Building a model of family house heating system using 1-wire sensor network protocol

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Abstract— The paper presents the parameter identification of a house heating system using a sensor network based on 1-wire protocol and the Raspberry Pi (RPi) computer. 46 sensors capture measurement data such as temperature, humidity, wind speed and fuel consumption using the 1-wire protocol. A fine-grained displacement of sensors throughout the house provides high measurement resolution. A high number of system inputs and outputs favors using a subspace identification algorithm. The identified model can be used to assess the effectiveness of heating system. To minimize computational burden, sensors delivering the greatest amount of information are chosen. All identification experiments have been carried out in a 270 m^2, 680 m^3 detached uninhabited house, in a period of 30 days.

Keywords— state space models, subspace methods, identification algorithms, parameter estimation.

I. INTRODUCTION

The aim of this paper is searching for energy saving solutions through using a family house heating model obtained via subspace identification. Recently, a profound research effort has been made on identification of buildings condition for the energy saving purposes [1]. A comprehensive results of subspace identification approach are presented in this paper. A high number of inputs and outputs results in a high complexity of the house heating model. Many works present the identification of selected parts of the heating system of building or the entire building by analyzing the individual parts [10], [1]. This paper proposes a new comprehensive approach to the identification using house heating model based on the real measurement data and subspace methods [3]. The house as a whole is treated as a black box and all measurements are acquired from a set of sensors [14], [18]. One possible approach to house heating model identification is to use a 2D model in which in one dimension the information is propagated from day to day and in the other along the day. Repetitive processes are a class of 2D systems in which information in the temporal domain is of finite duration [12]. Each execution is known as a pass (a day) and its duration as the pass length [4]. Design the house heating system requires a process model and this paper is addressed to the problem of its identification from the input-output data.

Identification of linear repetitive process dynamics is still a challenging problem in the system identification, and [5], [6], and [8] give the only published results. The approach proposed there is based on using an extended input sequence composed of the current pass input and the previous pass output, and the output sequence composed of the current pass output to determine the order of linear repetitive process, its unknown state-space model matrices and the noise covariance matrices [16], [17]. As such identification procedure uses the input output data from two successive passes, it can be restarted consecutively starting from the first pass data and boundary conditions. Therefore, it can be very useful for the identification of time invariant dynamics [2], [7], [21].

The need for fuel-saving results for consumption of natural fuels results both from the environmental and economic reasons. The need to optimize energy consumption, among others, arises from the growing number of buildings (up to 5 % a year in the EU countries). The energy consumption optimization leads to minimization of home maintenance costs. The proposed new approach to building house heating model is based on subspace identification methods. In the overall energy consumption of a residential building, about 50% is used for space heating, and about 19% for hot water heating, the remainder is associated with the use of household equipment. The annual cost of heating is from 30% to 50% of the overall cost of house maintaining. Therefore, the energy consumption reducing for heating residential buildings is important and affects all societies [19].

The house heating system consists of three main elements - a heat source, network pipes, and a heat receiver. To describe house heating system, the following classification features are to be specified:

1) Heat source type.
2) Heat source location.
3) Fuel type.
4) Heating medium type.
5) Heat dissipation method.

The domestic generation of hot water can be made using installation with or without the heat exchanger. The disadvantage of the first solution is the limited instantaneous maximum flow of hot water, while the other requires maintaining the stored heat energy. This highlights the diversity of simple heating systems in conjunction with different shapes of buildings [1]. The problem of heating is very extensive and therefore it is restricted here to the dwelling house with a central source of heat and a domestic hot water preparation system. An example of house heating system considered in this paper is shown in Fig. 1.

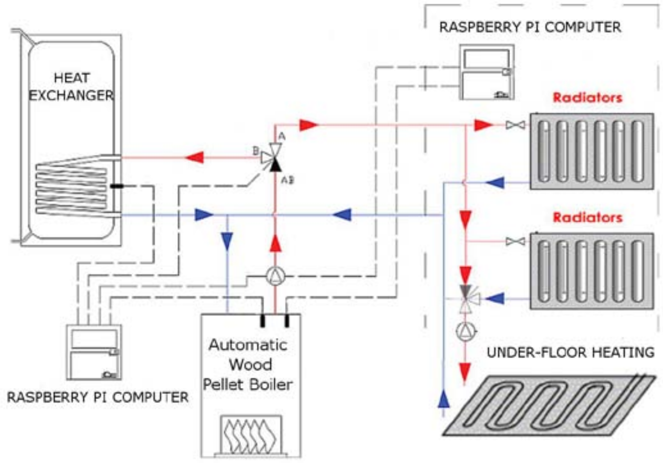

Fig. 1. Central heating with hot water buffer installation.

