Multi-Linear State Space Model Identification for Large Scale Building Systems

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Short Summary

Many Control Design approaches presuppose the knowledge of a state space description of the system. As in many real and large scale systems the construction of a state space model using analytical equations and rough assumptions is a time consuming process leading most of the times to questionable precision. System simulation software has been developed for several applications over the recent past decades. For this purpose a System Identification approach is proposed in the present paper. The idea of the System Identification from a simulation model using statistical measurements from the simulation output data has been of great interested for optimal control schemes which require accurate and furthermore, agile, simple and practical models to handle. In practice real systems and accurate simulation models, show nonlinear dynamic behavior which concludes to linear approximation-identification models being unsuitable for this purpose. The proposed Multi-Linear State Space Model Identification process is using the idea of mixing signals as weighted contribution factors for the final model behavior. A common Least Square error minimization process is used to minimize the model approximation error.

Keywords: Building, Simulation, SSM, Modeling, System Identification

1. Introduction

In control engineering, the field of system identification uses statistical methods to build mathematical models of dynamical systems from measured data. System identification also includes the optimal design of experiments for efficiently generating informative data for fitting such models as well as model reduction.

It must be noted that a white-box model based on first principles could be also build, e.g. a model for a physical process from the Newton equations. In many cases, though, such models are overly complex and possibly even impossible to obtain in reasonable time due to the complex nature of many systems and processes affecting the central model of interest.

A much more common approach is to start from measurements of the behavior of the system and the external influences (inputs to the system) and try to determine a mathematical relation between them without going into details of what is actually happening inside the system. Therefore a black-box (no prior knowledge for the system is available) system identification process is applicable to any measurable system and can be proven as a very efficient scheme for System State Space Model (SSM) realization.

Large scale non-linear systems are usually described in details by very large and complicated differential equations. These equations in order to be analytically complete usually demand the knowledge or the calculation from empirical graphs or tables, of many parameters. In addition, "necessary" physical simplifications and assumptions that conclude to fitting errors, between the constructed model of the system and the actual system, must be considered in order to make feasible the building process of a reliable model. Thus, control schemes, especially, for large scale systems (e.g. buildings, traffic networks) avoid dealing with state space models.

A common strategy is the use of precise and detailed simulation models to simulate systems. Simulation models require several calculations and much execution power. Many applications require fast simulation results due to their nature, thus even online control algorithms using co-simulation schemes can be proven impractical and not efficient at all. In addition a practical drawback in this strategy, is the mobility and compatibility of such model. Generating a precise enough, State Space Model (SSM) bypassing special and usually expensive simulators served by complicated connection interfaces which have to be incorporated in the system simulation scheme can be the only efficient solution to many practical applications.

This paper copes with the idea of approximating a dynamic SSM of a given, either simulation or real, system by using off line measurement data, using a common input-output system measurement database. The main idea is trying to minimize the approximation error of the state space realization matrices, using a simple and convenient way. The proposed strategy introduces state space subdivision and local linearization according to the current system working point - state. Locally referring but globally representative weight functions decide the contribution of each linear subsystem to the final model total dynamic behavior.

2. Transformations and Approximations

Let us consider a general non-linear system which assumes the following dynamics

$$\dot{\chi} = F(\chi, u, w) \tag{1}$$

where $\chi \in \Re^n, u \in \Re^m, w \in \Re^d$ denote the vectors of system states, control inputs and system disturbances, respectively, F is a nonlinear vector function which is assumed to be continuous.

2.1 Multi-Linear Subsystem Mixing Signals

The problem in large scale non-linear systems is the inherent inability of extracting a linear state space realization group of constant matrices in order to be able to design a convenient control system.

Assume that system function F can be approximated using smooth mixing signals membership functions, so as to have smooth switching between the linear subsystems and even more smooth switching between the linear subsystems respective controllers. Also assume as a first step that all states, control inputs and disturbances of the system can be measured or are given:

$$y = Cx = C\left[\chi, u, w, 1\right]^T \tag{2}$$

where matrix C is known and can be considered $C = I$ without loss of generality. Please note that the feedback vector is augmented using an ace at end, due to a constant term considered for all linear subsystems.

