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Scheduling and disturbance control of a water distribution network

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Abstract: The choice of a pump schedule has a great influence on the cost efficiency of a system, when the energy consumption charge changes during the day. The pump scheduling problem for a sub-system of a regional water network is considered, and the formulation of the problem as a MDP is given. The system under stochastic demand is modelled and an optimal controller is designed. Two implementations are considered: a direct application of MDP control actions, and local PI-controllers with a feedforward part. The experimental section shows computer simulations illustrating the considered approaches.

Keywords: distribution automation, Markov decision processes; optimal control; probabilistic models; scheduling algorithms

1. INTRODUCTION

Pumping of treated water represents a major fraction of the total operation costs in conventional water supply systems (Bene et al., 2009). The choice of a pump schedule has a great influence on the cost efficiency of a system, when the energy consumption charge changes during the day. If a sufficient storage capacity is available, the water demand can be satisfied with a large number of pump schedules.

The aim of water network optimization is to provide water to customers while minimising the operation costs and satisfying the various constraints (on reservoir levels, power levels, and other operational constraints). Typically human operators of water distribution systems use heuristic rules of thumb to minimize the costs. Several researchers have developed techniques for minimizing the operating costs associated with water supply pumping systems, for overviews see Mayes (1999) or Ormsbee and Lansely (1994). Among these techniques, methods based on evolutionary computation have been proposed, such as based on genetic algorithms (see Bene et al. 2010 for references). In this paper, the focus is on Markov decision processes (MDP).

The MDP are based on the controlled finite Markov chain formulation of the problem, and it's solution via dynamic programming using the Bellman optimality principle. The basic idea is simple (see, e.g., Kemeny and Snell, 1960; Bertsekas, 2007; Powell, 2007): The system state space is discretized (quantized, partitioned, granulated) into a finite set of states (cells) and the evolution of system state in time is mapped in a probabilistic manner, by specifying the transition probabilities from domain cells to image cells. With controlled finite Markov chains (CFMC), the transitions from each domain cell–action pair are mapped. It is straightforward to construct such a model by simulation of a physical model, for example. Once equipped with such a CFMC model, a control policy can be obtained by minimizing a cost function defined in a future horizon, based on a specification of immediate costs for each cell–action pair. Immediate costs allow versatile means for characterising the desired control behaviour. Dynamic programming offers a way to solve various types of expected costs in an optimal control framework.

As pointed out, e.g., by Lee and Lee (2004), applications of MDP in process control have been few. Whereas not-so-many years ago the computations associated with finite Markov chains were prohibitive, the computing power available today using cheap office-pc's encourages the re-exploration of these techniques (Ikonen and Najim, 2009).

This paper considers the application of the MDP for scheduling of a water distribution network with stochastic customer demands, and implementation of the solution via a direct (open loop feedback, see Sec 4.1) approach and with an approach based on local PI-controllers with feedforward from the MDP controller. The experimental section illustrates the approach in the case of plant–model mismatch.

This paper is organized as follows: A short introduction to CFMC is given in the next section. Section 3 explains the pump scheduling problem for the sub-system of the Sopron regional water network, and gives the formulation of the problem as a MDP. The basic schemes for implementing the MDP solution are outlined next, followed by simulation illustrations. Discussion and conclusions end the paper.

2. CONTROLLED FINITE MARKOV CHAINS

Let the process under study be described by the following discrete-time dynamic system equations

$$\mathbf{x}(k) = f(\mathbf{x}(k-1), \mathbf{u}(k-1), \mathbf{w}(k-1)) \qquad (1)$$

where $f : \Re^{n_x} \times \Re^{n_u} \times \Re^{n_w} \to \Re^{n_x}$ is a nonlinear function, n_x, n_u and n_w are the respective dimensions, and $w_k \in \Re^{n_w}$ is i.i.d. white noise with a probability density function (pdf) p_w. The initial condition is known via $p_X(0)$.

