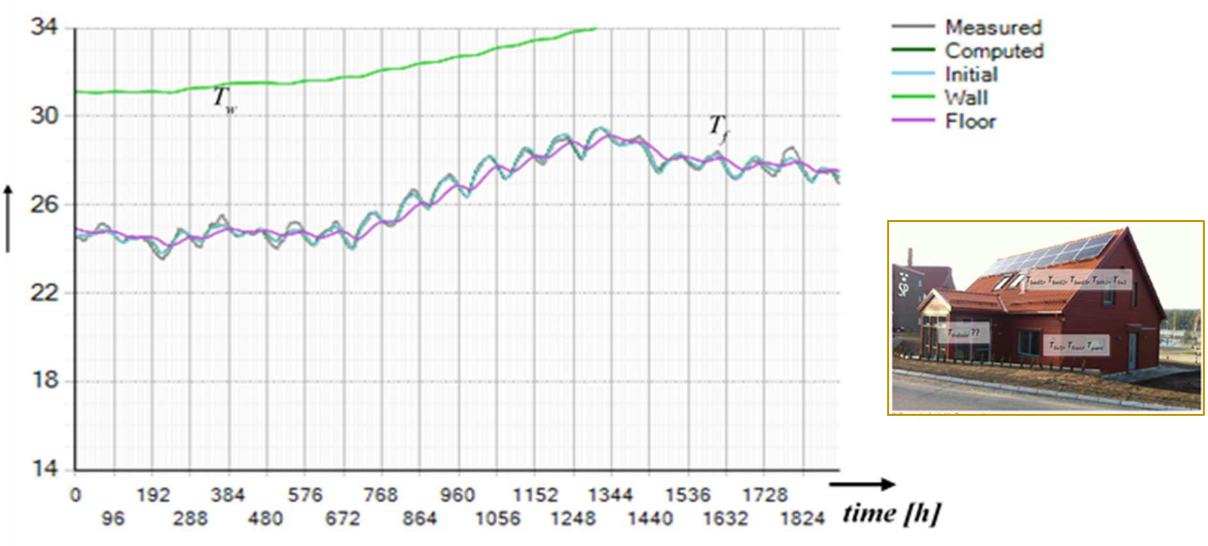

Figure 2. Summer thermal model of RISE experimental villa: The comparison of measurements and solutions of the calibrated model.

Due to complexity of the modelled system and to the limited number of calibration runs, we often get ambiguous parameter sets. Two calibrations started with different estimates of initial parameters usually terminate with quite diverse parameter values and strange initial states. This non-uniqueness is a common phenomenon, which does not need to matter. Simulations with these parameters give very close results for data inputs used for the calibration. However, if the simulation uses ambient or operation conditions distant from the calibration ones, then, dubious simulation results may be obtained and some provision to eliminate this ambiguity must be accepted.

Modelling of a real building

Grey-box model of the 5th order (Figure 1) was calibrated using four seasonal data sets acquired from experimental building in Sweden. The obtained calibrated parameters are different for each of four data sets, any satisfactory universal set of parameters could not be found. Yet, each seasonal model quite well matches measurements. Therefore, periodic re-calibrations with coming fresh data will be done and model parameters updated This may be a natural way, how to maintain accuracy of the model.

Concerning unknown initial values of state variables, we expect that their influence diminishes with the length of simulation period. This means, that for sufficiently long simulation an error caused by initial state estimate will be negligible.

Model based flexibility search

The calibrated building simulation model may be used to determine consumption flexibility. Before we proceed to the solution, we simplify the problem by converting the continuous simulation model to a discrete one using a suitable discretization method. Now, the problem is solved in finite dimensional space. Usual discretization step is often related to electricity tariffs, which may be e.g. 15 minutes.

Daily electricity price profile, time course of outdoor temperatures, solar irradiation and daily profile of expected inner heat gains are discretized or resampled with the same sampling period.

These data are completed by estimates of initial and terminal states, by upper and lower bounds of indoor temperatures and heating or cooling capacity and together with the calibrated discrete thermal model are processed by an optimization procedure. It minimizes total cost of heating and cooling and computes their economically optimal control. The result is a sequence of optimal virtual temperature profile and respective heating and cooling intensity in each sampling interval usually 15’ long.

