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Published in:
Elsevier IFAC Publications / IFAC Proceedings series

Publication date:
2008

Document Version
Early version, also known as pre-print

Plug and Play Process Control Applied to a District Heating System ⋆

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Abstract: The general ideas within plug and play process control (P^3C) are to initialize and reconfigure control systems just by plug and play. In this paper these ideas are applied to a district heating pressure control problem. First of all this serves as a concrete example of P^3C , secondly some of the first techniques developed in the project to solve the problems in P^3C are presented. These are in the area of incremental modelling and control and they make it possible to "plug" in a new sensor and actuator and make it "play" automatically.

Keywords: Least-squares identification; Closed-loop identification; Self organizing systems; Pressure control; District heating

1. INTRODUCTION

A new housing sector is to be planned, including a plan for a new district heating system. The planning shows that this calls for a redesign of the whole district heating system. However, it would be possible to change the system to a sector divided system, excluding the need for a total redesign, by introducing a number of pumps along the pipeline. Traditionally this requires a central and hard to implement control system. However, using a plug and play process control (P^3C) system, which can incorporate new actuators and sensors automatically, the whole design procedure is eliminated. This means that by using a P^3C system the above described control problem becomes easy and the cost is reduced considerably.

The idea of using pumps along the pipeline to increase the pressure gradually is also proposed in Bøhm et al. (2004). Here the distributed pumps are used to enable the possibility for reducing the diameter of the pipes. The reduced diameter will decrease the surface area of the pipes and thereby the loss of heat along the pipeline. The control problem is not considered.

The small example with the extended district heating system illustrates the idea behind P^3C . Here a redesign of the district heating system is described, but similar problems can be found in many everyday control problems. This spans from ventilation of stables to control of heating systems in one-family houses.

Thus the vision of the project P^3C is:

> When a new device e.g. a sensor or actuator is plugged into a functioning control system it will identify itself and the control system will automatically become aware of the new signal, determine its usefulness and exploit it in an optimal way over time.

The project covers a variety of problems from the optimal choice of sensors and actuators to controller design for a variety of model types ranging from black to white box. In this paper the focus is on system identification of black box models. Another paper Persis and Kallesøe (2008) from the P^3C project focuses on controller design for the district heating system which is also used here.

Like adaptive control P^3C aims at identifying and adapting to changes in system behavior. The crucial difference is that adaptive control deals with systems with fixed structure but varying parameters where P^3C includes systems with varying structure. That could be adding an additional sensor or actuator, to adding a whole new subsystem.

In this paper the P^3C concept, based on system identification (SI) and control, will be developed. The P^3C concept is verified on a small scale district heating system, with distributed pumping. The following general assumptions are made in the paper. They are considered acceptable in practice. They also help defining what P^3C is about.

(1) The present system is *under control* in the sense that a shut down should not be necessary.
(2) There is a known active controller.
(3) A model for the present system is known but it can of course be uncertain.
(4) The triggering event is when a device is plugged onto the network where it identifies itself with information such as type, preferred range etc.
(5) Online data are available both before and after the triggering event.
(6) Excitation can be used within specified limits.

⋆ This work is supported by The Danish Research Council for Technology and Production Sciences.

Section 2 explains what is meant by P^{3}C in the district heating pressure control application. A model for the district heating system is then briefly presented from a control engineering perspective in section 3. The SI methods developed so far in the project are then presented in section 4 and the results of using them are evaluated through simulation in section 5. Finally a conclusion is drawn in the last section.

2. PLUG AND PLAY FOR DISTRICT HEATING PRESSURE CONTROL

In the introduction the idea of the P^{3}C concept is introduced via an example of a district heating system. In this example the size of the district heating system is increased. However, in this paper we will restrict ourselves to the problem of introducing a new pump and a new pressure sensor in a control system. This could be seen as a case where the original system was poorly designed. The poor design is then fixed by introducing a pump and a sensor. The vision is therefore: when a new device e.g. a pump or/and a sensor is/are connected, the control system automatically reconfigures and achieves good performance again. This is exactly what the P^{3}C problem is all about.

In this work a simplified district heating system is considered. This is a minimal system with only one heat source and only two end-users (heat users). A sketch of the system is shown in Fig. 1.

