Flexibility potential analysis framework for power-thermal sector coupling leveraging advanced thermal storage solutions (TBD)

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1 Abstract

The decentralized energy techniques like heat pumps and storages are increasingly applied to ensure the balance between supply and demand. However, rather than barely meeting the demand, the need for zero energy buildings in the EU landscape aims to respond to the fluctuations and stabilize the grid by developing sector coupling between thermal and electricity systems. Accordingly, demand side thermal energy flexibility plays a key role in enhancing the stability of the power grid. Moreover, as the district heating transition towards fifth generation, the supply temperature can be reduced to 40°C, which faces challenge when peak load occurs. Hence, the coupling also contributes to the peak shaving in district heating networks. Due to efficient coupling of the thermal and electricity sectors, power-to-heat (P2H) assets such as heat pumps as well as electric boilers play an increasingly important role in unlocking flexibility, both as boosters of the district heating network or stand-alone devices. However, there is a research gap in comprehensively analyzing the flexibility potential in such sector coupling networks. This study aims to develop a data-driven demand response strategy for such power-heat coupling systems, and the flexibility potential will be analyzed thoroughly through simulation from a district heating connected energy community in Großschönau, Austria. Furthermore, novel midterm storage solutions, such as phase change materials (PCM), will be considered to incorporate with district heating and P2H assets.

(Ignore the abstract, it was written a long time ago for the conference.)

2 Data-driven thermal response model of the building

Figure 1 depicts the average values for indoor temperature, outdoor temperature, and electricity load for cooling at each hour of a day across cooling season, which is defined as from June to September in this study. There is a significant hysteresis correlation between indoor temperature and both outdoor temperature and cooling load, which is mainly deemed as the passive storage effect from building thermal mass

Figure 2 shows a representative RC network of a building, and Equation 1 derives the state parameters of the RC model as follows:

$$C\frac{dT_z}{dt} = \frac{T_{\text{amb}} - T_z}{R} + P_c + \alpha * I_s \tag{1}$$

where T_z and T_{amb} represent the zone temperature and outdoor temperature with units of K; C is the capacitance of the zone with unit of K*m^2/W; R is the resistance to heat exchange between outdoor and envelope, with unit of kJ*kg/K; P_c is the cooling power delivered by the heating/cooling system with unit of W; I_s is the solar irradiation with unit of W/m^2 and α is the heat gain coefficient. The discrete time thermal response of the building can be rewritten in the following form:

$$X_{k+1} = AX_k + Bu_k + Ed_k \tag{2}$$

where X_{k+1} is the state vector at k+1 time instance; u_k represents the system input (e.g. cooling load), and d_k is the disturbance vector, which consists of solar irradiation, internal heat gains, and outdoor temperature. A, B and E are the metrics of the discrete time state space model depending on the sampling time. However, such linearized approach is lack of accuracy when it comes to non-linear thermal response of buildings. On the other hand, it requires various information, including

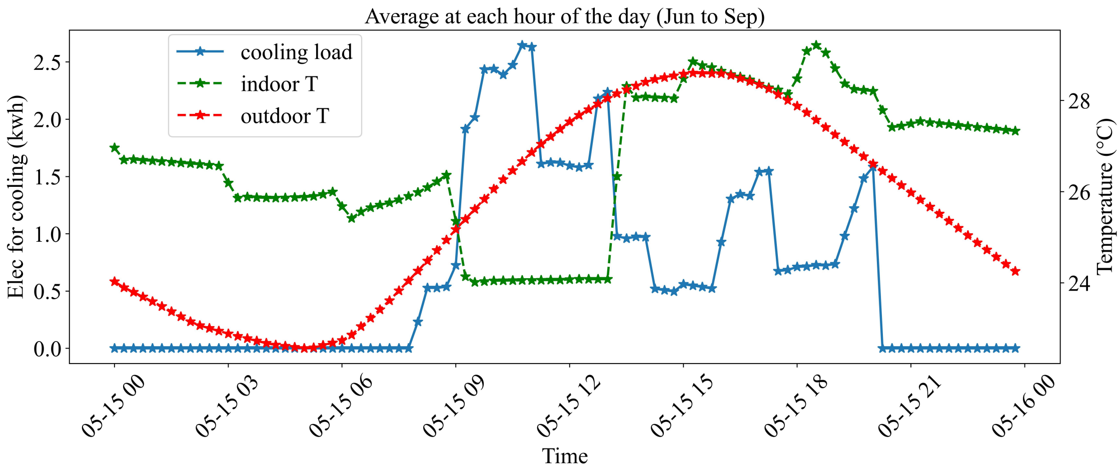

Figure 1: Average indoor temperature, outdoor temperature, and electricity load for cooling at each hour of a day across the whole cooling season ***(For x-axis, please ignore the date '05-15')***