The physical description of house heating system takes into account the following parameters:

1) Thermal resistance.
2) Heat transfer coefficients of different elements of the house.
3) Heat loss coefficients.
4) Heat transfer coefficients by thermal bridges.
5) Heat demand of the rooms.
6) Heating energy consumption.
7) Outdoor temperature.

The heat exchanger, which is a hot water buffer, can be characterized by the following parameters:

1) The rate of unit demand for hot water.
2) The number of recipients and the coefficient of simultaneity use.
3) The required intake water temperature.

The house heat exchanger specification is chosen on the basis of the most adverse weather conditions and the maximum water consumption for a given number of inhabitants [20].

The structure of the paper is as follows: In Section II, the metering building using 1-wire protocol is introduced, description of the test building is given in Section III. In section IV and section V deterministic model of a discrete linear repetitive process is introduced, the identification problem is formulated and its solution based on subspace algorithms is presented. Section VI deals with the stochastic identification problem.

Identification results are shown in Section VII. Finally, conclusions are given in section VIII.

II. METERING BUILDING USING 1-WIRE PROTOCOL

The considered dwelling house is inhabited. Hence, this test site allows parameter identification of building heating system using subspace methods in open loop.

Fig. 2. Experimental building area.

The heat receiver is a dual-circuit system with the reception radiator plugged to the underfloor heating system.

Simple control systems provide low effectiveness because they lack cost effectiveness and energy consumption optimization. The main elements of the proposed control system are three Raspberry Pi (RPi) computers, which have the advantage of small size, low cost and low power consumption, and the GPIO module which allow to gather data from all sensors deployed in the house. For the temperature and humidity measuring, DS18B20 temperature sensors and DHT11 humidity sensor are selected. The DHT11 humidity sensor allows the moisture measurement in the ranges of 10% – 40% and 20% – 90% with the accuracy of ±1%.

The weather transmitter WS2800 measures the outside temperature and it also allows to record:

1) Wind speed ranged from 0 to 35 m/s and from 0 to 60 m/s with the accuracy of 3%.
2) Wind direction ranged from 0 to 360 with the accuracy of 3%.
3) Relative humidity ranged from 0 to 100% with the accuracy of 3%.
4) Atmospheric pressure in the range from 600 hPa to 1100 hPa.
5) Intensity of precipitation and distinguishing the rain and the hail.

The full functionality of the described system is not only limited to collecting measurements. Due to the built-in GPIO module of the RPi computer, it is also possible to configure it with the SRD-05VDC-SL-C Power Relay Modules to control the system. The control system allows to control actuators using GPIO RPi ports. Fig. 3 presents the thermal drive whose action causes RPi computer algorithm to control the valve to save energy.

Fig. 3. Thermal driver allowing to control the valve via RPi computer.

RPis are interconnected through network adapters, which allows to monitor the RPis status. A radio card allows to view, monitor and program RPis from devices equipped with Wi-Fi cards. The RPi collects data from temperature sensors, humidity sensors and the weather station WS2800 using the GPIO module and shielded twisted cable. Having the communication protocol used in a given device, the interpretation of the results can be made after receiving all packages. In total, a set of three RPi computers, with GPIO interface and 1-Wire Dallas Semiconductor protocol, connected to 32 temperature DS18B20 sensors and 9 DHT11 humidity sensors are employed during the measuring experiments. Fig. 4 shows the patch panel which organizes all connections for controlling devices and all sensors placed in the house.

Fig. 4. Patch panel organizing connection of Raspberry Pi computers to sensors.

This configuration allows the input and output temperature measurement of the radiator, boiler and heat exchanger as well as the temperature in different rooms of the building. The measurement system also includes software archiving input and output measurements for the purpose of subspace identification. This software has been developed in PHP, and it provides the tools to easily create data in the form of a website. The program runs in a web browser enabling remote access to measurement data. For the purpose of communication via the RS485 port, the YUKO converter was used. This is an industrial solution, and it allows the choice of low data transmission rate for communication over a distance up to 5 km. Received packets with additional information describing the server status are stored as text files in the form of logs. This enables verification of the communication correctness. The main archiving is done using the MySQL database. The measurement ranges of physical values received by the server are determined by manufacturing specifications of measuring devices and stored in the respective tables along with the so-called time stamp. The server allows local instantaneous and historical visualization of measuring data in the form of graphs and text files conversion.