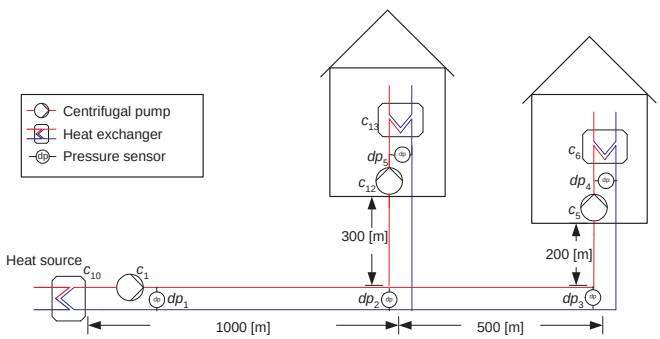

Fig. 1. Water distribution system Kallesøe (2007).

The boundaries of the pipeline system under consideration consist of the secondary side of the heat exchanger c_{10}, which can be modelled as a constant valve, and the primary side of the heat exchangers c_6 and c_{13}, which both can be modelled as variable valves. The latter two heat exchangers are controlled by the heating system of the buildings and can therefore be regarded as disturbances. The controllable inputs are the speed for the three pumps, one main pump c_1 and two building pumps c_5 and c_{12}. Further, there are eight pipes connecting everything. The measurable outputs are delivered by the 5 pressure sensors $dp_1 \ldots dp_5$.

The pressure sensor and pump in the last building are the devices which are not present in the initial system but which are finally added in the plug and play fashion.

3. A MODEL FOR THE DISTRICT HEATING SYSTEM

The model for simulation is developed in cooperation with Grundfos A/S who has specified the system parameters such that it represents a realistic system. This model only describes the pressure system. The pressure system can be separated from temperature control, as the latter is very slow compared to the dynamics of the pressure. Here the focus is not on hydraulic system modelling, therefore the model is only briefly presented.

A model for the system shown in Fig. 1 can be developed straight forward by using the system diagram shown in figure 2 and the component models.

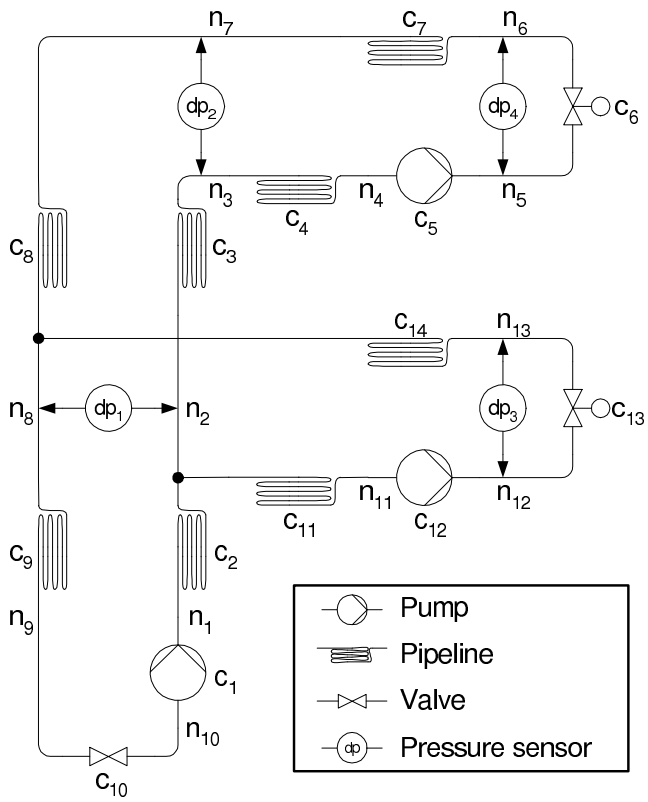

Fig. 2. Water distribution system Kallesøe (2007).

First notice that all component models can be described in the common form

$$k_{J,j}\frac{dq_j}{dt} = h_{i,j} - h_{o,j} - k_{q,j}|q_j|q_j + k_{q\omega,j}q_j\omega_j + k_{\omega,j}\omega_j^2 \tag{1}$$

where ω_j is the pump speed, q_j is flow and h_j is pressure of the jth component. $h_{i,j}$ and $h_{o,j}$ is the inlet and outlet pressure of the jth component, and $k_{J,j}$, $k_{q,j}$, $k_{q\omega,j}$, and $k_{\omega,j}$ are constant of the jth component model. The division between the different components is controlled by zeroing some of the constants of the given component. This is shown in Table 1. The component can then be connected in one state space model. After using the "Kirchoff" law, saying that the sum of flows to a node is zero, only two independent flows remains. Let these be denoted x_1 and x_2 respectively. Let the flow x_1 run through the component $\{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}\}$, and let

