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OPTIMISED ALLOCATION OF HARD QUALITY SENSORS FOR ROBUST MONITORING OF QUALITY IN DRINKING WATER DISTRIBUTION SYSTEMS

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Abstract: A problem of optimised placement of the hard quality sensors in Drinking Water Distribution Systems for robust quality monitoring is formulated. Two numerical algorithms to solve the problem are derived. The optimality is meant as achieving a desired trade off between the sensor capital and maintenance costs and resulting robust estimation accuracy of the monitoring algorithm. The robust estimation algorithm recently developed by the authors is applied as a soft quality in design of the sensor placement algorithms. The methods and algorithms are validated by application to Chojnice DWDS case study. *Copyright © 2010 IFAC*

Keywords: algorithms, monitoring, sensor placement, optimization problems, water quality.

1. INTRODUCTION

An operation of a drinking water distribution system (DWDS) aims at delivering to the users required amount of water satisfying the quality requirements (Brdys and Ulanicki, 1994). The goal is complex and suitable monitoring and control algorithms operating on line need to be applied in order to achieve it. Due to an uncertainty in the water demand and also in a mathematical model of water quality information about the quality delivered on line by the monitoring system is essential for decision making and control purposes. Placing hard quality sensors at all nodes of DWDS of interest is not possible due to the technical access difficulties and the sensor maintenance cost. Hence, the mathematical models are used to support the measurement information provided by the hard sensors. Integrating the models with the hard sensor readings into one estimation algorithms leads to so called soft sensor. The paper considers an optimised placement of the hard sensors within the DWDS. Such placement achieves a desired compromise between the capital cost and maintenance costs of the hard sensors and the resulting accuracy of the water quality estimates produced by the soft sensor. A robust quality soft sensor was proposed for the first time in (Łangowski and Brdys, 2007). It is fast enough for on line operation and at the same time not conservative with regard to handling an uncertainty in the hydraulic inputs, quality model parameters and measurement noise. The robustness is achieved by employing a set bounded model of the uncertainty (Milanese and Vicino, 1991; Brdys, 1999). The preliminary results regarding the placement produced by (Łangowski and Brdys, 2007) clearly show that under the same number of the hard sensors, accuracy of the resulting water quality estimates can vastly differ depending on at which nodes of DWDS the sensors are located.

The DWDS are classified as members of a general class of Critical Infrastructure Systems (Memorandum of Understanding, 2008), reliable, high performance and secure operation of which is very essential for the society. The problem considered in the paper is one of the key problems to be tackled by Working Group 4: Health Monitoring and Control of Water Systems within new EU Cost Action IC0806 – *IntelliCIS* (Memorandum of Understanding, 2008).

The paper is organised as follows. The information structure relevant for designing the soft quality sensor is discussed in Section 2. The one objective and two objective formulations of the optimised sensor allocation problem are presented in Section 3. Genetic solvers of the allocation task are presented in Section 4 and results of application to Chojnice case study are described in Section 5. The paper completes by conclusions in Section 6.

2. QUALITY MONITORING IN DRINKING WATER DISTRIBUTION SYSTEMS

There two aspects in operation of DWDS: quantity (hydraulics) and quality. They interact but the interaction is only one way from hydraulics to quality (Brdys, *et. al.*, 1995). This was efficiently utilised in (Brdys, *et. al.*, 1995; Brdys, *et. al.*, 2000; Duzinkiewicz, *et. al.*, 2005) where the structures and algorithms for an integrated quality and quantity control were proposed and investigated. From the monitoring point of view we have two cascaded monitoring systems. The robust quantity monitoring system (Brdys and Chen, 1995; Brdys, 1999) produces robust estimates of the flows and hadraulics model parameters. The flow estimates are the input data into the quality models (Łangowski and Brdys, 2007), hence to quality monitoring system. Water quality at DWDS can be determined by a number of quality parameters. The most popular parameter is the disinfectant concentration. Chlorine is commonly used at present as a disinfectant and its concentration will be considered in this paper as the quality parameter. Hence, the hard quality sensors will be the chlorine concentration measurement devices located at the water network nodes. The quality measurements in DWDS are taken from water samples in a laboratory or on line. The laboratory based measurements although useful are not suitable for on line monitoring performed in a natural quality time scale and therefore, they will not be utilised by the on line quality monitoring system considered in the paper.

