CONTROL DESIGN OF AN INDUSTRIAL EQUALIZATION SYSTEM - HANDLING SYSTEM CONSTRAINTS, ACTUATOR FAULTS AND VARYING OPERATING CONDITIONS

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Abstract: This paper describes the design and evaluation of a control system for an equalization system at the wastewater treatment plant of a pharmaceutical production facility. The design includes actuator fault tolerance, and measures are included to deal with physical constraints and changing operating conditions. A combination of linear quadratic techniques, fuzzy logic and disturbance accomodation theory is used. The controller is evaluated through simulation and is currently under full–scale test.

Keywords: Disturbance rejection, Fault tolerance, Fuzzy supervision

1. INTRODUCTION

Wastewater treatment systems in general are confronted with large fluctuations in both the waste concentration and the flow rate of the wastewater to be treated. This phenomenon is especially apparent in wastewater treatment systems of chemical plants, where batch-wise production of a wide range of chemicals results in a highly irregular pattern of waste flow rates and concentrations. These load variations have a negative influence on the biological processes that perform the purification processes. For this reason, in most plants equalization systems are constructed. These are systems composed of one or more interconnected tanks providing the necessary volume to dampen out these variations. In the following a control system for such an equalization system will be discussed.

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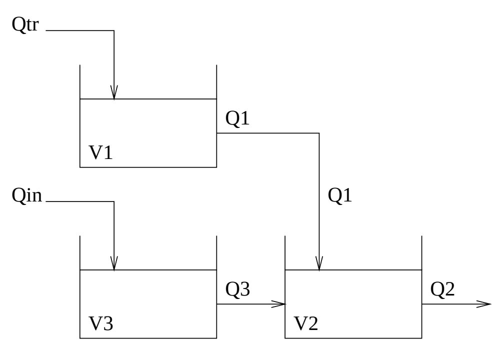


Fig. 1. Layout of the equalization system

2. PROCESS LAYOUT

The layout of the process under study is the following (Fig. 1). The system consists of three tanks V_1 (800 m^3), V_2 (1600 m^3) and V_3 (1600 m^3). A chemical waste stream, characterised by its flow rate Q_{in} (about 90 m^3/h on average) and its TOC (Total Organic Carbon) concentration C_{in} (mean value about 4000 mg/l) is flowing directly from the production facility into V_3. From this tank, the wastewater is pumped into V_2. The third tank V_1 receives truck loads with highly concentrated wastewater (mean flow rate $Q_{tr} = 1$ m^3/h, mean TOC = 40000 mg/l). The contents of this tank are also pumped into V_2. From V_2, the wastewater is pumped to the subsequent stages of the purification process.

The process imposes some constraints. To avoid overflowing, upper volume limits are set to 1485 m^3 for the 1600 m^3 tanks, and 745 m^3 for the 800 m^3 tank. Because of floating covering on the tanks, lower volume limits are set to 540 m^3 for the 1600 m^3 tanks and 270 m^3 for the 800 m^3 tank. The actuators considered are the pumps that pump the water from the tanks (screw pumps for V_2 and V_3, centrifugal pump in V_1). In the present study they are considered continuously variable. In the practical implementation, the flow rates will serve as setpoints for a timer-based slave controller.

Measured variables include measurements of the three volumes, and a measurement of the effluent TOC concentration.

3. CONTROLLER DEVELOPMENT

3.1 *Definition of the control objectives*

The primary objective of the controller to be designed is of course to attenuate the variations in flow rate and concentration, without violating the volume constraints. Secondly, since a major increase in the capacity of the production facility was anticipated, the controller had to be able to track these productivity changes. An additional objective was to provide some means of monitoring the pumps. Indeed, the harsh operating conditions that reign in industrial wastewater treatment systems can cause damage to the pumps. If this damage is not detected, this may even lead to breakdown. For example, it was recently discovered that the flow rate of two of the pumps had been reducing slowly over the course of several years. At the moment these two pumps only reach 10 % of their original capacity, and have to be replaced. If this decrease had been detected in time, maintenance could have prevented further damage.