Component	k_J	k_q	$k_{q\omega}$	$k_{q\omega}$
Pump	0	a_{h2}	a_{h1}	a_{h0}
Pipe	J	K_p	0	0
Valve	0	K_v	0	0

Table 1. Common component model parameterization

x_2 run through $\{c_1, c_2, c_{11}, c_{12}, c_{13}, c_{14}, c_9, c_{10}\}$. Then the connection between $x = (x_1,\ x_2)^T$ and the flows through each components $q = (q_1,\ q_2,\ \cdots,\ q_{14})^T$ is given by $q = \Phi x$, where

$$\Phi^T = \begin{pmatrix} 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0 \\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 1\ 1\ 1\ 1\ 1 \end{pmatrix} .$$

Using this connection the following input/output expression can be obtained

$$\frac{dx}{dt} = (\Phi^{\mathsf{T}} J \Phi)^{-1} \Phi^{\mathsf{T}} F(q,u)|_{q=\Phi x} \tag{2a}$$

$$y = S(H_r^{\mathsf{T}})^{\dagger} (J\Phi(\Phi^{\mathsf{T}} J \Phi)^{-1} \Phi^{\mathsf{T}} - I) F(q,u)|_{q=\Phi x} \tag{2b}$$

where $J = \mathrm{diag}\{k_{J,1}, \cdots, k_{J,14}\}$ and the vector field $F(q,u)$ is given by

$$F(q,u) = -K_q |q| \bullet q + K_{q\omega} q \bullet u + K_\omega u \bullet u \tag{3}$$

Here the matrices $K_q = \mathrm{diag}\{k_{q,1}, \cdots, k_{q,14}\}$, $K_{q\omega} = \mathrm{diag}\{k_{q\omega,1}, \cdots, k_{q\omega,14}\}$, and $K_\omega = \mathrm{diag}\{k_{\omega,1}, \cdots, k_{\omega,14}\}$. Finally H_r is the incident matrix for the graph described by the diagram shown in Fig. 2 Kallesøe (2007). All difference pressures can be found from flows and pump speeds and they are given by the last to factors in (2b). Multiplying by $S(H_r^{\mathsf{T}})^{\dagger}$ then selects the outputs $\mathrm{dp}_1 \ldots \mathrm{dp}_5$. In (2a) and (2b) standard notation is used i.e. u, x, and y for input, state, and output respectively. Also observe that $\bullet$ stands for element-wise multiplication. Notice that it is a nonlinear model as both states i.e. flows and inputs i.e. pump speeds enter the model squared.

The only time variation is from the valves c_6 and c_{13} which then changes the resistance that enters K_q and $K_{q\omega}$. All other matrix parameters remain constant. However, the result is still a time varying system.

The resistance variations in the heat exchanger valves c_6 and c_{13} are driven by the variation in energy demand for the buildings. This in turn can be separated into effects from outdoor temperature, sun radiation and hot water usages. Outdoor temperature changes are considered too slow to be important for control applications. Sun radiation for the two buildings is simulated as correlated low pass (LP) filtered (time constant= 10 min.) white noise processes. The hot water effects are simulated as the sum of 10 (apartments) LP filtered (time constant= 10 sec.) jump processes. Also white noise measurement noise (σ= 0.025 bar) are included on the sensors.

The above model is used for simulation in Section 5.

4. SYSTEM IDENTIFICATION METHODS FOR PLUG AND PLAY

In SI the goal is always to obtain the best model for the purpose. The special situation in P^{3}C modelling is when there is a known "present" model and a new device appears. The question is then if new and better SI methods can be developed for this situation.

4.1 Plug and Play modelling

In all the modelling development in P^{3}C the first objective is models which are useful for control. From this follows that simple models e.g linear time invariant (LTI) is a high priority.

As explained in section 2 the "initial" system is without pump and sensors in the last building. A "commissioning" model is first made for this system. The idea is that the initial 4 output $\times$ 2 input system is excited in open loop under the commissioning phase and a model is produced. This is done in a (semi) automatic way using quite standard SI methods and cross validation. The result is a Hammerstein model that is an LTI model where the inputs are squared pump speeds. This will however not be further discussed here but explains the existence of the "present" 4×2 model.