The quality state at DWDS is composed of chlorine concentrations along pipes, in tanks and reservoirs and in the pipe junction nodes. The hard sensors can be located only in the tanks and junction nodes. Due to limited number of sensors that can be placed in DWDS the quality mathematical models are needed in order to estimate the quality state. A fundamental partial differential equation derived in (Rossman, *et. al.*, 1993) was taken as a base to derive a lumped model of chlorine distribution along a pipe (Łangowski and Brdys, 2007). The overall quality model and the resulting soft sensor used in the paper are taken from (Łangowski and Brdys, 2007; Brdys and Łangowski, 2008).

3. OPTIMISED PLACEMENT OF HARD QUALITY SENSORS - PROBLEM FORMULATION

The optimised placement of hard quality sensors achieves a desired compromise between the capital cost and maintenance costs of the hard sensors and the resulting accuracy of robust quality estimates produced by the soft sensor. The robust quality estimates are produced by the soft sensor in a form of intervals lower and upper bounding the unknown chlorine concentrations. Hence, tighter the bounding intervals more accurate the estimates are. The estimate accuracy needs to be traded off against the hard sensor costs. Hence, a natural approach is to formulate the sensor allocation problem as multiobjective constrained optimisation task with Pareto definition of the optimality. However, the formulation with one performance function expressing the hard sensor costs by specifying how many of them are used and with properly designed bounds on satisfying accuracy of the estimates can be also useful if the accuracy bounds are suitably chosen. In the sequel two formulations in a form of the one objective optimisation and multiobjective optimisation are proposed and further discussed. A general structure of an algorithm solving the problem is illustrated in Fig. 1. The input data are generated as follows. Given water demand scenario at DWDS the integrated quantity and quality control algorithm produces trajectories of the quantity and quality control variables over certain prediction horizon (Kurek and Brdys, 2007). These control variable trajectories are applied to DWDS and the simulation results by Epanet (Łangowski and Brdys, 2007) include flows and chlorine concentrations over DWDS. The quantity monitoring system generates the robust flow estimates, which are the inputs to the quality soft sensor (see Fig. 1). Gathering the input data into the optimised placement algorithm has now been completed. The algorithm starts from an initially chosen hard sensor placement pattern and the chlorine concentrations at the measurement nodes are red from the obtained above chlorine concentration trajectories. Next the readings are disturbed randomly by the random bounded noise generator with the distribution parameters and bounds reflecting a priori available knowledge about the measurement noise. These simulated measurements are fed into the soft sensor where the corresponding robust quality estimates over a whole DWDS are produced. The optimiser can then evaluate fitness of the sensor placement and produce a better one or to stop the algorithm.

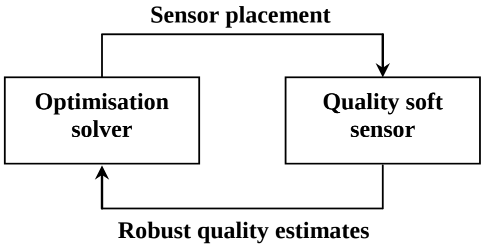

Fig. 1. General structure of an algorithm solving problem of optimised sensor placement over DWDS.