Let the state space be discretized into a finite number of non-overlapping sets called (state) cells, indexed by $s \in \mathcal{S} = \{1, 2, ..., S\}$. S is the number of state cells in the model. The discretization results in $\mathcal{X} = \cup_{s=1}^{S} \mathcal{X}_s$. The index s is determined from, e.g., $s = \arg\min_{s\in\mathcal{S}} \left\|\mathbf{x} - \mathbf{x}_s^{\mathrm{ref}}\right\|$where $\mathbf{x}_s^{\mathrm{ref}}$ are called reference points. An absorbing "sink" cell may be defined to cover the space outside of the region of interest. The finite action space can be defined in a similar manner, $a \in \mathcal{A} = \{1, 2, ..., A\}$; $\mathcal{U} = \cup_{a=1}^{A} \mathcal{U}_a$ where $\mathcal{U}_a$ are fixed points. The number and distribution of $\mathcal{X}_s$'s and $\mathcal{U}_a$'s determines the resolution of the system.

The CFMC/MDP approach relies heavily on the discretization of the state and action spaces. In some cases the decision variables or state variables are discrete by nature; in other cases a discrete approximation is required. A suitable discretization of a continuous variable space is a compromise between accuracy (modelling and control) and feasibility (memory/computational requirements), and can be posed as an optimization problem itself.

The evolution of the system (1) can now be approximated as a controlled finite Markov chain (CFMC) over the cell space. Let the state pdf be approximated as a $S \times 1$ cell probability vector $\mathbf{p}_X(k) = [p_{X,s}(k)]$ where $p_{X,s}(k)$ is the cell probability mass. The evolution of cell probability vectors is described by a Markov chain represented by a set of linear equations

$$\mathbf{p}_X(k+1) = \mathbf{P}^{a(k)}\mathbf{p}_X(k) \qquad (2)$$

where $\mathbf{P}^a$ is the $S \times S$ transition probability matrix under action a, $\mathbf{P}^a = \left[p_{s',s}^a\right]$. A finite Markov chain is a finite Markov process such that the transition probabilities do not depend on k (Kemeny and Snell, 1960). A CFMC model of (1) will consist of A transition probability matrices. In general, the state may not be measurable, in which case a state estimator may be constructed.

Using a CFMC model of the plant, an optimal control action for each state can be solved by minimizing a cost function. In optimal control, the control task is to find an appropriate mapping (optimal policy or control table) π from cells s to control actions a, given the immediate costs for each cell–action pair, r_s^a. The infinite-horizon discounted model attempts to minimize the geometrically discounted (using parameter $\gamma < 1$) immediate costs,

$$J(s) = \sum_{k=0}^{\infty} \gamma^k r_s^{\pi(s)},$$

under initial conditions at $k = 0$. The optimal control policy π^* is the one that minimizes J. According to Bellman's principle of optimality, we have for the infinite-horizon discounted model:

$$J^*(s) = \min_a \left[r_s^a + \gamma \sum_{s'\in\mathcal{S}} p_{s',s}^a J^*(s')\right]. \qquad (3)$$

Application of the Bellman equation (Powell 2007, Ch 3) leads to methods of dynamic programming. In value iteration, for example, the optimal value function is determined by a simple iterative algorithm derived directly from the Bellman equation. As a result of the optimization, an optimal control policy table is obtained: $a = \pi^*(s)$. The controller is simple to implement, requiring only a mapping from the current (measured or estimated) state $\mathbf{x}$ to cell s, the table π^* from s to a, and a mapping from control action a to the actual manipulations $\mathbf{u}$. No iterative on-line computations are required.