Let $\beta_i, i = 1, \ldots, L$ denote a set of smooth *mixing signals* that satisfy the following properties:

$$\beta_i(y) \in [0,1], \quad \sum_{i=1}^{L} \beta_i(y) = 1, \forall y \tag{3}$$

and, moreover,

$$\sum_{i=1}^{L} I\left(\beta_i(y)\right) \leq 2 \tag{4}$$

where $I(\beta_i(y))$ denotes the indicator function $I(\beta_i(y))=1$ if $\beta_i(y)>0$ and $I(\beta_i(y))=0$ if $\beta_i(y)=0$.

The activation functions β_i separate the system augmented state space $x\in\Re^{\dim(x)}$, where $\dim(x)=n+m+d+1$, into L overlapping regions, with each of the activation functions assigned to one of these regions. An activation function $\beta_i(y)$ is active [i.e., $\beta_i(y)>0$] whenever y ($y=x$ since $C=I$ is assumed) belongs to the respective region $\beta_i(y)$ has been assigned to. Please note that due to Eq. (4), every time there are maximum 2 activation functions active. We will, moreover, assume that the mixing signals β_i span the whole space y lies on, i.e., we will assume that for each possible y, there exists at least one i such that $I(\beta_i(y))=1$. In order to avoid degenerate cases where two or more mixing signals coincide, we will also assume that $\beta_i(y)\neq\beta_j(y), i\neq j$ holds over a non-negligible subset of $\Re^{\dim(x)}$.

Remark 1: Condition Eq. (4) can be relaxed by requiring – with the exception of at most two mixing signals – all mixing signals take negligible values for each particular y. In such case, the design of mixing signals becomes less complicated by using, e.g. Gaussian functions which show very good fitting properties.

2.2 Multi-Linear State Space Model

Using the above design considerations for the mixing signals β_i we can employ standard function approximation techniques to approximate the system dynamics. Instead of approximating a pure linear model for the specified system, an iterative exploration process decides the number of mixing functions to be used by giving the smallest approximation total error. The idea is to identify many linear subsystems describing the system dynamics in different working areas respectively, where the system behaviour usually changes in a significant manner. At each state the selection of the respective active linear subsystems is decided by the weight factors (mixing functions) and the total system behaviour can be represented analytically by the following equation:

$$\dot{\chi}\approx\sum_{i=1}^{L}S_i\approx\sum_{i=1}^{L}\beta_i(y)\left(\overline{A}_i\chi+\overline{B}_iu+\overline{G}_iw+\overline{F}_i\right) \tag{5}$$

If we group the state space matrices and vectors in one matrix that incorporates them we can write:

$$\dot{\chi}\approx\underbrace{\left([\overline{A}_1\overline{B}_1\overline{G}_1\overline{F}_1][\overline{A}_2\overline{B}_2\overline{G}_2\overline{F}_2]\ldots[\overline{A}_L\overline{B}_L\overline{G}_L\overline{F}_L]\right)}_{=:\Theta}\underbrace{\begin{pmatrix}\beta_1(y)\begin{bmatrix}\chi\\u\\w\\1\end{bmatrix}\\ \beta_2(y)\begin{bmatrix}\chi\\u\\w\\1\end{bmatrix}\\ \cdots\\ \beta_L(y)\begin{bmatrix}\chi\\u\\w\\1\end{bmatrix}\end{pmatrix}}_{=:\Lambda}, \tag{6}$$

and replacing the derivative by the difference quotient the compact form of the equation reads:

$$\frac{\chi_{[new]}-\chi_{[old]}}{\Delta t}=\dot{\chi}\approx\Theta\Lambda \tag{7}$$