3.1 One objective based sensor allocation problem formulation

Let us define the following:
Ω_1 - set of all nodes and $|\Omega_1|$ denoting a number of nodes in Ω_1; Ω_2 - set of all tanks and $|\Omega_2|$ denoting a number of tanks in Ω_2; Ω_E - set of monitored nodes where there are no sensors and $|\Omega_E|$ denoting a number of nodes in Ω_E, $\Omega_E \subset \Omega_1$; SFN - set of nodes where the sensors can be placed (sensor feasible nodes) and $|SFN|$ denoting a number of nodes in SFN, $SFN \subset \Omega_1$; $c^+_{out,n}(t)$ - upper envelope bounding the unknown chlorine concentration in n-th node, $n \in \Omega_E$; $c^-_{out,n}(t)$ - lower envelope bounding the unknown chlorine concentration in n-th node, $n \in \Omega_E$; $X_{1,\max n}$ - upper limit on estimation accuracy in n-th node, $n \in \Omega_E$ (maximal allowed length of the bounding interval); $c^+_{t,p}(t)$ - upper envelope bounding the unknown chlorine concentration in p-th tank, $p \in \Omega_2$; $c^-_{t,p}(t)$ - lower envelope bounding the unknown chlorine concentration in p-th tank, $p \in \Omega_2$; $X_{2,\max,p}$ - upper limit on estimation accuracy in p-th tank, $p \in \Omega_2$ (maximal allowed length of the bounding interval); ASN - number of available sensors; g_{sfn} - decision variable allocating sensor to the sensor feasible nodes $sfn \in SFN$; $g_{sfn} \in \{0,1\}$ and if $g_{sfn} = 1$ a sensor is placed in the sfn node while if $g_{sfn} = 0$ it is not placed there.

The sensor allocation problem is formulated as a one objective constrained optimisation problem to minimise a number of sensors allocated at the feasible nodes of DWDS from the set of available sensors so that the required estimation accuracy is robustly achieved. The mathematical formulation is as follows:

$$\min \mathrm{Z} \tag{1}$$

$$\mathrm{Z} = \sum_{sfn=1}^{|SFN|} g_{sfn} \tag{2}$$

subject to:

$$\sum_{sfn=1}^{|SFN|} g_{sfn} \leq ASN \tag{3}$$

$$\left[c^{+}_{out,n}(t) - c^{-}_{out,n}(t)\right] \leq \mathrm{X}_{1,\max,n}, \; n \in \Omega_E \tag{4}$$

$$\left[c^{+}_{t,p}(t) - c^{-}_{t,p}(t)\right] \leq \mathrm{X}_{2,\max,p}, \; p \in \Omega_2 \tag{5}$$

The guaranteed upper limits $\mathrm{X}_{1,\max,n}$ and $\mathrm{X}_{2,\max,p}$ on the estimation accuracy in (4) and (5) are in the above formulation the same. Clearly, they can be made different depending on how important the water user at a particular demand node is. This would not complicate the above formulation. Determining the limits is not always an obvious task. Too small ones may not be achievable and an attempt to do so by slightly relaxing the limits may lead to a long and computationally demanding trial and error exercise resulting in a very expensive, in terms of a number of allocated sensors, solution not much improving the estimation accuracy. Operator experience regarding propagation of chlorine throughout the DWDS network can be very useful in determining a prior the sensor feasible nodes. Limiting the set SFN to truly effective nodes strongly linked, regarding the propagated chlorine impact, to other network nodes can significantly ease the optimisation problem solver task and reduce the computational efficiency.

3.2 Two objectives based sensor allocation problem formulation

In this multiobjective formulation the estimation accuracy objective is traded off against the sensor costs maintaining the same priority of importance. Once the Pareto front has been determined the final solution can be selected by the system user. The formulation is as follows:

$$\min \mathrm{Z}_1 \tag{6}$$

$$\mathrm{Z}_1 = \sum_{sfn=1}^{|SFN|} g_{sfn} \tag{7}$$

$$\min \mathrm{Z}_2 \tag{8}$$

$$\mathrm{Z}_2 = \sum_{n=1}^{|\Omega_E|} \left(c^{+}_{out,n}(t) - c^{-}_{out,n}(t)\right) + \sum_{p=1}^{|\Omega_2|} \left(c^{+}_{t,p}(t) - c^{-}_{t,p}(t)\right) \tag{9}$$

subiect to:

$$\sum_{sfn=1}^{|SFN|} g_{sfn} \leq ASN \tag{10}$$

A great advantage of the two objective formulation is that the guaranteed upper limits $\mathrm{X}_{1,\max,n}$ and $\mathrm{X}_{2,\max,p}$ are not needed a prior. In fact they can be very reasonably determined after solving the problem as a full range of options is available in a form of a Pareto front. The different options can be screened and evaluated and a final choice can be made interacting with the decision makers meeting their preferences not included in the problem formulation.