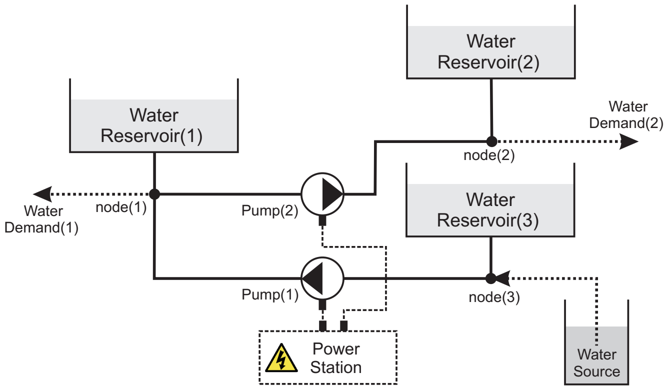

Fig. 1. The topology of the water network in the subsystem of the Sopron problem (Bene et al., 2010).

A priori, a set of powerful tools exists for analysing the behaviour of a CFMC, based on the probability transition matrices. In particular, tools for global analysis of the dynamic, nonlinear, stochastic, multidimensional closed-loop system exist, in addition to local and simulation-based verifications of the system behaviour. However, the finite state system suffers badly from the curse(s) of dimensionality (Powell, 2007) which limits the applicability of the direct approaches for analysis (such as in Kemeny and Snell, 1960).

3. SOPRON PUMP SCHEDULING PROBLEM

The background of the considered problem lies in the regional water network of the city of Sopron in Hungary (see Selek, 2009); this system operates with eight pumps, five power stations, eight water reservoirs and five water demand points. In this paper, a sub-problem of the full water distribution system is considered, however, as a first step towards problems of more realistic scale. The considered set-up follows closely the one detailed in Selek (2009) and Bene et al. (2010). The aim of the optimization was to find a schedule that would minimize the costs under the given demand scenario, without violating the reservoir limits or the power limit.

3.1 A sub-system of the Sopron regional water network

The considered water network topology sub-system is shown in Fig. 1. The pumps were on/off-type. In this case the optimal pump schedule is a set of rules indicating which pumps should be turned on/off during the optimization period. As there are several pumps in a pump group (pump station) delivering water to the same pipeline, they were handled as a single pump with a set of discrete flow rates. The pipeline was considered frictionless (friction losses are assumed negligible compared to geodetic height differences). Water sources (wells) were modelled as negative consumptions, thereby representing a constraint on the pump schedule. The mass balance equations for the system (see Fig. 1) are given by

$$\begin{aligned} R_1(t+T_{\mathrm{s}}) &= R_1(t) + T_{\mathrm{s}}\left[Q_1(t) - Q_2(t) - D_1(t)\right] \\ R_2(t+T_{\mathrm{s}}) &= R_2(t) + T_{\mathrm{s}}\left[Q_2(t) - D_2(t)\right] \\ R_3(t+T_{\mathrm{s}}) &= R_3(t) + T_{\mathrm{s}}\left[W(t) - Q_1(t)\right] \end{aligned} \tag{4}$$

where R_i is the volume of water (m^3) in reservoir i, Q_j is the pump flow (m^3/h) of pump j, D_k is the consumer demand (m^3/h) at node k, and W is the flow from the well (m^3/h). The reservoir levels are constrained by physical upper and lower limits; T_s is the time interval (h) used in the discretization ($T_s = 0.5$h was used throughout). Demands (customer consumptions) were modelled following an a priori given distribution scenario for each hour of the day, in this case truncated Gaussian distributions with a time varying mean and variance were considered.

The cost of the operation was assumed to consist of the energy consumption charge and the energy demand charge. The energy consumption charge was based on the amout of consumed energy, taking into account that there are morning and evening peak hours when the energy was more expensive. The demand charge represents the cost of peak consumption. The daily costs of the operation were then given by

$$J = \sum_{t=T_{\mathrm{s}},2T_{\mathrm{s}},\ldots}^{24} \sum_{j=1}^{2} T_s Z_j(t)\, C(t)$$

where $Z_j(t)$ denotes the input power consumption (kW) of the j'th pump at time interval t (h), and $C(t)$ is the corresponding energy price. At cheap hours (from 0 to 8, 13 to 16 and 20 to 24 hours) the price was set to one euro/kWh, doubled at the peak hours. The two pumps were assumed to have three operating states each, with energy consumptions 0, 55, and 110 kW corresponding to flow rates 0, 100 and 420 m^3/h for pump 1 and 0, 110 and 200 kW corrponding to flow rates 0, 320 and 550 m^3/h for pump 2, respectively. The power limit was set to 300 kW at all times; the reservoir lower limits were set to 100 m^3; the upper limit was set to 3600 m^3 for reservoir 1, 2000 m^3 for the other two reservoirs. A final constraint was to return to the initial state after 24 hours of operation, within a given tolerance of ± 100 m^3.