2.3 Discrete Time Analysis

To simplify even more Eq. (7) we can use discrete time analysis and assume that the Δt -time step of the generated or measured data is significantly smaller than the time constant values, referring to the dynamics of the system. This assumption is reasonable in large building systems where the time constants have values (depending on the construction) up to 100 hours, compared to the data time step (usually few minutes). Thus alternatively Eq. (7) can then be written as (consider Δt = 1):

$$\chi_{[next]} \approx \chi_{[old]} + \Theta\Lambda \quad . \tag{8}$$

3. Approximation Error Minimization Analysis

After the problem formulation, the main problem is the approximation – calculate Θ matrix which contains all the state space realization constant matrices for every linear approximation member subsystem S_i as described above. In order to form the Least Square problem the following calculations are presented. From Eq. (8) we have:

$$\Lambda^T \Theta^T \approx (\chi_{[z+1]} - \chi_{[z]})^T \quad . \tag{9}$$

The above equation has the general form of the Least Square problem $QX = B$ which is used to minimize the approximation error of X vector. Consider:

$$Q = \Lambda^T,\ X = \Theta^T, B = (\chi_{[next]} - \chi_{[old]})^T \quad . \tag{10}$$

Matrix Λ and tall vectors $\chi_{[next]}, \chi_{[old]}$ include simulation output data or measurement data of the system to be identified. The values of β_i functions (normalised Gaussian functions) are formed using for each data time step the whole or part (C matrix depends on the specific application) of feedback vector y. The kernel functions used in this proposed application are normalised scalar Gaussian functions using the norm of y vector to decide the maximum two active subsets at each given state – working point of the system.

This vector is formed to decide the membership magnitude of the respective linear subsystem. Each row of Θ matrix is approximated using Least Square method with Λ vector and the respective $j-th$ state variable vector $(\chi^{(j)}_{[next]} - \chi^{(j)}_{[old]})$.

In conclusion the problem becomes a regression approximation problem in which we want to minimize the approximation error e using the Least Squares method. The optimization problem becomes:

$$\min \quad T = \sum_{j=1}^{n} \sum_{z=1}^{\mathcal{N}} e_{zj}^2 \tag{13}$$

where $\mathcal{N}$ is the total sample number of the training data set, n is the number of state variables and e_{zj} is the approximation error defined by

$$e_{zj} = (\chi_{[z+1]} - \chi_{[z]})^{(j)} - \Theta^{(j)}_{row}\Lambda_{[z]} \tag{14}$$

where $z = 1, 2, ..., \mathcal{N}$ and $j = 1, 2, ..., n$.

4. Building Model and Zoning Procedure

To test the developed system identification algorithm we use a validated building model generated with TRNSYS [1]. This model has been developed during the project PEBBLE (for details see http://www.pebble-fp7.eu/).

4.1 Center for Sustainable Building (ZUB)

The ZUB building, built in 2001, located at the campus of the University of Kassel, Germany is an exemplary low-energy building. The ZUB has three floors, a basement and an atrium in contact with a nearby building. It is occupied by researchers in the field of building physics, equipped with a significant number of sensors, and used for experimental investigations in the field of energy optimization and building technologies.

The overall volume of the heavy-weight construction is 6882 m³, the net heated floor area is 1332 m^2 and the main floor space is 892 m² [2]. Floor height is close to 4 m and the annual heat demand is between that of a low-energy building and a passive house, approximately 30 kWh/m² or 5.3 kWh/m³; electricity consumption based on the heated net floor area is approximately 20 kWh/m^2 a. More details about the ZUB and its energy concept are given in [3, 2].

Fig. 1a shows the ZUB building model, designed using Google SketchUp, with shading groups in purple. Since the building is equipped with Thermally Activated Building Systems (TABS): independent radiant floors, and radiant ceiling systems in each room, each physical room was defined as a separate thermal zone. In total 26 zones are required to model the whole building. The atrium at the back of the building consists of three thermal (convective) air-nodes, – one per floor, – combined to a single (radiative) zone, for more details on the model and the simplification see [4, 5].

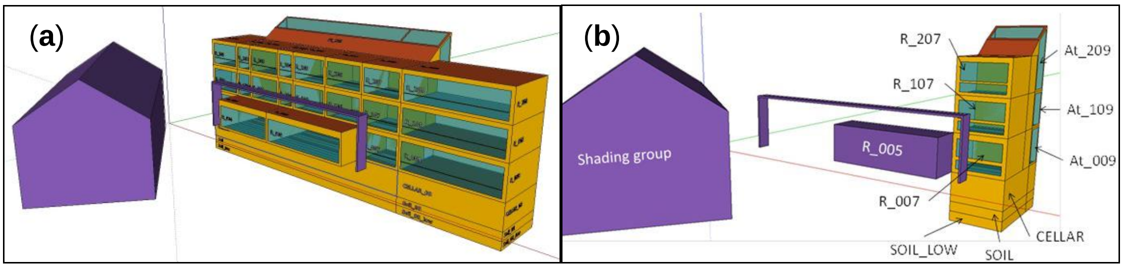

Fig. 1: building model for the ZUB (a) and reduced building model (Tower); designed in Google SketchUp.