4. SOLVERS OF THE SENSOR ALLOCATION TASKS

The optimisation tasks corresponding to the one objective and two objective formulations of the sensor allocation problem and defined by (1) - (5) and (6) - (10), respectively are with binary decision variables and under the real valued and integer valued constraints. Moreover, the optimisation task defined by (6) - (10) has two objective functions. Hence, a genetic algorithm NSGA – II is chosen as solver of the optimisation tasks. Applied to multiobjective optimisation tasks the algorithm determines a solution set optimal in a Pareto sense (Deb, *et. al.*, 2000; Deb, 2001). The algorithm has been already successfully applied to as a solver of a problem of an optimised placement of the quality control system actuators, the post-chlorination booster station, over the DWDS (Kurek and Brdys, 2006; Ewald, *et. al.*, 2008; Drewa and Brdys, 2008).

A formulation of the optimisation task (1) - (5) in order to apply the NSGA-II solver is as follows:

$$F = \sum_{sfn=1}^{|SFN|} g_{sfn} + pf_1 + pf_2 + pf_3 + pf_4 \tag{11}$$

where:
F - objective function to be minimised
pf_1 - penalty function handling the upper constraint (3) on a number of available sensors defined as:

$$pf_1 = \begin{cases} 0 & if \quad \sum_{sfn=1}^{|SFN|} g_{sfn} \leq ASN \\ \psi & if \quad \sum_{sfn=1}^{|SFN|} g_{sfn} > ASN \end{cases} \tag{12}$$

pf_2 - penalty function handling the upper constraints (4) on the guaranteed estimation accuracy in junction nodes defined as:

$$pf_2 = \sum_{n\in\Omega_E}\alpha_{n,2}\left[\min\left\{0,\left(X_{1,\max,n} - \left(c^{+}_{out,n}(t) - c^{-}_{out,n}(t)\right)\right)\right\}\right]^2 \quad (13)$$

where: $\alpha_{n,2}$ are positive real numbers;

pf_3 - penalty function handling the upper constraints (5) on the guaranteed estimation accuracy in tanks defined as:

$$pf_3 = \sum_{n\in\Omega_2}\alpha_{p,3}\left[\min\left\{0,\left(X_{2,\max,p} - \left(c^{+}_{t,p}(t) - c^{-}_{t,p}(t)\right)\right)\right\}\right]^2 \quad (14)$$

where: $\alpha_{p,3}$ are positive real numbers;

pf_4 - penalty function forcing placement of at least one sensor defined as:

$$pf_4 = \begin{cases} 0 & if \quad \sum_{sfn=1}^{|SFN|} g_{sfn} \neq 0 \\ \Phi & if \quad \sum_{sfn=1}^{|SFN|} g_{sfn} = 0 \end{cases} \quad (15)$$

Formulation of the two objective optimisation task (6) - (10) in order to apply the NSGA-II solver is as follows:

$$F_1 = \sum_{sfn=1}^{|SFN|} g_{sfn} + pf_1 + pf_4 \quad (16)$$

$$F_2 = \left[\sum_{n=1}^{|\Omega_E|}\left(c^{+}_{out,n}(t) - c^{-}_{out,n}(t)\right) + \sum_{p=1}^{|\Omega_2|}\left(c^{+}_{t,p}(t) - c^{-}_{t,p}(t)\right)\right] + \\ + pf_1 + pf_4 \quad (17)$$

where F_1, F_2 are the objective functions to be minimised in a Pareto sense.

As it has been stated earlier selection of the final placement from the Pareto front is to be done by a decision maker. However, this process can be supported by a decision model. In the paper a model, which achieves a minimum distance from the coordinate system origin to the Pareto set is chosen.

5. APPLICATION TO CHOJNICE DWDS CASE STUDY

5.1 Preliminaries

In this section the algorithms for an optimised placement of quality sensors are applied to DWDS at Chojnice. This DWDS performs daily delivery of drinking water to 40 thousands of users. A skeleton model of the DWDS containing all essential futures of the real system is composed of 2 raw water sources, 177 nodes including 7 demand nodes, 1 tank, 271 pipes and 3 pumps. Details can be found in (Duzinkiewicz and Cimiński, 2006). The model structure is illustrated in Fig. 2.