When a new device announces its entrance on the network a process towards model updating starts. Notice though that the update only takes place when the new model has a "superior" performance compared to the the present model. The modelling and update must be done in closed loop. One possibility would of course be to start from scratch as if nothing was known already. As a well performing present model and controller is assumed it seems wiser to build on top of this. The advantages are that the known part of the model remains the same, there are fewer parameters to estimate and for new actuators not all inputs but only the new one needs excitation.

Prediction error (PE) methods can be used for estimating the necessary new parameters while the present parameters are fixed. This is e.g. possible with PEM from the matlab toolbox IDENT Ljung (2007). PE methods use iterative non convex numerical minimization. Especially for online use more simple and robust methods are preferable. Methods using only convex minimization are therefore developed below to see what can be achieved with these simple methods.

For this purpose state space (SS) models in innovation form is appropriate. The least squares (LS) method developed can be separated in two steps. First the state or other signals are generated from the known present model assuming it is correct. Then the additional parameters can be estimated in an LS fashion from the output equation which includes the additional device. For both the additional input and output case it is important how this signal generating is done. To show this it is necessary to review some of the stochastic description for SS models.

Given the SS model in innovation form

$$x(t+1) = Ax(t) + Bu(t) + Ke(t) \tag{4a}$$

$$y(t) = Cx(t) + Du(t) + e(t) \tag{4b}$$

$$\mathrm{E}(e(t)e(s)^{\mathsf{T}}) = \delta_{ts} R\ ,\ \mathrm{E}(e(t)) = 0 \Rightarrow R = \mathrm{Cov}(e) \tag{4c}$$

Then the mean value and corresponding deviation to state and measurement are

$$\mu_x(t+1) = A\mu_x(t) + Bu(t) \tag{5a}$$

$$\mu_y(t) = C\mu_x(t) + Du(t) \tag{5b}$$

$$\left.\begin{aligned} \delta_x(t) &\triangleq x(t) - \mu_x(t+1)\ , \\ \delta_y(t) &\triangleq y(t) - \mu_y(t+1) \end{aligned}\right\} \Rightarrow \tag{5c}$$

$$\delta_x(t+1) = A\delta_x(t) + Ke(t)\ , \tag{5d}$$
$$\delta_y(t) = C\delta_x(t) + e(t)\ ,\ R = \mathrm{Cov}(e) \tag{5e}$$

For one step predictions there is no stationary error between state (4a) and prediction (6a) in a innovation model as $x(t) \triangleq \hat{x}(t) \triangleq \mathrm{E}(x(t)|Y^{t-1})$ by construction. Here Y^{t-1} is the measurement until and including time $t-1$. This gives a prediction error for output y which is white (6c).

$$x(t+1) = (A-KC)x(t) + (B-KD)u(t) + Ky(t) \tag{6a}$$
$$\hat{y}(t) = Cx(t) + Du(t) \Rightarrow \tag{6b}$$
$$y(t) - \hat{y}(t) = e(t) \Leftrightarrow \tag{6c}$$
$$y(t) = \hat{y}(t) + e(t)\ ,\ R = \mathrm{Cov}(e) \tag{6d}$$

4.2 Including an additional actuator

After this preliminary review the LS solution for a additional input is developed. In this case the SS model can be divided as (7)–(8) where subscript p and a means present and additional respectively e.g. u_p are the inputs in the present/initial system and u_a is the additional input.

$$x_p(t+1) = A_p x_p(t) + (B_p\ B_{pa})\begin{pmatrix} u_p(t) \\ u_a(t) \end{pmatrix} + K_p e_p(t) \tag{7}$$

$$\begin{aligned} y_p(t) &= C_p x_p(t) + (D_p\ D_{pa})\begin{pmatrix} u_p(t) \\ u_a(t) \end{pmatrix} + e_p(t)\ , \\ R_p &= \mathrm{Cov}(e_p) \end{aligned} \tag{8}$$

$$u_p \in \mathcal{R}^m\ ,\ u_a \in \mathcal{R}\ ,\ x_p \in \mathcal{R}^n\ ,\ y_p, e_p \in \mathcal{R}^l \tag{9}$$

Then it is only necessary to estimate B_{pa}, D_{pa}. Notice that both the mean output and the predicted output are linear in these parameters. This means the output can be separated in a part from the present system and a linear combination of parts assuming that each new parameter is one while the rest are zero.