The goals set forward for the controller design were thus the following:

- Attenuate variations in flow rate and concentration as much as possible
- Respect physical constraints
- Track changes in production capacity of the plant
- Detect and accomodate as many actuator faults as possible

3.2 *The process model*

A first principles model based on mass balances was developed for this process. This nonlinear model was then linearized around the steady state working point, and discretized to obtain a model of the form:

$$\begin{cases} \tilde{x}_{k+1} = A\tilde{x}_k + B\tilde{u}_k + E_x\tilde{d}_k + F_x\tilde{f}_k + H\omega \\ \tilde{y}_k = C\tilde{x}_k + D\tilde{u}_k + E_y\tilde{d}_k + F_y\tilde{f}_k + \nu \end{cases} \quad (1)$$

In this equation, $x = [V_1\ V_2\ V_3\ C_1\ C_2\ C_3]^T$ is the system state, $y = [V_1\ V_2\ V_3\ C_2\ Q_2]^T$ is the output vector, $u = [Q_1\ Q_2\ Q_3]^T$, d is the disturbance vector and f is the fault vector. Both will be specified further on. The vectors ω and ν are the state noise and output noise, respectively. The matrices A, B, C, D, E_x, F_x, E_y, F_y, G and H are of appropriate dimensions. The tildes in equation 1 indicate that the model is defined in terms of deviations from the working points. For example $\tilde{x} = x - \bar{x}$, where $\bar{x}$ represents the working point of the system state.

3.3 *The disturbance modelling principle*

The disturbance modelling principle (Johnson, 1976; Harmand, 1997), or DMP, is a way to deal with disturbances that are not irreducible signals such as white noise, or equivalently, series of impulses. In fact, real life disturbances rarely behave exactly like this. The key idea of the DMP is that the disturbances in question are represented by a model, which itself is excited by signals such as white noise or impulse sequences. This model is a representation of the *behaviour* of the input. By appropriate choice of this model, almost any real life disturbance can be represented. When the plant model is augmented with these *disturbance* models, a model is obtained, which is only excited by irreducible signals. That model can then be used in classical control design schemes.

While the DMP was originally developed for disturbances, it can also be applied to the actuator faults in the present study, since faults can be considered a special type of disturbances that happen to be detrimental for the system itself.

The DMP was applied to this system as follows. For both the disturbance and the fault, a model was designed to represent their behaviour:

The disturbance model:

$$\begin{cases} z^d_{k+1} = A^d z^d_k + H^d \omega^d \\ \tilde{d}_k = C^d z^d_k \end{cases} \quad (2)$$

The fault model:

$$\begin{cases} z^f_{k+1} = A^f z^f_k + H^f \omega^f \\ \tilde{f}_k = C^f z^f_k \end{cases} \quad (3)$$

The augmented model, only excited by irreducible signals, then becomes:

$$\begin{cases} x_{k+1}^t = A^t x_k^t + B^t u_k + H^t \omega^t \\ y_k = C^t x_k^t + D^t u_k + \nu \end{cases} \quad (4)$$

where

$$A^t = \begin{bmatrix} A & E_x C^d & F_x C^f \\ 0 & A^d & 0 \\ 0 & 0 & A^f \end{bmatrix}$$
$$H^t = \begin{bmatrix} H & 0 & 0 \\ 0 & H^d & 0 \\ 0 & 0 & H^f \end{bmatrix} \quad (5)$$

and $x^t = [\tilde{x}\ z^d\ z^f]^T$, $u^t = u$, $\omega^t = [\omega\ \omega^d\ \omega^f]^T$, $B^t = [B\ 0\ 0]^T$, $C^t = [C\ E_y C^d\ F_y C^f]$ and $D^t = D$.