3.2 Formulation as a MDP problem

In order to formulate the pump scheduling problem as a Markov decision problem, the system propagation needs to be modelled as a Markov chain, i.e., a finite discretization for the state and action spaces needs to be given (the states were assumed to be fully and noiselessly measurable), and the costs need to be expressed as immediate costs depending on the state and action.

From equation (4) we see that the reservoir states provide a possible state formulation for the system. However, since the demands and costs depend on the hour of the day, an additional state involving this information needs to be included. This results in a state-vector $\mathbf{x}$ and control-vector $\mathbf{u}$

$$\mathbf{x} = [R_1, R_2, R_3, h]^{\mathrm{T}}, \mathbf{u} = [Q_1, Q_2]^{\mathrm{T}}$$

where h represents the time interval. The system can now be expressed in the discrete-time state-space form $\mathbf{x}(k+1) = f(\mathbf{x}(k), \mathbf{u}(k))$ with the evolution of the first three states given by (4), and $h(t+T_{\mathrm{s}}) = h(t) + T_{\mathrm{s}}$ if $h(t) < 24$, $h(t+1) = T_{\mathrm{s}}$ otherwise.

From design point of view, the critical phase in the formulation is in the discretization of the system states. Let us consider discretization of the reservoir states (volumes) into a finite number of intervals, a natural discretization for the time intervals is readily provided. The discretization of the full state space is then provided by a four-dimensional grid, with $24N^3/T_s$ cells. A dense discretization results in a large number of states which makes the system computationally infeasible; too rough a discretization may result in a poor solution or even prevent its existance. However, with the small problem setting of the Sopron sub-problem, this did not present a serious difficulty (using $N = 19$).

Since the pumps are on/off, resulting in pumping stations with discrete-valued operating points, a finite set of pump controls are naturally provided by considering all possible combinations. With the two pumping groups of the Sopron sub-problem, nine control actions were available. As the target of the optimization was to minimize the operation costs due to energy consumption (with a given hourly energy price), the constraints were handled by penalizing infeasible solutions with excessive costs.

Given the state-space representation, dynamic programming can be used to solve the problem, using either finite or infinite horizon approaches. The benefit of using an infinite horizon formulation is in that a stationary control policy is obtained, which takes into account the fact that the operation of the water supply system is not terminated after 24 hours, but continues 'infinitely'. However, the requirement to 'return to the initial state after 24 hours' needs to be replaced by a requirement to 'return to a state q at 24 hours' in the MDP approach, and a different controller computed for each q. This is not likely to be a significant drawback, however. In fact, this constraint is more or less artificial, and was included in the study only to keep the results comparable with the past works (Selek 2009; Bene et al 2010). Note, that modifying the constraints is feasible in practice, as it does not require re-modelling, only re-solving for the optimal controller.

4. CONTROLLER IMPLEMENTATION

The MDP approach aims at optimizing the behavior of the water distribution network for a couple of days ahead, based on a given scenario of customer demands. The optimal pump schedule can then be directly applied for controlling the plant, or used as set points for local controllers (recall that optimality is with respect to the considered resolution, however.) The former approach is straightforward and simple, and can be easily made to suit the needs for on/off pumps (or n-ary pumps/pump groups). The latter approach has the advantages of supporting non-centralized design (robustness and safety) and enabling the use of feedback controllers (to handle plant–model mismatch and disturbances), and can take a full advantage of control abilities provided by pumps with frequency control.