Define y_0 as the output from the present system i.e. where all additional parameters i.e B_{pa}, D_{pa} are zero and y_i as the output where all additional parameters are zero except number i which is one. Then the output is a linear combination of these signals. If the one step predictor (6a)–(6b) is used to generate the signals y_i the relation between measurements and signals is (10) where e_p is the innovation. If the "mean" filter (5) generates the signals y_i the relation is also (10) except the innovation e_p is replaced with the deviation δ_y (5e).

$$y_p(t) = y_0(t) + \sum_{i=1}^{n+l} \theta_i y_i(t) + e_p(t)\ , \tag{10}$$

$$(\theta_1\ \dots\ \theta_n)^{\mathsf{T}} \triangleq B_{pa}\ ,\ (\theta_{n+1}\ \dots\ \theta_{n+l})^{\mathsf{T}} \triangleq D_{pa} \tag{11}$$

If signals for the whole measurement sequence are stacked into vectors and some more notation is introduced, (10) can be turned into a linear regression equation (13) with the LS solution (14).

$$\left.\begin{aligned} &Y_p \triangleq \begin{pmatrix} y_p(1) \\ \vdots \\ y_p(N) \end{pmatrix} \text{ and similar for } Y_i\ ,\ E_p\ , \\ &\Theta \triangleq (\theta_1\ \dots\ \theta_{n+l})^{\mathsf{T}}\ , \\ &X \triangleq (Y_1\ \cdots\ Y_{n+l})\quad ,\ Z \triangleq Y_p - Y_0 \end{aligned}\right\} \Rightarrow \tag{12}$$

$$\begin{aligned} &Y_p = Y_0 + Y_1\theta_1 + \dots + \theta_{n+l}Y_{n+l} + E_p\ , \\ &Z = X\Theta + E_p \end{aligned} \tag{13}$$

$$\widehat{\Theta} = (X^{\mathsf{T}}X)^{-1}X^{\mathsf{T}}Z \tag{14}$$

To see if this LS solution is consistent, the limit value w.p.1 for $N \to \infty$ is found in (15). The step from (15a) to (15b) follows from ergodicity which can be assumed.

$$\begin{aligned} \widehat{\Theta} &= (X^{\mathsf{T}}X)^{-1}X^{\mathsf{T}}Z \\ &= (X^{\mathsf{T}}X)^{-1}X^{\mathsf{T}}(X\Theta + E_p) \\ &= \Theta + (X^{\mathsf{T}}X)^{-1}X^{\mathsf{T}}E_p \\ &= \Theta + \left(\frac{1}{Nl}X^{\mathsf{T}}X\right)^{-1}\frac{1}{Nl}X^{\mathsf{T}}E_p && (15a) \\ &\to \Theta + \left[\mathrm{E}\left(\frac{1}{Nl}X^{\mathsf{T}}X\right)\right]^{-1}\mathrm{E}\left(\frac{1}{Nl}X^{\mathsf{T}}E_p\right) && (15b) \\ &\text{for } N \to \infty \qquad \text{(wp1)} \end{aligned}$$

If the rows in X and the rows in E_p are uncorrelated the last term in (15) will go to zero. This is the case if the one step predictor is used as the elements in the last vector in (15) then is (16) where $y_{ij}(t)$ is signal i output channel j at time t which is generated from inputs and outputs until and including time $t-1$ plus $u(t)$ for $D \neq \underline{\underline{0}}$ and these are uncorrelated with the innovation $e_{p,j}(t)$ even in closed loop (CL). Therefore the last vector $\mathrm{E}\left(\frac{1}{Nl}X^{\mathsf{T}}E_p\right)$ goes to zero w.p.1. and consequently so does the last term in (15) as the part $\mathrm{E}\left(\frac{1}{Nl}X^{\mathsf{T}}X\right)$ is invertible due to sufficient excitation (see also (Ljung, 1999, sec. 7.3)).

$$\begin{aligned} &\left(\frac{1}{Nl}X^{\mathsf{T}}E_p\right)_{(i)} = \sum_{t=1}^{N}\sum_{j=1}^{l} y_{ij}(t)e_{p,j}(t)\ , \\ &i = 1, \dots, n+l \end{aligned} \tag{16}$$

In contrast if mean values are used then the rows in E_p will be auto correlated as they consist of $\delta_y(t)$ (5e) and the variance will be large compared to the prediction errors. However, no bias will occur in open loop (OL) as the mean values are only generated from input u. In CL, bias will occur because then u is correlated with y which is correlated with $\delta_y(t)$.