III. DESCRIPTION OF THE TEST BUILDING

We distinguish among three types of single-family houses: detached, semi-detached, terraced. The detached house heat losses are greater than those of terraced ones. The test building includes a basement which better insulates heat from the ground. Heating water distribution lines are routed in floors and radiators circulation. Diversity of design features of the building determines its dynamic properties as an identification object. These, in turn, can be determined by examining the mutual relationship between the measured signals. Some of these relationships may prove to be irrelevant, what determines the later choice of a control systems structure.

The test building is a detached house consisting of two apartments with a total area of 270 square meters. It consists of 18 heated rooms and a stairwell. The cubic heated space equals to $630m^3$. The building was designed as a detached bungalow with a usable floor space attic, entirely cellared with not heated garage located in the cellar part. The building has a single-layered exterior walls made of Porotherm ceramic blocks and 12cm thick styrofoam insulation layer. On the outside, the walls are covered with mesh and glue and a decorative plaster, while on the inside with a mineral plaster. The wall heat transfer coefficient lambda is less than 0.25 W/m^2K. The floors of the building are made of prestressed concrete panels. The roof is covered with ceramic tiles, insulated with 20cm and 5cm thick mineral wool layer. The insulation layer is protected from the inside by a vapor barrier film, and by a highly permeable foil on the outside. The building has 24 plastic windows, two patio doors, eight roof windows, and one garage gate. The windows heat transfer coefficient lambda is 1.1 W/m^2K. The ventilation used in the building is natural one and it consists of five channels. In the basement of the house, there is a boiler room in which a central source of heat was placed. It is the solid fuel 25 kW Brass boiler. The house is heated by a floor-mixed installation of radiators. For the water stream distribution, a mixing valve connected to underfloor heating, radiators and water heating is employed. Each of the radiators is equipped with a thermoregulation valve. The water is distributed via a switchboard system (3 sections) and the forced circulation pump. Heating cables are made using the PEX Wavin technology. The system pressure is 0.9MPa. The boiler is equipped with a hot water storage tank of 300l capacity. The building meets the criteria of representativeness associated with the widespread use of technical solutions. The approximate values of heat transfer coefficient for the tested building are given in Table 1.

Table 1. The approximate values of heat transfer coefficient.

No	Bulkhead	Heat transfer coefficient (kW/m^2 K)	Area (m^2)
1	Walls	0.22	233
2	Roof	0.27	203
3	Floors	0.68	180
4	Doors	2.01	3.6
5	Windows	1.1	35

A proper design of house heating control system can increase the overall heating system efficiency. The test building was not inhabited during the period of study. The ways of controlling the boiler and an accurate predictability of the noise variability, which are external weather conditions, were limited. Major weather changes during the observation gave a large variety of object excitations. The difficulty in the test was a correct choice of the sampling period of measured continuous signals. The measuring tests included 30 days in the heating season, whereas the next 10 days were reserved only for the efficiency verification of the proposed identification system. The effect of external conditions changes on the thermal state of the building and the performance of heating system were studied. For the experiment, the measuring data were collected at wide variations of weather conditions and constant values of selected heating system parameters such as pump flow, and required temperatures. The outdoor temperature measurement was performed at three points: on the western, southern and eastern side of the house, and the measured values were averaged. Fig. 5 shows the registered temperature, humidity and wind speed. The boiler water temperature and temperatures of individual radiators and floor heating inputs were also measured for the purpose of identification. The output signal is the amount of fuel consumed within 30 minutes. The effectiveness of the heating system is evaluated due to observation of the ZM_H8C-C3-500k ZEMIC extensometer that monitors the boiler fuel consumption. The input signals for identification are temperatures, humidity, and wind force, and the output signal is the amount of consumed fuel. In the context of measuring experiments co-financed by the EU within 30 days of the heating season, more than 2 GB of data were collected. In addition, for comparison a set of weather data gathered by the Wroclaw weather station in the years 2006 - 2012, and the year 2012 weather data registered in Szczecin and Zakopane were collected. This allows the reliable identification of the building model and the following simulation studies using registered excitations. In the course of the simulation studies, the model can be stimulated by input signals without any geographical limitations.

IV. DETERMINISTIC DISCRETE REPETITIVE PROCESSES

Consider the state-space model [17] of a discrete linear repetitive process of the following form:

$$x_{k+1}(p+1) = Ax_{k+1}(p) + B_0 y_k(p) + Bu_{k+1}(p) \tag{1}$$

$$y_{k+1}(p) = Cx_{k+1}(p) + D_0 y_k(p) + Du_{k+1}(p) \tag{2}$$

where:

$0 \le p \le \alpha - 1 \in Z_+ -$ the independent spatial or temporal variable,

$k \in Z_+ -$ the current pass number,

$x_k(p) \in R^n -$ the state vector,,

$y_k(p) \in R^l -$ the pass profile (output) vector,

$u_k(p) \in R^m -$ the input vector,

$A, B, B_0, C, D, D_0 -$ matrices of appropriate dimensions.