4.1 Open-loop feedback

In the direct approach, the pump actions are taken from the optimal MDP sequence, and applied for the whole sampling period

$$s(k) = \arg_{s\in\mathcal{S}} \mathbf{x}(k) \in \mathcal{X}_s$$
$$a(k) = \pi^*(s(k))$$
$$\overline{\mathbf{u}}(k) = \mathcal{U}_{a(k)}; \mathbf{u}(k) = \overline{\mathbf{u}}(k)$$

In case of disturbances, the optimal control action may change when the system moves into a new state cell $(s(k+1) \neq s(k))$, resulting in feedback.

4.2 Local controllers

The MDP provides the optimal controller π^*, which gives the associated action sequence $\{\overline{\mathbf{u}}(k), \overline{\mathbf{u}}(k+1), ...\}$. As PID's operate based on deviation from a set point, the action sequence needs to be converted into a set point sequence. These set points can be obtained from the action sequence as follows: Using the plant model, there is a transition from a state $\mathbf{x}_s \in \mathcal{X}_s \in \mathcal{X}$ (subsets of $\Re$), under action $\mathbf{u}_a \in \mathcal{U}$ (finite set), to state $\mathbf{x}_{s'} \in \mathcal{X}_{s'} \in \mathcal{X}$ (subsets of $\Re$), using a sampling interval T_s. The associated set point is given by $\mathbf{w} = \mathbf{x}_{s\prime} \in \mathcal{X}_{s'}$. In closed-loop the control action a depends on the state cell that the system is in, $\mathbf{u}_a = \pi^*(s(\mathbf{x}_s))$. As an approximation, a single point in each cell $\mathcal{X}_s$ can be considered as a representative of the domain cell, such as $\mathbf{x}_s = \mathbf{x}_s^{\mathrm{ref}}$. The plant model then gives $\mathbf{z}_{s'} = f\left(\mathbf{x}_s^{\mathrm{ref}}, \mathbf{u}_a, .\right)$. This results in a map from each state–action pair $(\mathbf{x}_s, \mathbf{u}_a)$ to $(\mathbf{x}_s^{\mathrm{ref}}, \mathbf{u}_a)$ (a finite set) and further to a vector of set points $\mathbf{w} = \mathbf{z}_{s'}$, where $\mathbf{w}$ is a vector of reservoir volumes (plus time).

Local (presumably SISO) controllers can then be implemented so that during each optimization interval T_s, a shorter control interval T_s' is used (or a continuous controller is considered) and the set point for (each of) the local controller(s) is taken to be w_i during the interval from t to $t + T_\mathrm{s}$. Next, a decision is needed on the plant control structure, i.e., how to couple the controlled variables with the manipulated variables (Skogestad, 2000). Note that in the water distribution system there are three reservoirs but only two pump groups. In the simulations, the largest reservoir (1, in the middle) was considered as a buffer, and reservoir 2 was controlled with pump 2 (inflow), and reservoir 3 with pump 1 (outflow). Finally, a feedforward action from the MDP was added, so that the full effect from $\overline{\mathbf{u}}$ was always used as the base for the PI-control output: $u_i(t) = K_i\left[e_i(t) + \frac{1}{T_{\mathrm{int},i}}\int_0^t e_i(\tau)\,d\tau\right] + \overline{u}_i(t)$, where e_i, u_i and $\overline{u}_i$ refer to the set point, plant output, manipulated input and feedforward part of the ith control loop, $e_i = w_i - y_i$. The controllers were tuned to be fairly slow (settling time of 2 hours, critically damped). The actual PI-controller was implemented digitally, with the control interval T_s' set to one tenth of T_s (0.05h), and physical constraints for pumps taken from the minimum and maximum flows used in MDP design.