For testing the proposed system identification procedure a reduced model the so called Tower is used. This Tower is essentially a cut-out of the building that preserves all relevant characteristics from the whole model, compare Fig. 1b. The implementation approach of SysID, uses TRNSYS simulation output data for system identification. Used weather data are for 2003.

Another major discussion topic of building simulation and control schemes is the zoning procedure. Zoning is defined by simple but often not clear principles. A thermal zone is defined as an individual space or group of neighbouring indoor spaces that is expected to have quite similar thermal loads and behaviour. Zones are defined in thermal building simulation to reduce the number of independent HVAC subsystems. The zone room demarcation in the subject building is done under this simple principle. The three zones due to their orientation and corner position, subject to the whole construction, are expected to have different thermal behaviour depended on unpredictable outdoor environment thermal loads.

A common concept in system identification schemes is the excitation persistency of the system so as the input signal should be such as to excite all the modes of the plant to be identified to assure the convergence of the parameters to their true values. For this reason a simulation schedule is followed in the building simulations in order to generate proper data for the identification scheme: Every six hours (that is every 24th time step) random control actions were generated and applied to the system to ensure all system dynamics are excited fairly (Fig. 2).

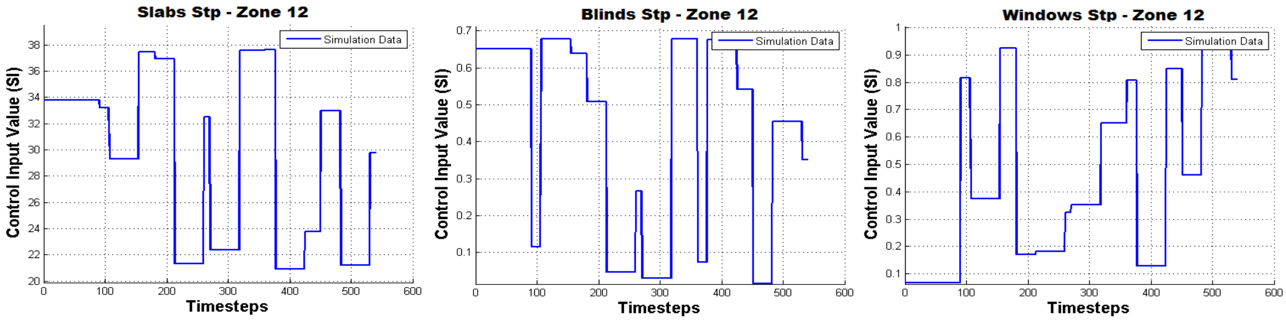

Fig. 2: Simulation random system excitation control signals

5. Parameterization and Identification Results

5.1 Discussion of State-Control-Disturbance Variables

Deciding the proper state and control variables that provide satisfying results with less data complexity and data size is discussed in the present section. In our approach these variables were defined and grouped as:

- Indoor mean air temperature and indoor humidity ratio (consider each zone as a single simulation node – uniform mean temperature and humidity ratio for the whole volume of each zone) were used as state variables (χ vector) because these are the main two physical variables deciding the user comfort level (Fanger [6]).
- Schedule ventilation for openings (windows-doors), schedule for blinds, HVAC temperature set points were considered as the controllable signals for the building model (u vector).
- Outdoor humidity ratio, outdoor temperature, wind speed, wind direction, total solar radiation and office occupancy schedule were considered as uncertain disturbances (w vector).