To complete process description, it is necessary to specify the boundary conditions [9]:

$$x_{k+1}(0) = d_{k+1}$$
$$y_0(p) = f(p) \tag{3}$$

where $d_{k+1} \in R^n$ is a vector with known constant entries and

$$f(p) \in R^l \tag{4}$$

Define the following input Hankel Block matrix [9]:

$$U_{0|2i-1} \overset{def}{=} \left[\begin{array}{ccc} u_{k+1}(0) & \dots & u_{k+1}(j-1) \\ y_k(0) & \dots & y_k(j-1) \\ \dots & \dots & \dots \\ u_{k+1}(i-1) & \dots & u_{k+1}(i+j-2) \\ y_k(i-1) & \dots & y_k(i+j-2) \\ \hline u_{k+1}(i) & \dots & u_{k+1}(i+j-1) \\ y_k(i) & \dots & y_k(i+j-1) \\ u_{k+1}(j+1) & \dots & u_{k+1}(i+j) \\ y_k(i+1) & \dots & y_k(i+j) \\ \dots & \dots & \dots \\ u_{k+1}(2i-1) & \dots & u_{k+1}(2i+j-2) \\ y_k(2i-1) & \dots & y_k(2i+j-2) \end{array}\right]$$

$$\overset{def}{=} \left[\frac{U_{0|i-1}}{U_{i|2i-1}}\right] \overset{def}{=} \left[\frac{U_p}{U_f}\right] \tag{5}$$

$$U_{0|2i-1} \overset{def}{=} \left[\frac{U_{0|i}}{U_{i+1|2i-1}}\right] \overset{def}{=} \left[\frac{U_p^+}{U_f^-}\right] \tag{6}$$

Define also the output block matrix $Y_{0|2i-1}$:

$$Y_{0|2i-1} \overset{def}{=} \left[\begin{array}{ccc} y_{k+1}(0) & \dots & y_{k+1}(j-1) \\ \dots & \dots & \dots \\ y_{k+1}(i-1) & \dots & y_{k+1}(i+j-2) \\ \hline y_{k+1}(i) & \dots & y_{k+1}(i+j-1) \\ y_{k+1}(i+1) & \dots & y_{k+1}(i+j) \\ \dots & \dots & \dots \\ y_{k+1}(2i-1) & \dots & y_{k+1}(2i+j-2) \end{array}\right]$$

$$= \left[\frac{Y_{0|i-1}}{Y_{i|2i-1}}\right] = \left[\frac{Y_p}{Y_f}\right] \tag{7}$$

$$Y_{0|2i-1} \overset{def}{=} \left[\frac{Y_{0|i}}{Y_{i+1|2i-1}}\right] = \left[\frac{Y_p^+}{Y_f^-}\right] \tag{8}$$

The number of block rows i should be larger than the maximum order of the LRP [11].

Define block Hankel matrices W_p and W_p^+ consisting of Y_p, U_p and Y_p^+, U_p^+, respectively:

$$W_{0|i-1} \overset{def}{=} \begin{bmatrix} U_{0|i-1} \\ Y_{0|i-1} \end{bmatrix} = \begin{bmatrix} U_p \\ Y_p \end{bmatrix} = W_p \tag{9}$$

$$W_p^+ = \begin{bmatrix} U_p^+ \\ Y_p^+ \end{bmatrix} \tag{10}$$

The state-sequence matrix X_i is defined as:

$$X_i \overset{def}{=} \left[x_{k+1}(i) \; ... \; x_{k+1}(i+j-1) \right] \tag{11}$$

Define the extended observability matrix Γ_i and the reversed extended controllability matrix Δ_i

$$\Gamma_i \overset{def}{=} \begin{bmatrix} C \\ CA \\ CA^2 \\ ... \\ CA^{i-1} \end{bmatrix} \tag{12}$$

$$\Delta_i \overset{def}{=} \left[A^{i-1}[B\,B_0] ... A[B\,B_0][B\,B_0] \right] \tag{13}$$