Major benefits of the suggested control structure are in the feedback (ability to cope with plant–model mismatch with PI), safety (local controllers are able to operate autonomously), and ability to use continous control actions (pumps with frequency control). Drawbacks can be expected due to that the robustness/optimality of the overall system may deteriorate from the optimized one. In fact, the optimal solution is not calculated for the system with local continuous control actions, for which it may differ. Any practical problems due to roughness of the finite state discription also need to be checked for, and handled by filtering in space and time or by providing a denser resolution.

5. SIMULATIONS

The system model was built in Matlab and the optimal pumping policy found using the developed MGCM toolbox. The same problem was considered by Selek (Bene et al., 2010; Selek, 2009) where the solution was seeked for using a new genetic algorithm with neutrality (NGA). Full details of the simulation set-up, including demand scenarios and well data, can be found from `www.artificialevolution.net`. The MDP and NGA were approaches were compared in Ikonen and Selek (2010), while Ikonen and Bene (2010) considered the MDP approach with stochastic demands.

5.1 CFMC/MDP setup

The state space was partitioned into a grid (hyperrectangles) by discretizing each dimension separately. For each dimension, centers for the finite states were taken as equidistant:

$$c_n^{\mathrm{ref}} \in \{c_0, c_0 + \Delta c, ..., c_0 + (N-1)\,\Delta c\}$$

where N is the number of partitions, $\Delta c = \frac{c_{\max} - c_{\min}}{N}$ and $c_0 = c_{\min} + \frac{\Delta c}{2}$. The sink cell was used, so that any variable falling outside of the range $[c_{\min}, c_{\max}]$ would be associated with the sink cell, and the values $c_{\min}$ and $c_{\max}$ were determined by the reservoir lower and upper volume constraints. $N = 19$ was used for the reservoirs, the time-of-the-day was always partitioned into 48 values (30 min sampling time). This resulted in $S = 329233$ state cells. There were three actions for both pumps in all experiments, i.e., $A = 9$.

The consumer demands were modelled as truncated Gaussian distributions, with mean taken from a given scenario and setting the standard deviation to 10% of the mean value. The normal distribution was limited between zero and 100 m^3 (demand 1) and 500 m^3 (demand 2), see Fig 2. Note, that the truncation was implemented by replacing any realization outside of a given min–max range by a new draw. The plant CFMC models were built based on 108 random evaluations from each cell–action pair and counting the number of observed transitions. This was the most time consuming phase of the simulations.

An optimal infinite horizon controller was designed using value iteration and a discount factor $\gamma = 0.98$. The immediate costs were based on the costs of pumping. Constraints in reservoir volumes were handled by limiting the system state cells only to feasible area, mapping the space outside of feasible range to a sink cell, and

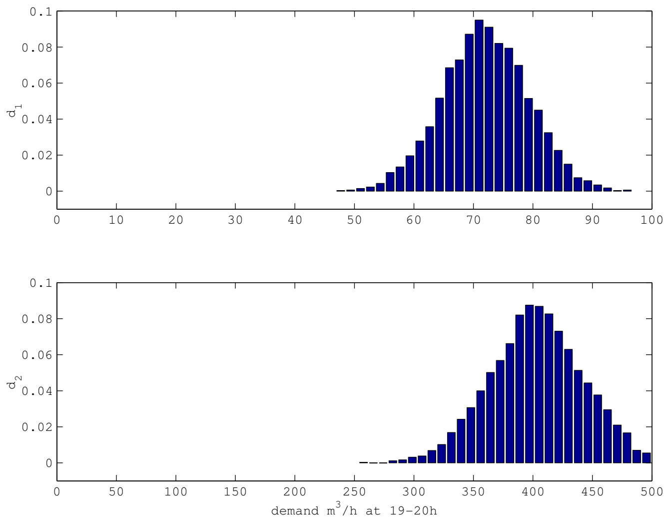

Fig. 2. The stochastic water demand (consumer consumption) was taken from a truncated normal distribution. The figure shows the experimental distribution for demand 1 (top plot) and demand 2 (lower plot) between 19 and 20 hours.

associating an excessive immediate cost with the sink cell. The power limit (300 kW) and requirement to return to a given state at 24h were implemented by setting an excessive immediate cost if these constraints were violated. In fact, the power limit was satisfied if both of the pumps were not used at full power.