One is not completely free in assigning disturbance (or fault) models to certain disturbances or faults. Limits to this are set by the system structure. Indeed, since the approach consists of designing an observer for the augmented system, it is necessary that this model remains observable. Furthermore, a must be made which faults/disturbances are of the noise type and which are of the *waveform* type, these are disturbances satisfying a model as pointed out above. This choice has to be made considering

- the system structure: one must make optimal use of the degrees of freedom available in the system
- reality: best performance will be reached when the waveform components chosen match reality as close as possible.

In the case under study, the fault vector considered was $f = [\Delta Q_1\ \Delta Q_2\ \Delta Q_3]^T$ and the disturbance vector $d = Q_{in}$. The other disturbances are considered as noise, i.e. $\omega = [Q_{tr}\ C_{in}\ C_{tr}]^T$.

This choice is motivated by the following observations:

- Q_{in} is the flow coming from the plant. It was apparent from plant data that the behaviour of this disturbance resembles random–like step jumps in flow rate. The gradual increase in production capacity of the plant is expected to result in a gradual flow rate increase, therefore the estimation of Q_{in} is of major importance to the controller.
- Q_{tr} consists in reality of truck loads being dumped in the first tank. These are in essence pulse-type disturbances, which are equivalent to noise.
- Since the plant capacity increase is expected to result more likely in a flow rate increase than in a concentration increase. It is thus quite safe to consider C_{in} and C_{tr} as random deviations from a mean value.

Both A_f and A_d are chosen to be a zero matrix of appropriate dimension, while C_f and C_d are the identity matrices of the same size. This is a representation of the assumption that the disturbances and faults considered are constants over short periods of time.

3.4 *Controller design*

3.4.1. *General* The control action is composed of the summation of four additional terms, each dealing with a separate objective of the controller:

$$u = u^n + u^c + u^f + u^a \quad (6)$$

The different terms are discussed in the following.

3.4.2. *Nominal controller* In the nominal case, i.e. in the absence of faults, and far away from the constraints, an LQG controller is used. The design of the LQ controller was done using classical techniques and considering only the system (A, B, C, D). The weighting matrices for the LQ design were chosen to be:

$$Q = \begin{bmatrix} 10 & 0 & 0 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 & 0 & 0 \\ 0 & 0 & 10 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 10^{10} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$
$$R = \begin{bmatrix} 10^{-2} & 0 & 0 \\ 0 & 10^{10} & 0 \\ 0 & 0 & 10^{-2} \end{bmatrix} \quad (7)$$

where Q and R represent the state and input weighting matrices, respectively. This part of the controller performs the primary task of attenuating variations in flow rate and concentration. As can be seen from the choice of Q and R, this objective is translated into the weighting matrices in that the output concentration (C_2) and output flow rate (Q_2) receive the highest weight values. This nominal controller will result in a control action:

$$u^n = K^n \hat{\tilde{x}} \quad (8)$$

Where the hat indicates that an estimate of the system state is used. The states are observed by a Kalman observer on the augmented system (4).

3.4.3. *Constraint handling* For constraint handling, a fuzzy logic element was used for short term adaptations of the flow rate working points. Specifically, the working points of a certain flow rate are increased, resp. decreased when the corresponding volume approaches the upper, resp.

Table 1. Fuzzy inference table for the constraint terms Q_2^c and Q_3^c in function of V_2 and V_3

Q_2^c/Q_3^c		V_3		
		Low	*Normal*	*High*
V_2	*Low*	–/–	0/+	0/+
	Normal	0/–	0/0	0/+
	High	0/–	0/–	+/+

lower boundary. To achieve this, the volumes are fuzzified into three classes: 'low', 'normal' and 'high', and a rule base is used to translate these into a flow rate change Q^c (fuzzy classes '–', '0', or '+') to be added to the working point. The rules for tank 2 and 3 are shown in Table 1.