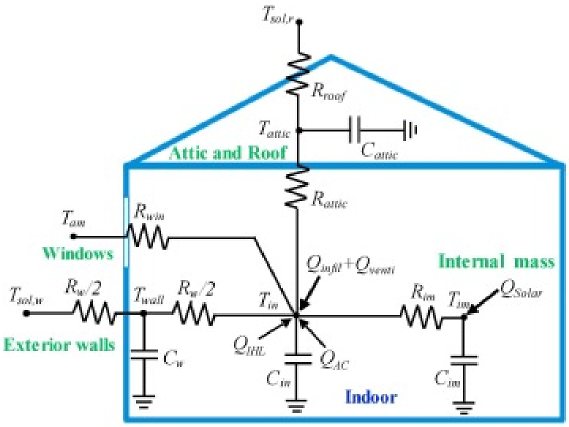

Figure 2: An example of a building RC network [1]

detailed internal heat gains and solar heat gains, which are difficult to estimate. Therefore, a data driven model is proposed in this study leveraging reduced amount of data varieties.

System identification refers to the process of leveraging time series measurement data to infer governing equations, in the form of dynamical systems, describing the data. With the discovered governing equations, future states can be predicted with control signal as the inputs [2].

Nonlinear Autoregressive models with Moving Average and Exogenous Input (NARMAX) stands out as an effective model for forecasting time series data when it comes to identifying nonlinear systems. Introduced by Electrical Engineer Stephen A. Billings in 1981, NARMAX are described as follows:

$$y_k = F^{\ell}[y_{k-1}, ..., y_{k-n_y}, x_{k-1}, ..., x_{k-n_x}, e_{k-1}, ..., e_{k-e_x}] + e_k \tag{3}$$

where $n_y \in \mathbb{N}$, $n_x \in \mathbb{N}$, $n_e \in \mathbb{N}$, are the lag length for the system output, control input, and exogenous input; $x_k \in \mathbb{R}^{n_x}$ is the system control input and $y_k \in \mathbb{R}^{n_y}$ is the system output at discrete time k; $e_k \in \mathbb{R}^{n_e}$ represents the uncertainties and possible noise at discrete time k. In this case, F^{ℓ} is one of the nonlinear functions of the input and output regressor with nonlinearity degree ℓ. Cooling load, outdoor temperature, along with the indoor temperature at the previous time step are included in the inputs, while the indoor temperature at the next time step is the output. It is worthy to notice that, solar and internal heat are assumed as the exogenous inputs, which will be estimated by the model.

There are several nonlinear functions to approximate the $F^l[\cdot]$, such as polynomial basis, fuzzy-logic based models, neural networks, and so on. Among those, polynomial basis is the most commonly used representation for its simplicity and accuracy, which is illustrated as follows:

$$y_k = \sum_{i=1}^{p} \Theta_i \prod_{j=1}^{n_x} x_{k-j}^{b_{i,j}} \prod_{l=1}^{n_e} e_{k-l}^{d_{i,l}} \prod_{m=1}^{n_y} y_{k-m}^{a_{i,m}} \tag{4}$$

where p is the number of regressors; Θ_i represents the parameters; $a_{i,m}$, $b_{i,j}$, and $d_{i,l}$ are the exponents of outputs, inputs, and noise terms, respectively; x_{k-j} e_{k-l} y_{k-m} refer to lagged input variables, noise terms, and output variables, respectively. Therefore, the core of polynomial based NARMAX methods is the estimation of parameters Θ_i. One of the approach is Forward Regression Orthogonal Least Squares (FROLS), which builds NARMAX models by trying regressors iteratively, and uses orthogonal least squares to identify relevant terms [3]. Moreover, it estimates the model parameters leveraging methods like least squares and extended least squares while regularizing parameters to prevent overfitting. CatBoostRegressor is a gradient boosting algorithm that builds an ensemble of decision trees and stands out as another approach for NARMAX [4]. In this case, in order to reduce measurement costs, only electricity load of heat pump and outdoor temperature are chosen as the inputs variable to infer indoor temperature trajectory. The fitting validation results are shown in the following figures. Table 1 shows different metrics of two models.