5.2 Identification Results

Simulation and identification results are depicted below. The simulation data used for the identification process (Training) were chosen during winter period and specifically during the first week of the year i.e. 4th – 12th January 2003 (Fig. 3). The simulation data were divided into two data groups the one used for the model training process (70% of total data) and the other one to validate the identified model with unknown validation data (30% of total data). The sampling frequency was set in the simulation model equal to 15 minutes.
The model was validated using different state resetting frequency (f). In the model integration process three different time horizon scenarios were tested as follows:

- Every validation period time step simulation data were used to integrate the model only to the next time step state variable values (f = 1 step – 15 min).
- Every 25 validation period time steps simulation data were used to integrate the model to the next time step state variable values (f = 25 steps – 6 hours).
- Every 96 validation period time steps simulation data were used to integrate the model to the next time step state variable values (f = 96 steps – 24 hours).

Please note that due to lack of space the results included in the present paper refer only to one thermal zone of the building (Zone R_107). Please also note that the first day of every simulation is used as settling time so as the building reaches a reasonable state – working point.

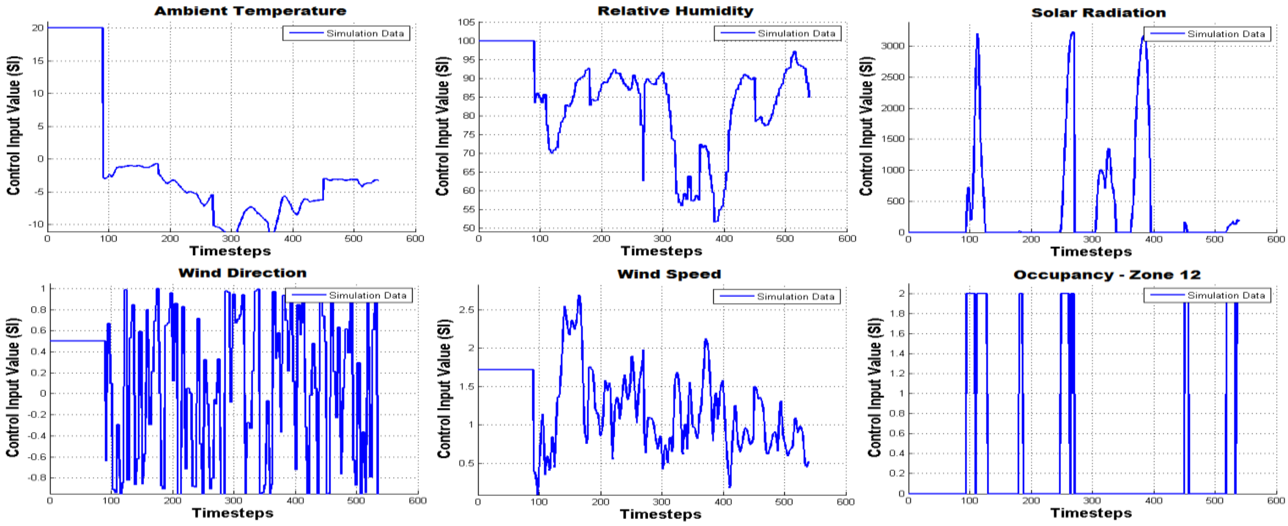

Fig. 3: Simulation Weather Data during the training period which is the first week in January

The summary for the identified model is incorporated in Table 1 below. The respective transients for the validation period are shown in Fig. 4. Note that the blue curves refer to the building simulation results and the green ones to the identified model simulation.