Assume also that the pair $\{A,C\}$ is observable and the pair $\{A,[B\,B_0]\}$ is controllable [9]. Finally, define the lower block triangular Toeplitz matrix H_i

$$H_i \overset{def}{=} \begin{bmatrix} [D\,D_0] & 0 & ... & 0 \\ C[B\,B_0] & [D\,D_0] & ... & 0 \\ CA[B\,B_0] & C[B\,B_0] & ... & 0 \\ ... & ... & ... & ... \\ CA^{i-2}[B\,B_0] & CA^{i-3}[B\,B_0] & ... & [D\,D_0] \end{bmatrix} \tag{14}$$

The block Hankel matrices (5) – (10) along with the extended observability matrix (12), the reversed extended controllability matrix (13) and the lower block triangular Toeplitz matrix play an important role in the development of subspace identification methods [7].

V. IDENTIFICATION PROBLEM

Given α measurements of the input $u_{k+1}(p)$ and the outputs $y_k(p)$ and $y_{k+1}(p)$ generated by the LRP (1) – (2) determine its order and the LRP matrices A, B, B_0, C, D, D_0 up to within a similarity transformation.

Following Theorem 1 [15], the state-space model (1) – (2) can be written in a matrix form

$$\begin{aligned} Y_p &= \Gamma_i X_p + H_i U_p, \\ Y_f &= \Gamma_i X_f + H_i U_f, \\ X_f &= A^i X_p + \Delta_i U_p, \end{aligned} \tag{15}$$

The LRP system matrices can be computed using Algorithm1 or Algorithm 2 of Van Overschee and De Moor [15], assuming actual pass input and previous pass output as model input [7].

VI. STOCHASTIC DISCRETE REPETITIVE PROCESSES

Consider the state-space model of a discrete linear repetitive process of the following form

$$x_{r+1}(p+1) = Ax_{r+1}(p) + B_0 y_r(p) + Bu_{r+1}(p) + w_{r+1}(p) \tag{16}$$

$$y_{r+1}(p) = Cx_{r+1}(p) + D_0 y_r(p) + Du_{r+1}(p) + v_{r+1}(p) \tag{17}$$

Where the covariance matrix of the zero mean white vector sequences $w_{r+1}(p)$ and $v_{r+1}(p)$ is

$$E\left\{ \begin{bmatrix} w_{r+1}(k) \\ v_{r+1}(k) \end{bmatrix} \left[w_{r+1}^T(q) \;\; w_{r+1}^T(q) \right] \right\} = \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \delta_{rq} \tag{18}$$

and δ_{rq} denotes the discrete Kronecker delta.

The identification problem is: given αK measurements of the input $u_{r+1}(p)$ and the outputs $y_r(p)$ and $y_{r+1}(p)$ generated by (29) – (30) determine the order of this process and the matrices A, B, B_0, C, D and D_0 up to a similarity transformation, and the covariance matrices Q, S and R.

We assume that $u_{r+1}(p)$ and $y_r(p)$ are uncorrelated with $w_{r+1}(p)$ and $v_{r+1}(p)$, $u_{r+1}(p)$ and $y_r(p)$ are persistently exciting of order $2i$, $j \to \infty$, and $w_{r+1}(p)$ and $v_{r+1}(p)$ are not identically zero.

Based on Theorem 12 [15], the combined Algorithm 1 or its robust version can be applied to determine the process order and the unknown matrices $A, B, B_0, C, D, D_0, Q, S, R.$ The combined Algorithm 1 consists of the following steps [13]:

1) Calculate the oblique projection

$$O_i = Y_f /_{U_f} W_p \tag{19}$$

2) Calculate the singular value decomposition

$$W_1 O_i W_2 = [U_1 U_2] \begin{bmatrix} S_1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} = U_1 S_1 V_1^T \tag{20}$$

3) Find the order of the process (16) – (17) by the inspection of the singular values in S_1.

4) Calculate $\mathbf{\Gamma}_i$ from

$$\mathbf{\Gamma}_i = W_1^{-1} U_1 S_1^{1/2} T \tag{21}$$

5) Solve the following set of linear equations in a least squares sense for A, C and K

$$\begin{bmatrix} \mathbf{\Gamma}_{i-1}^{\mathrm{I}} Z_{i+1} \\ Y_{i|i} \end{bmatrix} = \begin{bmatrix} A \\ C \end{bmatrix} \mathbf{\Gamma}_i^{\mathrm{I}} Z_i + KU_f + \begin{bmatrix} \rho_w \\ \rho_v \end{bmatrix} \tag{22}$$

where Z_i and Z_{i+1} are the orthogonal projections:

$$Z_i = Y_f / \begin{bmatrix} W_p \\ U_f \end{bmatrix} \tag{23}$$

$$Z_i = Y_f^- / \begin{bmatrix} W_p^+ \\ U_f \end{bmatrix} \tag{24}$$

6) Determine $B, B_0, D,$ and D_0 from the following over-determined set of equations using least squares method

$$\begin{bmatrix} K_{1|1} \\ \vdots \\ K_{1|i} \\ K_{2|1} \\ \vdots \\ K_{2|i} \end{bmatrix} = N \begin{bmatrix} D & D_0 \\ B & B_0 \end{bmatrix} \tag{25}$$

where

$$N = \begin{bmatrix} -\lambda_{1|1} & M_1 - \lambda_{1|1} & \cdots & M_{i-2} - \lambda_{1|i-1} & M_{i-1} - \lambda_{1|i} \\ M_1 - \lambda_{1|2} & M_2 \lambda_{1|3} & \cdots & M_{i-1} - \lambda_{1|i} & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ M_{i-1} - \lambda_{1|i} & 0 & \cdots & 0 & 0 \\ I_l - \lambda_{2|1} & -\lambda_{2|2} & \cdots & -\lambda_{2|i-1} & -\lambda_{2|i} \\ -\lambda_{2|2} & -\lambda_{2|3} & \cdots & -\lambda_{2|i} & 0 \\ \cdots & \cdots & \cdots & -\lambda_{2|i} & 0 \\ -\lambda_{2|i} & 0 & \cdots & 0 & 0 \end{bmatrix}$$

$$\times \begin{bmatrix} I_l & 0 \\ 0 & \mathbf{\Gamma}_{i-1} \end{bmatrix} \tag{26}$$

with

$$\lambda = \begin{bmatrix} A \\ C \end{bmatrix} \mathbf{\Gamma}_i^{\mathrm{I}} = \begin{bmatrix} \lambda_{1|1} & \lambda_{1|2} & \cdots & \lambda_{1|i} \\ \lambda_{2|1} & \lambda_{2|2} & \cdots & \lambda_{2|i} \end{bmatrix} \tag{27}$$

$$M = \mathbf{\Gamma}_i^I = \begin{bmatrix} M_1 & M_1 & \cdots & M_{i-1} \end{bmatrix} \tag{28}$$

$$K = \begin{bmatrix} K_{1|1} & K_{1|2} & \cdots & K_{1|i} \\ K_{2|1} & K_{2|2} & \cdots & K_{2|i} \end{bmatrix} \tag{29}$$

7) Determine Q, S and R from the residuals ρ_w and ρ_v

$$\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} = E\left\{ \begin{bmatrix} \rho_w \\ \rho_v \end{bmatrix} \begin{bmatrix} \rho_w^T & \rho_v^T \end{bmatrix} \right\} \tag{30}$$

VII. IDENTIFICATION RESULTS

The modified subspace identification algorithm has been applied to collected input-output data. The subsequent one-day data have provided the information to build the house heating model. The following input and output signals have been accepted: the house inside temperature, the outdoor temperature as the inputs, and the fuel consumption as the output. Fig. 5 shows the outside temperature, humidity, pressure, and wind force during carrying out the experiments, while Fig. 6 shows the change of inside temperature with changing weather conditions.

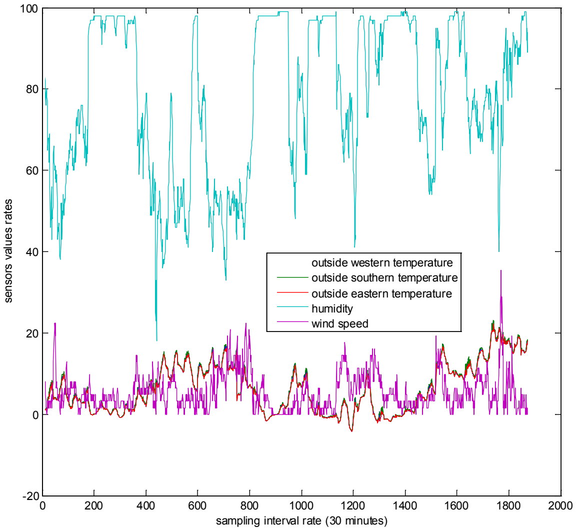

Fig. 5. Sensors values of western temperature, southern temperature, eastern temperature, humidity, and wind force.