The performance of the closed-loop system under several discretizations and demand noise levels was analyzed in an earlier study (Ikonen and Bene, 2010). The following observations were made: i) The controller designed for a particular noise scenario provided the best solution for controlling the plant, with probabilities of instability close to zero. ii) The solution improved with an denser grid resolution. iii) The controllers designed under milder noise assumptions performed poorly in stronger noise situations, while the opposite was not true. However, this observed robustness was shadowed by the reduction in economical performance, i.e., the controllers became overly cautios when the real noise situations were less severe than the expected ones.

5.2 Local PI's

Local PI controllers were then implemented for controlling reservoirs 2 and 3. Reservoir 1 was left uncontrolled. Figures 3 and 4 show a two day simulation starting from the nominal initial point. At 24h, the characteristics of the pump 2 change so that the pumped volume is decreased by 25% from the required value.

Figure 3 illustates the control with no local PI's, i.e. the control actions were taken directly from the MDP controller. The operation is optimal during the first day, but deviates significantly during the second day. As the efficiency of the pump is decreased, the volume in reservoir 2 decreases and the volume in reservoir 1 increases. With local PI-controls, see Fig. 4, the mismatch in the model is compensated for and the system operation remains much

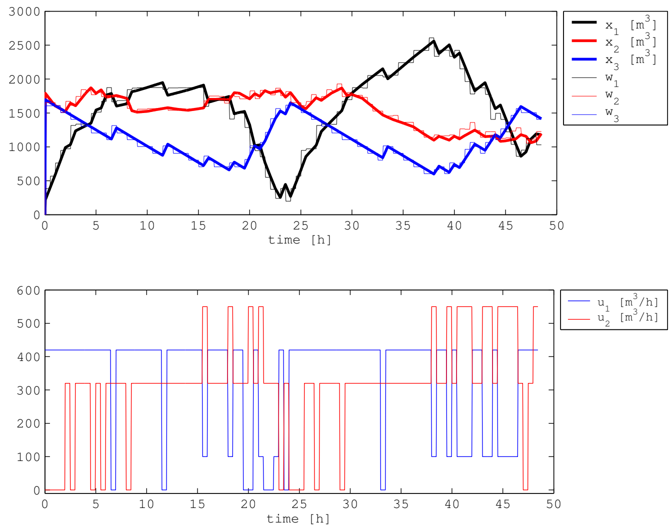

Fig. 3. 2-day simulation using MDP control actions. At 24h, the efficiency of the pump 2 is decreased by 25%. As pump 2 controls the outflow from tank 1 (inflow to tank 2), the reservoir volume increases (decreases) accordingly. The 'open loop feedback' via state information attempts to correct the situation, but there is a significant mismatch between the plant and the model the controller was based on. The controlled system fails to meet the requirement to return to the initial state at 48 hours.

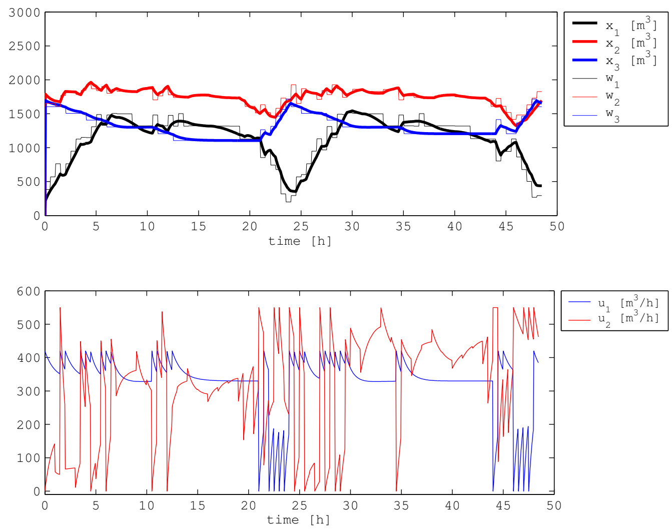

Fig. 4. A 2-day simulation using local controllers with set points from MDP control actions plus a feedforward from MDP control actions. The PI-controllers control the volumes in tanks 2 and 3. At 24h, the efficiency of the pump 2 is decreased by 25%. The feedback control is able to correct the change in pump performance. The controlled system meets the requirement to return to the initial state at 48 hours.