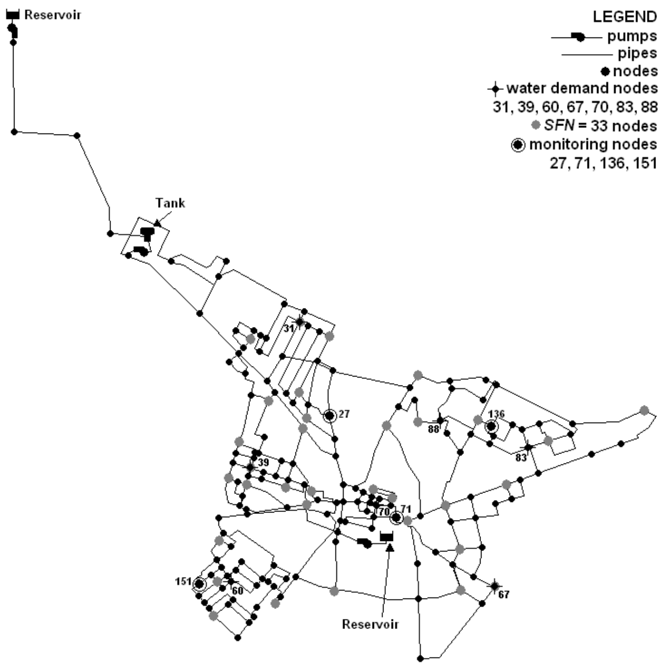

Fig. 2. Model of Chojnice DWDS.

The DWDS model was implemented in a simulation package EPANET (US EPA, 2001) to produce the input data to the sensor allocation algorithms as described in Section 3. Moreover, the DWDS simulator was also used to validate the allocation results. The EPANET was coupled to MATLAB in order to create a computational environment for the quality soft sensor and NSGA - II based optimisation solver.

5.2 Simulation results

Results obtained by the two objectives based algorithm are presented in this section. The basic parameters are: a population composed of 80 chromosomes, *SFN* composed of 33 nodes, *ASN* = 20. The resulting Pareto front is shown in Fig. 3 where the best chromosome is marked. The optimal placement is illustrated in Fig. 4.

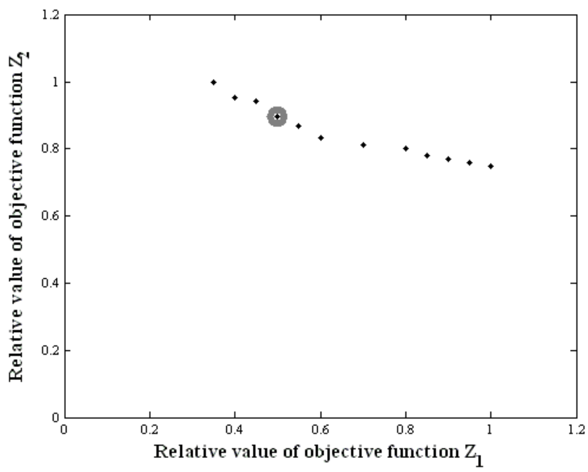

Fig. 3. Two objective algorithm of monitoring stations - Pareto front.

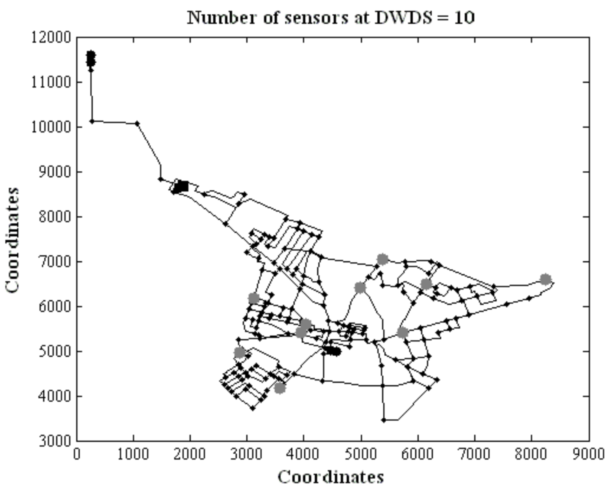

Fig. 4. Two objective algorithm of monitoring stations - sensors placement.