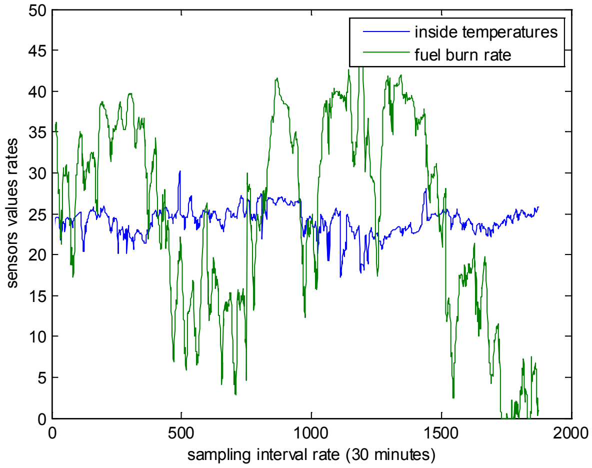

Fig. 6. Change of inside temperature; fuel burn rate [dag/h]

To identify repetitive process model, it is assumed that each pass corresponds to data acquired in 24 hours, and subsequent 24 hours data have been merged. The data are sampled every 30 minutes, hence one pass contains 48 samples. Fig. 7 shows comparison of the second order model response with the actual data. In this case, fitting model response to the actual data achieves 41%. Increasing the order of estimated model to 4, results in the fitting level of 91.61% – Fig. 8.

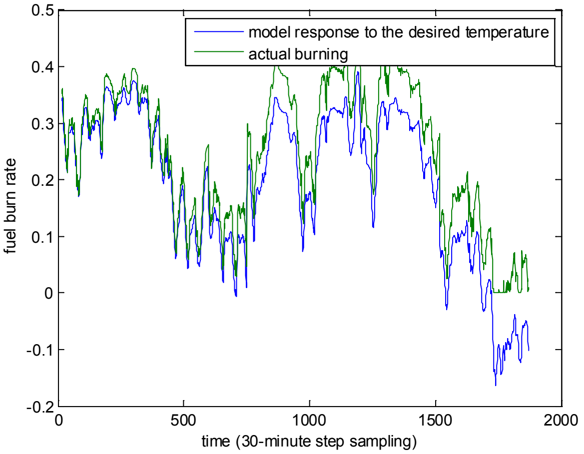

Fig. 7. System fuel burn rate and the second order model response.

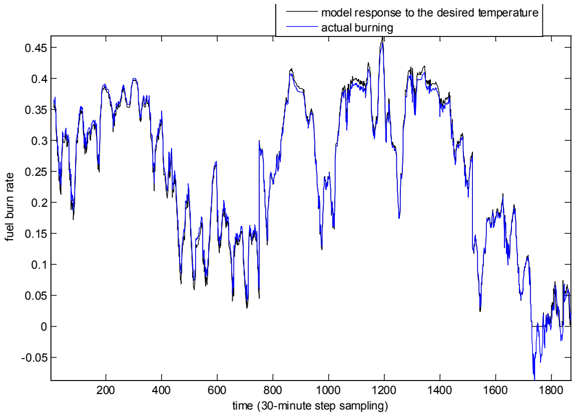

Fig. 8. System fuel burn rate and the fourth order model response.

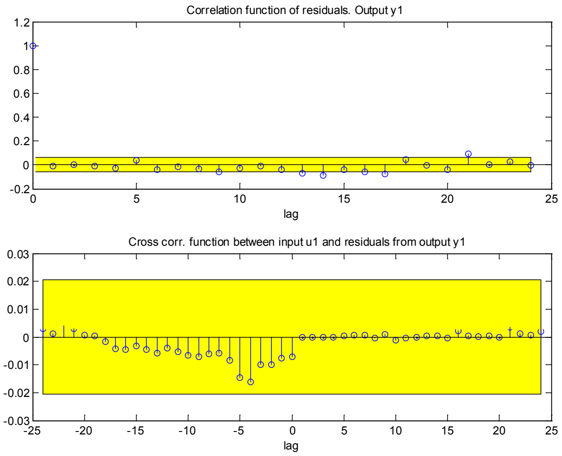

Fig. 9. Correlation function and cross correlation function of the model residuals.

In Fig. 9, the upper plot shows the autocorrelation function of fuel burn rate residuals. The horizontal solid lines correspond to the 95% confidence interval of the corresponding estimates. Any fluctuations within the confidence interval are considered to be insignificant. Subspace identification approach results in a reliable model as the residual autocorrelation function within the confidence interval indicates that the residuals are uncorrelated.

The bottom plot presents the cross-correlation of the residuals with the input. The obtained model residuals are uncorrelated with system inputs.