4.3 Including an additional sensor

If the new device is a sensor the new system is then given by (17)–(18).

$$\begin{aligned} &x_p(t+1) = \\ &\quad A_p x_p(t) + B_p u_p(t) + (K_p\ K_{pa})\begin{pmatrix} e_p(t) \\ e_a(t) \end{pmatrix} \end{aligned} \tag{17}$$

$$\begin{aligned} &\begin{pmatrix} y_p(t) \\ y_a(t) \end{pmatrix} = \begin{pmatrix} C_p \\ C_{ap} \end{pmatrix} x_p(t) + \begin{pmatrix} D_p \\ D_{ap} \end{pmatrix} u_p(t) \\ &\quad + \begin{pmatrix} e_p(t) \\ e_a(t) \end{pmatrix}\ ,\ R = \begin{pmatrix} R_p & R_{pa} \\ R_{ap} & R_a \end{pmatrix} = \mathrm{Cov}\begin{pmatrix} e_p \\ e_a \end{pmatrix} \end{aligned} \tag{18}$$

$$u_p \in \mathcal{R}^m\ ,\ x_p \in \mathcal{R}^n\ ,\ y_p, e_p \in \mathcal{R}^l\ ,\ y_a, e_a \in \mathcal{R} \tag{19}$$

An LS solution for an additional output should ideally estimate $C_{ap}, D_{ap}, K_p, K_{pa}$ and the covariance R. It could be tempting also to fix K_p and R_p as they "belong" to the present model. However, this will only be correct in the special case where the additional output is independent of the present output because then the state estimate is additive in the two outputs.

If the present model is correct it can be used to generate the mean state for the present system. This will be exactly the same as the mean state for the new system. Then the output equation for the additional sensor can be used to make a LS estimate for C_{ap}, D_{ap} as follows.

$$\mu_{ya}(t) = C_{ap}\mu_x(t) + D_{ap}u(t) \Rightarrow \tag{20a}$$

$$y_a(t) = C_{ap}\mu_x(t) + D_{ap}u(t) + \delta_{ya}(t) \tag{20b}$$

$$\left.\begin{array}{l} Y_a \triangleq \begin{pmatrix} y_a(1) \\ \vdots \\ y_a(N) \end{pmatrix}, \; X \triangleq \begin{pmatrix} \mu_x(1)^{\mathrm{T}} & u(1)^{\mathrm{T}} \\ \vdots & \vdots \\ \mu_x(N)^{\mathrm{T}} & u(N)^{\mathrm{T}} \end{pmatrix}, \\ \Theta \triangleq (C_{ap} \;\; D_{ap})^{\mathrm{T}} \end{array}\right\} \Rightarrow$$

$$\widehat{\Theta} = (X^{\mathrm{T}}X)^{-1}X^{\mathrm{T}}Y_a \tag{20c}$$

Similar to additional input this will not give bias in OL but it will in CL. Also, there is no immediate good way to update the stochastic part K, R.

If instead the predictor (6) is used to generate the state there is the following complication. Ideally the additional output part in innovation form (21) is preferred as the regression equation. However, only the present model is available to generate the innovation state x_p which is not exactly the same as the innovation state x_n where also the additional output is included in the measurements. This means that the actual regression model (22) does not have exactly the same state and noise as the innovation model we like to estimate parameters for. Further the residual in the regression model is not perfectly white. On the other hand it is much closer to the ideal situation compared to the mean state version.

$$y_a(t) = C_{ap}x_n(t) + D_{ap}u(t) + e_a(t) \tag{21}$$

$$y_a(t) = C_{ap}x_p(t) + D_{ap}u(t) + e'_a(t) \tag{22}$$

It is possible to estimate the covariance $\mathrm{Cov}(\begin{pmatrix} e_a^{\mathrm{T}} & e'_a \end{pmatrix}^{\mathrm{T}})$ and recalculate the Kalman gain for the extended model. However, the result with this application is that the present part K_p is nearly unchanged and the new part K_{pa} is nearly zero. Still, the covariance $\widehat{\mathrm{Cov}}(\begin{pmatrix} e_p^{\mathrm{T}} & e'_a \end{pmatrix}^{\mathrm{T}})$ and $\widehat{K} = \begin{bmatrix} \widehat{K}_p & \widehat{K}_{pa} \end{bmatrix}$ constitutes a noise model even if it is biased.