However, computation of controls for past influences is not what is needed, but flexibility *prediction* is. The problem formulation is similar, the model is the same, the input variables are the same. But the uncertainties of the results are higher due to uncertainties of forecasted inputs. In practice, these uncertainties are reduced adding safety margins to constraints and repeating periodically the optimization with corrected latest measurements and updated forecasts of inputs.

There is yet one question. In an ideal case, solution horizon is extended quite far ahead to eliminate negative influence of free terminal states on optimal solution. FHP flexibility optimization is performed only one or several days ahead and the horizon of constant length is moved forward accordingly This can alleviate inexactness caused by solution on a short finite interval.

Outline of follow-up tasks

The described approach is a simple smooth way, how to estimate flexibility of electricity consumption. By automating all the described steps, one can get close to desired expert free ideal. However, some sort of self-check procedure must be added, because the described solution changes settings of the control loop and has a direct impact on inner building conditions.

An important safeguard provision consists in adding an extra feedback with comfort specifications, which must be given absolute priority in the final control overwrites. If the system departs from expected behaviour, this feedback controller must intervene to return inner conditions to desired limits.

Another follow-up problem is, how to implement control strategy that activates flexibility and how will temperatures in zones change after the flexibility activation. For this, another model of distributing temperatures and heat flows must be designed.

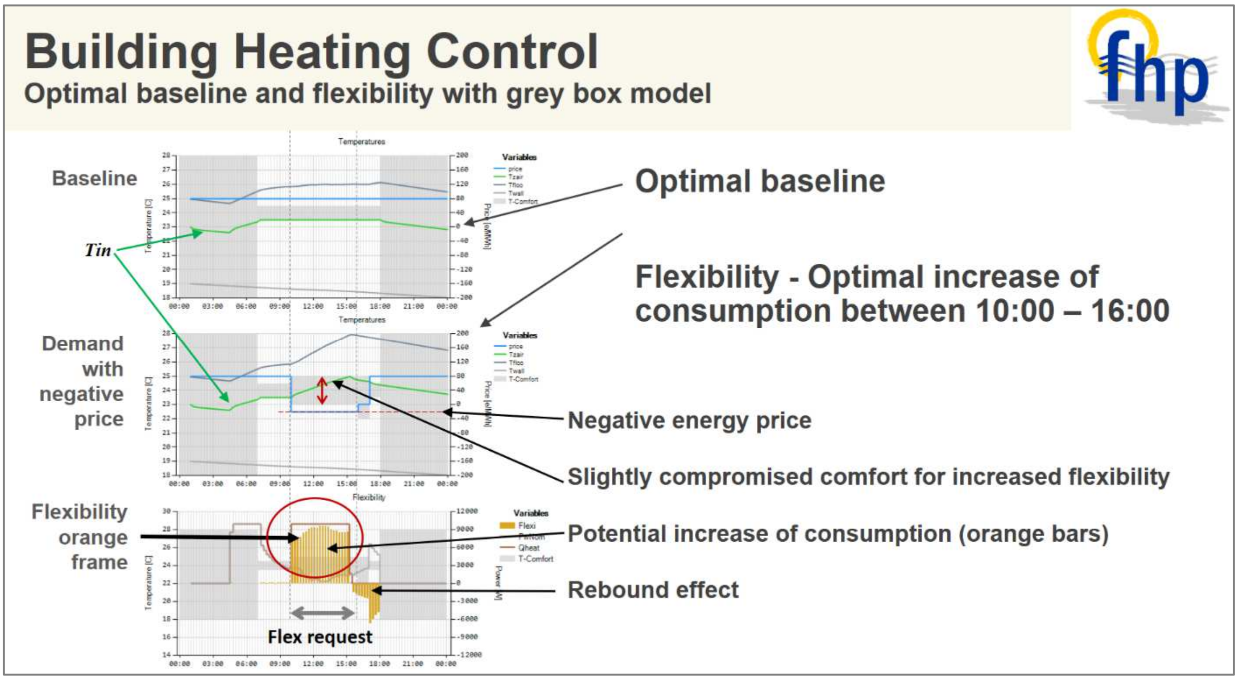

Figure 3. Detected flexibility of building power consumption, which exploits building thermal capacity. Flexibility enablers are varied energy price and relaxed thermal comfort

Partners

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Contact details:
web: www.fph-h2020.eu
e-mail: info@fhp-h2020.eu

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