Since Q_2 is the wastewater stream going to the biological treatment, i.e. the flow rate which has to be dampened, its flow rate is manipulated as little as possible, while most situations are handled by adapting Q_3. We shall call

$$u^c = [Q_1^c \; Q_2^c \; Q_3^c]^T \tag{9}$$

3.4.4. *Actuator fault tolerance* This part of the design was performed using the theory of disturbance accomodation (Harmand, 1997; Johnson, 1976). A first issue to be considered when studying fault tolerance is the question if the fault in question can actually be accomodated. In fact, a fault is absorbable when its effect on the system state can be totally annihilated by an appropriate action of the input. This is the case when a control action

$$u^f = K^f z^f \tag{10}$$

can be found, such that

$$\begin{bmatrix} B \\ D \end{bmatrix} u^f = - \begin{bmatrix} F_x C^f \\ F_y C^f \end{bmatrix} z^f \tag{11}$$

for any z^f. If a solution exists, that is when

$$\text{rank} \begin{bmatrix} B \\ D \end{bmatrix} = \text{rank} \left[\begin{array}{c|c} B & F_x C^f \\ D & F_y C^f \end{array}\right] \tag{12}$$

the solution that yields minimal energy control action is:

$$K^f = \begin{bmatrix} B \\ D \end{bmatrix}^+ \begin{bmatrix} F_x C^f \\ F_y C^f \end{bmatrix} \tag{13}$$

where the $^+$ sign denotes the Moore-Penrose generalized inverse. For this particular case, the solution becomes:

$$K^f = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix} \tag{14}$$

This solution is easily understood considering the following. In the case under study, $C_f = I$, so z_f actually represents an estimation of the flow rate deviations. Therefore, to counteract a flow rate deviation of e.g. 10 m^3/h, it suffices to decrease the flow rate action with 10 m^3/h.

The estimates of the state z^f are available from the Kalman observer on 4.

The approach adopted here was chosen because it provides at the same time a fault detection mechanism (through the estimation of the 'fault state') and a mechanism for fault accomodation (the absorbing term).

3.4.5. *Adaptation* The controller had to be adaptive with respect to an anticipated gradual increase in the flow rate. For this purpose, the estimation of z^d, available from the Kalman observer on the augmented system (4), was used to obtain an estimate of Q_{in}. This estimate was then passed through a long term first order filter (time constant 30 days) to provide the working points for Q_2 and Q_3. A last term in the controller then becomes

$$u^a = [\bar{Q}_1 \; \bar{Q}_2 \; \bar{Q}_3]^T \tag{15}$$

where the barred flow rates denote the working points of the flow rates. $\bar{Q}_1$ is a constant.

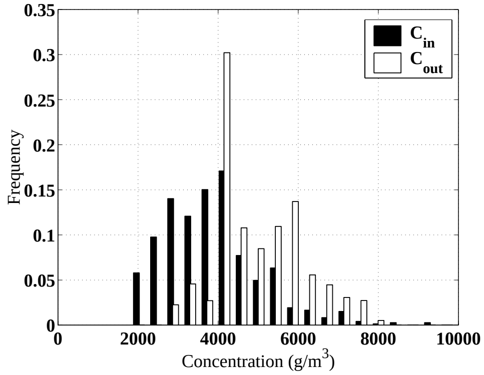
4. EVALUATION THROUGH SIMULATION

4.1 *Principle*

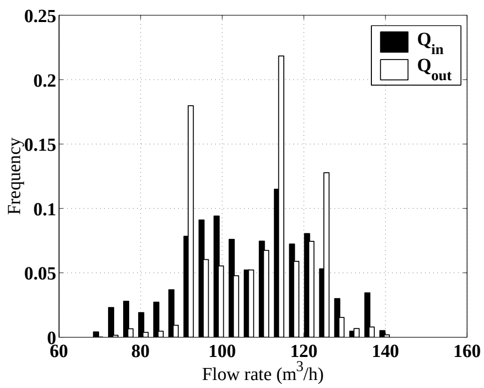
The controller was evaluated as follows. The controller was implemented in Simulink® on the full non–linear model of the equalization system. Pulses were used to simulate $Q_t r$. The Q_{in}, C_{in} data were constructed as follows. For a first two months, a set of data collected on the plant was used. In the next two months, a linear increase of 25 % in the mean flow rate was added to simulate the plant capacity increase. The high mean flow rate at the end of this period was then kept constant for another four months. To simulate actuator faults, deviations were deliberately imposed on the flow rates.