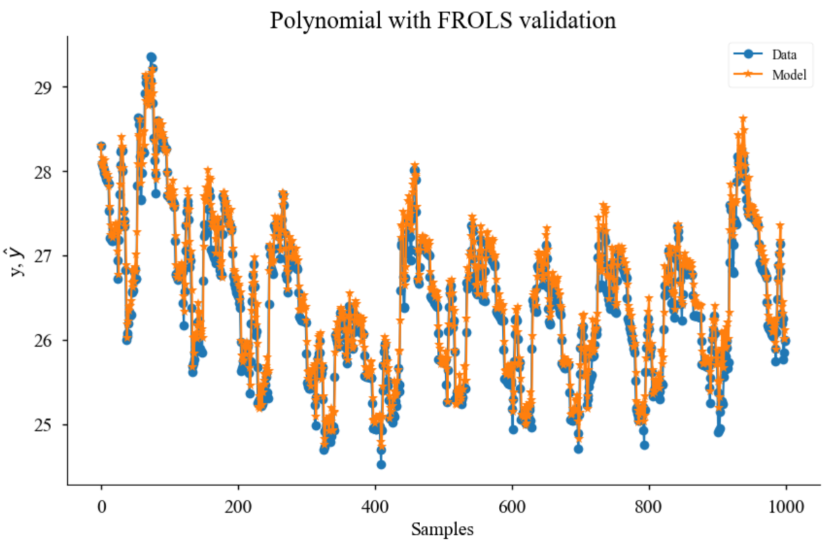

Figure 3: Validation results for NARMAX with FROLS

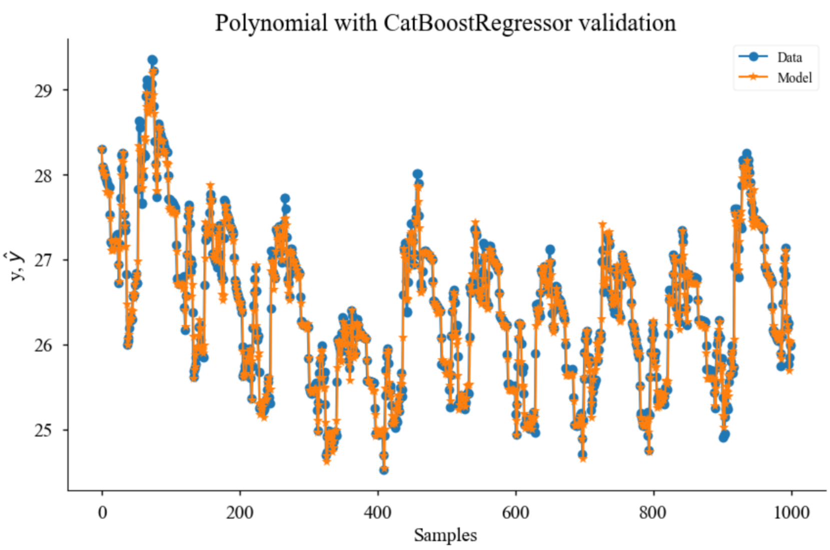

Figure 4: Validation results for NARMAX with CatBoostRegressor

	RRSE	MSE	MAE	MAPE
NARMAX with FROLS	0.2016	0.0620	0.1439	0.0053
NARMAX with CatBoostRegressor	0.1698	0.0440	0.1375	0.0050

Table 1: Different metrics of two models

3 Control formulation

The barriers for predictive control application in practice:

1. Complexity and uncertain disturbances
2. Computational speed of real time optimization
3. Sensor placement and data availability
4. (Human interaction and integration with existing systems)

References

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