VIII. CONCLUSIONS

In the paper, the use of 1-wire protocol and Raspberry Pi computers as a useful technology to collect data for the house parameter heating model is proposed and tested.

1-wire protocol by Dallas Semiconductor allows a low-cost data collection from hundreds of sensors measuring temperature, humidity, atmospheric pressure located in the house for a long period of time.

The identification experiments are performed on the basis of real measurement input-output data. To identify the repetitive process model, the modified subspace identification method, in which the actual pass input and the previous pass output are employed as model input, is applied.

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X. REFERENCES

[1] L. Perez-Lombard, J. Ortiz, and C. Pout, A review on buildings energy consumption information, Energy and buildings, vol. 40, no. 3, pp. 394–398, 2008.

[2] J. Bochniak, K. Galkowski, E. Rogers, and A. Kummert, Robust stabilization of discrete linear repetitive processes with switched dynamics, Int. Journal of Applied Mathematics and Computer Science, vol. 16, pp. 441–462, 2006.

[3] A. Chiuso and G. Picci, Some algorithmic aspects of subspace identification with inputs, Int. Journal of Applied Mathematics and Computer Science, vol. 11, pp. 55–75, 2001.

[4] L. Hladowski, K. Galkowski, Z. Cai, E. Rogers, C. T. Freeman, P. L. Lewin, Experimentally supported 2D systems based iterative learning control law design for error convergence and performance, Control Engineering Practice, vol. 18, no. 4, pp. 339–348, 2010.

[5] A. Janczak and D. Kujawa, Subspace approach to identification of linear repetitive processes, Proceedings of the 2009 Int. Workshop on Multidimensional (nD) Systems, Thessaloniki, Grece, pp. 120–123, 2009.

[6] A. Janczak and D.. Kujawa, Identification of linear repetitive processes using subspace algorithms, Proceedings of 15th Int. Conference on Methods and Models in Automation and Robotics (MMAR 2010), Miedzyzdroje, Poland, pp. 371–376, 2010.

[7] A. Janczak, D. Kujawa, E. Rogers, Z Cai, Subspace identification of process dynamica for iterative learning control, Proceedings of the 8th International Workshop on Multidimensional Systems - nDS' 13. Erlangen, Germany, 2013.

[8] T. Katayama, Subspace Methods for System Identification. Springer, Berlin, 2005.

[9] L. Ljung, System Identification: Theory for the User, 2nd ed, Prentice Hall, Upper Saddle River, N.J., 1999.

[10] M. Gwerder, B. Lehmann, J. Todtli, V. Dorer, and F. Renggli, "Control of thermally-activated building systems (tabs)," Applied energy, vol. 85, no. 7, pp. 565–581, 2008.

[11] S. J. Qin, An overview of subspace identification, Computers and Chemical Engineering, vol. 30, no. 10-12, pp. 1502–1513, 2006.

[12] E. Rogers, K. Galkowski, and D. H. Owens, Theory and Applications for Linear Repetitive Processes, Springer, Berlin, 2007.

[13] P. Van Overschee and B. De Moor, N4SID: Subspace algorithms for identification of combined deterministic-stochastic systems, Automatica, vol. 30, no. 1, pp. 75–93, 1994.

[14] P. Van Overschee and B. De Moor, A unifying theorem for three subspace identification algorithms, Automatica, vol. 31, no. 12, pp. 1853–1864, 1995.

[15] P. Van Overschee and B. De Moor, Subspace Identification for Linear Systems: Theory, Implementation, Applications, Kluwer Academic Publishers, Boston, 1996.

[16] M. Verhaegen, Application of subspace model identification technique to identify LTI systems operating in closed-loop, Automatica, vol. 29, no. 4, pp. 1027–11040, 1993.

[17] M. Verhaegen, Identification of deterministic part of MIMO state space models given in innovation form from input-output data, Automatica, vol. 30, no. 1, pp. 61–74, 1994.

[18] V. Viberg, Subspace-based methods for the identification of linear time invariant systems, Automatica, vol. 31, no. 12, pp. 1835–1851, 1995.

[19] H. Madsen and J. Holst, Estimation of continuous-time models for the heat dynamics of a building, Energy and Buildings, vol. 22, no. 1, pp. 67–79, 1995.

[20] K. Andersen, H. Madsen, and L. Hansen, Modelling the heat dynamics of a building using stochastic differential equations, Energy and Buildings, vol. 31, no. 1, pp. 13–24, 2000.

[21] Luiza Ocheană, Dan Popescu, Luca Ferrarini , Europment, Proc. of the International Conference on Systems, Control and Informatics, 2013.