4.2 *Results*

4.2.1. *Equalization performance* Figure 2 illustrates the general performance of the equalization system on concentration and flow rate. From figures 2(a) and 2(b) it is clear that the equalization has skimmed off the extremely high and low flow rates, and that also the concentration profile has narrowed considerably. The flow rate profile shows two peaks because of the form of the influent profile used.



(a) Concentration distribution before and after equalization



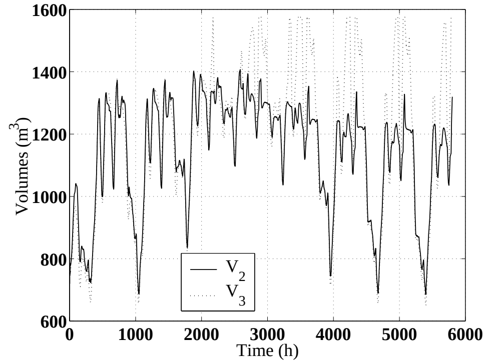
(b) Flow rate distribution before and after equalization

Fig. 2. Global results indicating equalization performance

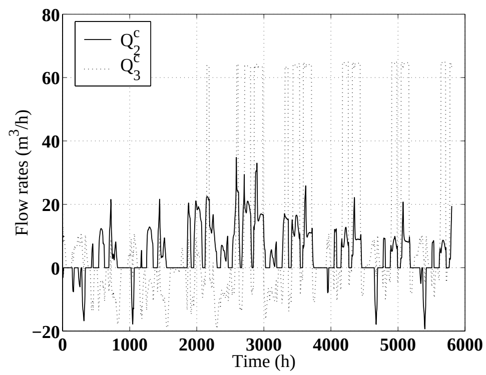
4.2.2. *Constraint handling* Figure 3 illustrates the constraint handling of the controller. The fuzzy terms in the flow rates efficiently adapt the working points when the volumes reach their constraints. This is realized by acting more on Q_3 than on Q_2, which has to be manipulated as little as possible since it is the flow that leaves the equalization system.

At some times, overflowing of V_3 cannot be avoided. This is because the incoming flow rate occasionally exceeds the maximal flow rate of pump 3 (120 m^3/h). The water then automatically flows into tank 2. The pumps in this tank can handle flow rates up to 180 m^3/h, a flow rate higher than the maximal capacity of the pipes leading to V_3.

During the flow rate increase (from 1400 h to 2800 h) there is significantly more action from the fuzzy terms. This is because the flow rate working point lags behind the real flow rate increase, so that the working point is temporarily too low and the volumes increase. This phenomenon disappears when the working points have sufficiently adapted.



(a) Volumes 2 and 3



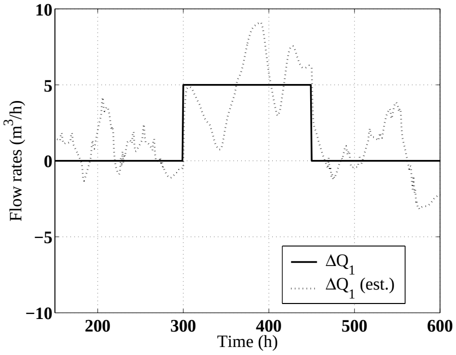
(b) Fuzzy terms in flow rates 2 and 3

Fig. 3. Illustration of constraint handling

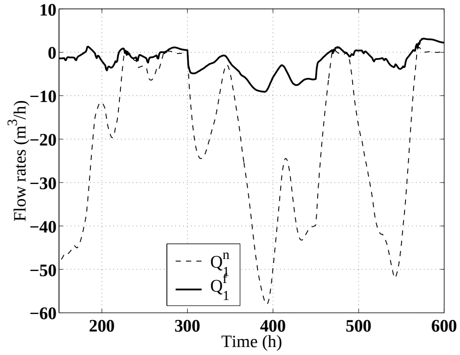
4.2.3. *Fault accomodation* To illustrate the effect of the fault absorbing term in the controller, deviations ΔQ_i were deliberately imposed on the flow rates. These deviations, together with their estimations by the Kalman filter, are illustrated in figure 4. The corresponding actuator action Q_i^f is shown on the right, compared with the nominal control term Q_i^n.