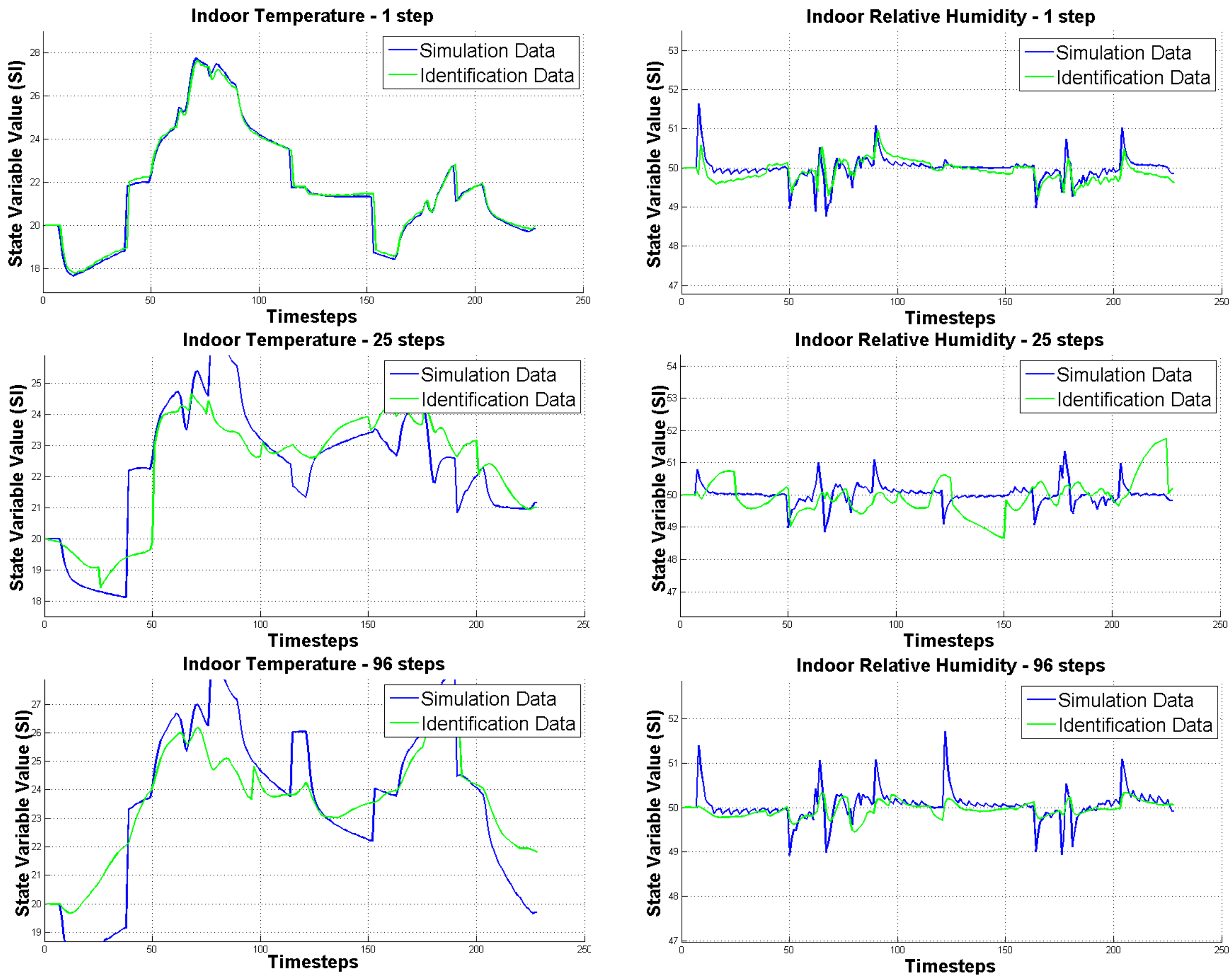

Fig. 4: ID results for indoor temperature in °C (first column) and relative humidity in % (second column) with different state resetting frequency f (different prediction horizon for each row)

Table 1: Identified model summary of results, for three different state resetting frequencies (different prediction horizons)

Steps (1 Step = 0.25 h)	*Prediction Horizon 1*	*Prediction Horizon 25 (6.25 h)*	*Prediction Horizon 96 (24 h)*
Number of mixing functions	2	3	2
Training Period Error (%)	0.9	4.7	6.6
Validation Period Error (%)	1.1	4.5	14.7

6. Conclusion

A system identification approach was proposed in this paper. The identification of a multi-linear state space model which is viable to describe the thermal dynamics of an office building for the near future – based on (simulation) training data from the past – was successfully demonstrated. In this paper simulation data from a validated TRNSYS model of an office building were used for demonstration, but practically these data may stem from measurement data of a real building. Real building data, describing usual operation of the building, however, might not lead to sufficient excitation, which is needed to obtain a "good" model. The idea of mixing signals as weighted factors for the linear sub-models to form the multi-linear state space model proved to work very well if the current state is updated frequently. As the update frequency is increased the modeling error increases significantly for the training period, but especially for the validation period.

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