5. SIMULATION RESULTS

Results from using the methods and scenario from section 4 are presented below. The different system configurations and corresponding control objectives are as follows:

Present system As in Fig. 2 but with pump c_5 at zero speed and without the pressure transducer dp_4. The control requirements are then $dp_1, dp_2 \in [0, 4]$ $dp_3 \in [1, 4]$ $dp_5 \sim 0.5$.

New sensor As above but with the pressure transducer dp_4. The control requirements are then $dp_1, dp_2, dp_3 \in [0, 4]$ $dp_4, dp_5 \sim 0.5$.

New actuator As above but with the pump c_5 active. The control requirements are as above.

The entire simulation example is shown in Fig. 3. The pressures are shown without measurement noise which otherwise would blur the picture. In the beginning, only the pumps c_1 and c_{12} are present, along with pressure sensors dp_1, dp_2, dp_3, and dp_5. The pressure at dp_4 is shown for the entire sequence but the measurement is not available until Interval 3. Interval 1 is mainly included as a reference to show the system in open loop in the original operating point. In the commissioning phase, a reliable 4 outputs × 2 inputs (4th order) model on innovations form has been obtained through open loop excitation and subsequent SI. The control design in this example is fairly standard and will not be described in detail. An observer-based state space controller with integral action, $C_{4\times2}$, is designed using the 4×2 model. The Kalman gain of the innovations model is used directly as the observer gain. The state feedback is designed for the model augmented with integrators on the inputs. This allows penalizing changes to the pump speeds rather than their deviations from the operating point.

The controller $C_{4\times2}$ is applied in Interval 2 and good performance is achieved at dp_5. The pressure dp_4 is not known yet, but complaints from the inhabitants in the last building indicate that something might be wrong. In Interval 3, the dp_4 sensor is therefore added, and the control system is informed that a pressure of 0.5 *bar* is desired. With the $C_{4\times2}$ controller still operating, a small excitation signal is added to the two control inputs. Using the method described in section 4.3, the new sensor is added to the model. The excitation is too weak to obtain a reliable model for control design, but the objective at this point is only to assess the possibilities.

From the new 5×2 model, the control system assesses that achieving a satisfactory control with the existing actuators is not possible. This is done mainly by observing that the low frequency gain from the two pumps to dp_4 and dp_5 is almost singular, making it difficult to obtain a satisfactory control. This information is passed to the operator, who therefore decides to add the pump c_5 near dp_4.

In Interval 4, the $C_{4\times2}$ controller remains in action, while a small excitation signal is added to the new pump. Using the method in Section 4.2, the model is augmented with the new actuator. Again, the model is not sufficiently reliable for a full control design. Instead an additional controller, C_{add}, to be placed in parallel with $C_{4\times2}$ is designed.

C_{add} is designed with a high level of robustness and only serves to move the operating point, which is done in Interval 5.

Once the new operating has been reached, C_{add} is removed, leaving $C_{4\times2}$ as before but with a new operating point subtracted from the measurements and added to the control signal. This is seen in Interval 6.

At this point, the augmented model has only been used to move the operating point. Since it was obtained in the old operating point and with only weak excitation, it would be risky to design a new control system from this model. Therefore, additional excitation is performed in two steps. In Interval 7, excitation is added to the old pumps, in order to augment the original 4×2 model with the new sensor. In Interval 8, excitation is added to the new pump, in order to augment the model with the new actuator. Especially for interval 7 this excitation gives disturbances in the building pressures dp_4 and dp_5. However the disturbances are below 1 bar which is acceptable for a limited time.