These figures show that the deviations are satisfactorily estimated, resulting in an appropriate corrective control action. The estimation of ΔQ_1 is subject to most agitation. This is caused by the fact that the disturbance, Q_{tr} is modelled as a noise type disturbance. The imprecision on the estimation does not cause problems since the resulting corrective action is small compared to the nominal term. The fault on Q_3 is estimated more effectively, since Q_{in} is modelled as a waveform disturbance, which fits the true characteristics of the disturbance better. The fault on Q_2 (not shown) is estimated nearly perfectly since a measurement of the actual Q_2 is present in the system.

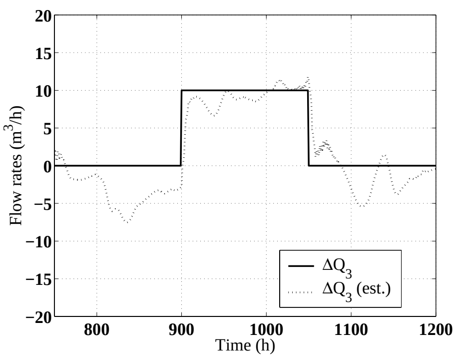
4.2.4. *Adaptation to changing flow rate* Figure 5 illustrates the well–functioning estimation of the disturbance Q_{in}. This disturbance is passed



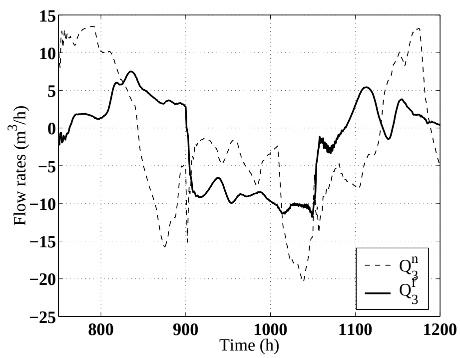
(a) Real and estimated deviation on Q_1



(b) Nominal (Q_1^n) and fault accomodating (Q_1^f) terms in Q_1



(c) Real and estimated deviation on Q_3



(d) Nominal (Q_3^n) and fault accomodating (Q_3^f) terms in Q_3

Fig. 4. Illustration of actuator fault accomodation

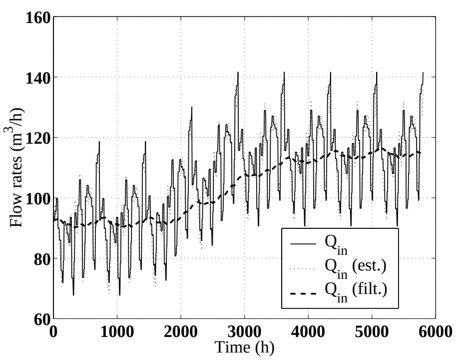


Fig. 5. Illustration of the estimation of Q_{in} and corresponding working point for Q_3

through a long–term filter to form the working point of Q_3.

5. CONCLUSIONS

The results indicate that all controller objectives are satisfactorily attained. All objectives are satisfied by a specific term in the control action vector. The controller can thus be implemented in steps, adding functionality as the project advances, and the benefits of each step can be evaluated as it is implemented. The controller is now being gradually implemented in full scale. In a first stage, a simplified version of the nominal terms, together with the constraint handling (Harmand *et al.*, 1999) have been implemented and are being evaluated. Upon successful evaluation of full–scale plant results, the remaining parts will be implemented and evaluated.

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