the same also during the second day. Comparing lower plots in Figs. 3 and 4 showing the control actions, the effect of integral control action at the medium pumping level is clearly visible.

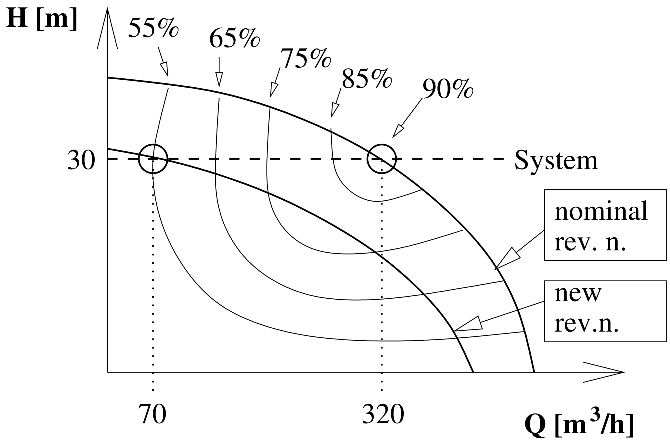

Fig. 5. Revolution number vs system efficiency.

5.3 Hydraulic considerations

In real applications, the total cost will definitely be higher with local PI's compared with pure MDP control. The reason of this phenomenon is the hydraulic behaviour of the pumps. Consider for example the pump group 2 which consists of two pumps. The nominal flow rates are 320 m^3/h and 550 m^3/h, respectively (The two pumps cannot run at the same time.) It can be seen in Fig. 4 that the actual flow rate of the pump (nom. flow rate: 330 m^3/h) is about 70 m^3/h at many times. Setting different flow rates than the nominal by the same head (we assume that the friction losses can be neglected) can be realized by different modes. The two most frequent methods are regulating by a bypass valve or by revolution number control (Mays, 1999; Brennen, 1994).

In the case of a bypass passage the unnecessary amount of water is conducted back to the suction side of the pump. Note that the resistance of the bypass has to be set by a valve in order to keep the value of the original head. Due to the fact that the power of a pump is proportional to the flow rate the efficiency of the pump drops as a function of the bypass: 70/320 in our example case.

To investigate the case of revolution number control see Fig. 5. The two thick lines show the characteristic curves of the pump by the nominal and a new revolution number, while the dashed line is the constant system characteristic curve. The operating points in both flow rate cases are marked by circles. The iso-lines of the pump efficiency are drawn in the picture by thin lines. It is clearly to seen that the efficiency is low at low flow rates.

Even if the cost is higher due to the hydraulic behaviour of the pumps, using the local PI controllers may be justified when the safety of the plant (resulting from better control) is important. On the other hand, if the pumps are equipped with frequency inverters, which gives the possibility to control their revolution number, the loss of efficiency should be considered already during the optimization phase.

6. DISCUSSION AND CONCLUSIONS

The choice of a pump schedule has a great influence on the cost efficiency of a water distribution system. This paper considered energy efficiency in pumping of treated water, under stochastic customer demand scenarios, hourly pricing, and power consumption constraints. The pump scheduling problem for a sub-problem of the Sopron regional water network was considered. The problem was formulated and solved as a CFMC/MDP problem, and the control solution was implemented both directly and using additional local PI controllers. With the increased availability of cheap memory/computing power, the potentials of the CFMC/MDP approach are worth examining also for problems previously considered as computationally infeasible, such as the optimization in the full Sopron water distribution network.

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