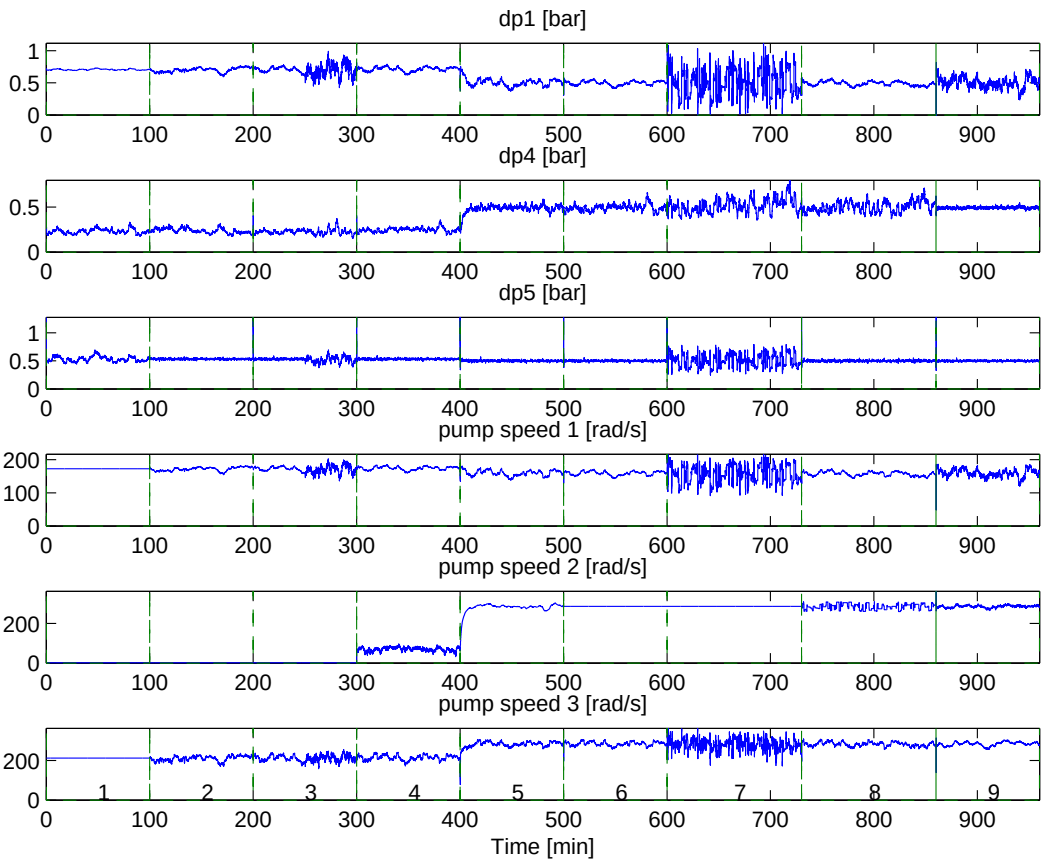

Fig. 3. Simulation example. Selected differential pressures (measured outputs) and pump speeds (controlled inputs).

At this point, a reliable 5×3 model has been obtained, and a new controller, $C_{5\times3}$, can be designed. This new controller is applied in Interval 9. Comparing with Intervals 2 and 6, we see that a significant improvement of the performance at dp_4 has been achieved. The variations at dp_1 have increased, but that is not considered to be a problem as it complies with the control specifications stated in the beginning of this section.

Note that from Interval 2 and onwards, everything has been performed in closed loop.

6. CONCLUSION

The theme for this work is plug and play process control where new devices are included in the control system automatically.

Using model based control design calls for new/updated models when a new device enters the system. Methods for this is the focus of this paper. Since a good model for the present system is assumed, it is chosen to keep this and only estimate the new part. It is investigated what can be achieved with LS methods i.e. avoiding iterative numerical minimization. For a new actuator there is an LS method which is shown to give a consistent estimate. Further, simulations not documented here indicate it performs similar to standard PE methods and better than incremental PE methods. For a new sensor, approximations are needed which causes bias on the stochastic part.

These LS methods are used with success in a simulation example of a district heating system, where a new sensor and a new actuator are added to the system. Using almost fully automated methods, the model and consequently the control system are updated, resulting in an improved performance.

Other possible advantages of the developed LS methods are that it is possible to put the algorithms on a recursive form. Also, at least approximative uncertainty measures can be derived for the additional parameters. These issues still require further research.

REFERENCES

B. Bøhm, N. K. Vejen, J. Rasmussen, N. Bidstrup, K. P. Christensen, and H. Kristjansson. Efp-2001 fjernvarmeforsyning af lavenergiomrder. Technical Report Journal No. 1373/01-0035, Danish Energy Authority, 2004. In Danish.

Carsten Skovmose Kallesøe. Simulation of a district heating system with a new network structure. Technical report, Grundfos Management A/S, 2007.

Lennart Ljung. *System Identification, Theory for the User*. Prentice-Hall information and system sciences series. Prentice-Hall, second edition, 1999.

Lennart Ljung. *System Identification Toolbox*. The MathWorks, Inc., Marts 2007.

Claudio De Persis and Carsten Skovmose Kallesøe. Proportional and proportional-integral controllers for a nonlinear hydralic network. In *17th IFAC Worl Congress*. IFAC, 2008. Submitted.