With the optimally placed hard sensors the resulting monitoring results are presented in Figs. 5 to 8 There are three trajectories illustrated in these Figures, which represent: the real chlorine concentration obtained from the EPANET simulator and upper and lower envelopes robustly bounding the estimated concentration.

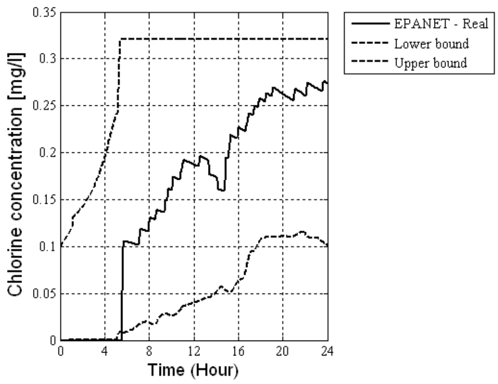

Fig. 5. Two objective algorithm of monitoring stations - estimated chlorine concentration bounds at node 27.

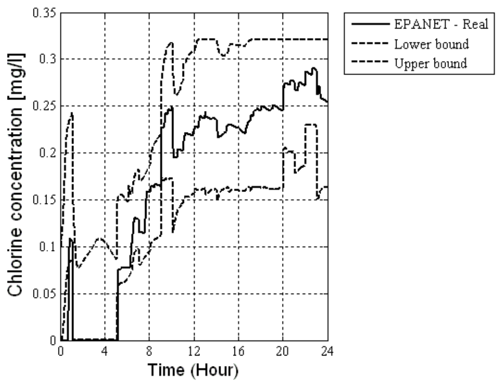

Fig. 6. Two objective algorithm of monitoring stations - estimated chlorine concentration bounds at node 71.

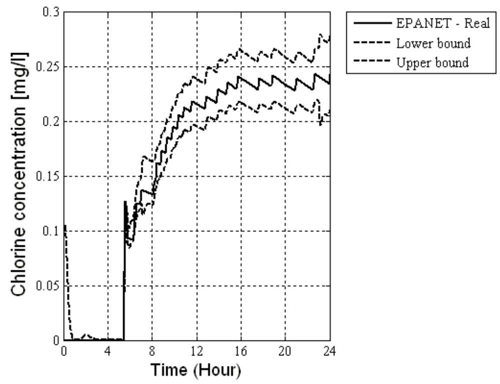

Fig. 7. Two objective algorithm of monitoring stations - estimated chlorine concentration bounds at node 136.

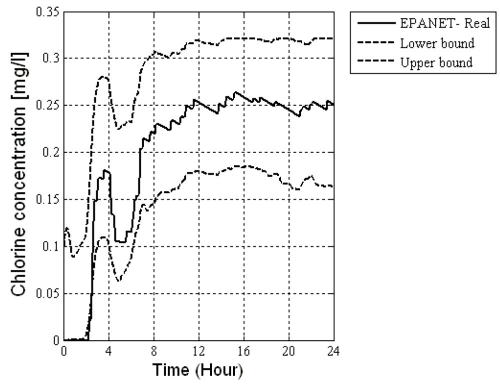

Fig. 8. Two-objective algorithm of monitoring stations - estimated chlorine concentration bounds at node 151.

6. CONCLUSIONS

The paper has formulated a problem of optimised placement of the hard quality sensors in Drinking Water Distribution Systems for robust quality monitoring. It has derived two numerical algorithms to solve the problem. The optimality has been understood as achieving a desired trade off between the sensor capital and maintenance costs and resulting robust estimation accuracy of the monitoring algorithm. The robust estimation algorithm recently developed by the authors has been applied as a soft sensor for the monitoring purposes. The results have been successfully validated by application to Chojnice DWDS case study. The sensor placement produced by the derived algorithm is valid for one water demand scenario, hopefully adequately representing the DWDS disturbance inputs. Deriving the optimised placement methods and algorithms achieving at the same time the optimised trade off between the hard sensor costs and resulting monitoring accuracy for several disturbance scenarios is under current research.

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