Journal of Water Supply: Research and Technology—AQUA | 62.1 | 2013

Better water quality and higher energy efficiency by using model predictive flow control at water supply systems

M. Bakker, J. H. G. Vreeburg, L. J. Palmen, V. Sperber, G. Bakker and L. C. Rietveld

ABSTRACT

Fifty-seven per cent of all water supply systems in the Netherlands are controlled by model predictive flow control; the other 43% are controlled by conventional level-based flow control. The differences between conventional level-based flow control and model predictive control were investigated in experiments at five full-scale water supply systems in the first half of 2011. Quality parameters of the drinking water and energy consumption of the treatment and distribution processes were measured and analysed. The experiments showed that the turbidity values are 12–28% lower, and particle volume values 12–42% lower for the systems which are controlled by model predictive flow control. The overall energy consumption of water supply systems controlled by predictive flow control is 1.0–5.3% lower than conventional level-based flow controlled systems, and the overall energy costs are 1.7–7.4% lower.

Key words | demand prediction, drinking water, energy reduction, optimal control, water quality

M. Bakker (corresponding author)
J. H. G. Vreeburg
L. C. Rietveld
Delft University of Technology,
PO Box 5048, 2600 GA Delft,
The Netherlands
E-mail: *martijn.bakker@rhdhv.com*

M. Bakker
Royal Haskoning DHV B.V.,
PO Box 1132, 3800 BC Amersfoort,
The Netherlands

J. H. G. Vreeburg
KWR Watercycle Research Institute,
PO Box 1072, 4330 BB Nieuwegein,
The Netherlands

L. J. Palmen
WML N.V.,
PO Box 1060, 6201 BB Maastricht,
The Netherlands

V. Sperber
Brabant Water N.V.,
PO Box 1068, 5200 BC 's-Hertogenbosch,
The Netherlands

G. Bakker
Vitens N.V.,
PO Box 1090, 8200 BB Lelystad,
The Netherlands

INTRODUCTION

Automation of water supply systems

Water utilities around the developed world started automating their water supply systems around the mid-1970s by installing and operating telemetry and Supervisory Control And Data Acquisition (SCADA) systems (Bunn 2007; Bunn & Reynolds 2009). Prior to this period, the treatment plants and pumping facilities were mainly operated manually. In the Netherlands, most small-scale water treatment plants (typically groundwater treatment plants serving on average 50,000 people, producing and distributing 6,000 m^3 per day) were automated extensively at that time, enabling unmanned operation. Unmanned operation in this perspective means that under normal operational conditions no manual actions of operators are needed for pressure and flow control. Therefore, both pressure control of the pumping stations and flow control of the water treatment plants were fully automated. At night and during the weekends, no personnel is present at the small-scale facilities since the automation systems were implemented. Small-scale water supply systems were automated extensively at an early stage due to two reasons. The first is that manually operating small-scale systems is labour intensive and therefore rather expensive. The second reason is that small-scale systems are rather simple systems: the treatment plants consist mainly of robust aeration and filtration steps,

doi: 10.2166/aqua.2013.063

and also the distribution systems are rather straightforward. Initially, the small-scale water supply systems were automated with relatively simple control loops: the set-point for the production flow was derived directly from the level in the reservoir. This level-based production flow control is simple and robust. However, this way of control results in variations in the production flow, which causes variations in the water quality. In the 1990s, the desire for more advanced control loops grew in order to achieve a more constant production flow.

Level-based versus model predictive flow control

Principally there are two options for the automatic production flow control: level-based control and model predictive control. In level-based control loops (see Figure 1), the production flow set-point is directly related to the level in the reservoir. The production flow set-point increases at a decreasing level in the reservoir, the set-point decreases at an increasing level. This set-point can be given as discrete commands to start or stop pumps or filters (based on fixed switch levels), or a continuous value for variable speed pumps. In general, the production flow set-point more or less follows the outgoing flow, with a time lag of 2–4 h. The reservoir is merely used as a switching buffer, rather than a buffer to balance the variation in the distribution flow. The production flow varies and the maximum and minimum flow values of the production flow are comparable with the maximum and minimum flow values of the distribution flow (Bakker *et al.* 2003).

A model predictive flow control algorithm (see Figure 2) consists of a short-term water demand prediction algorithm and a control algorithm. For production flow control, the prediction horizon is typically 24–48 h (Bakker *et al.* 2003). An extensive review of concepts, methods and organizing principles of water demand prediction is presented by House-Peters & Chang (2011). The control algorithm calculates production flow set-points matching the predicted demand, under the condition that the level in the reservoir stays between a chosen upper and lower limit. The control algorithm can be configured to optimize various optimization goals, such as minimal changes in production flow, minimal energy use, minimal energy costs or a combination of them. In most cases, mathematical optimization techniques are applied in the control algorithm in order to find an optimum. However, if the optimization goal is formulated strictly (e.g., constant production flow), the optimum can be calculated directly by a deterministic model (Bakker *et al.* 2003). Like level-based flow control, the set-point can be either discrete switching commands for wells, filters or pumps, or a continuous value. In general, predictive flow control results in a constant production flow, where the reservoir is used to balance the fluctuations in the outgoing distribution flow (see Figure 2).

Application of predictive flow control in the Netherlands

In this research all 10 Dutch drinking water utilities were interviewed to determine the penetration of predictive flow

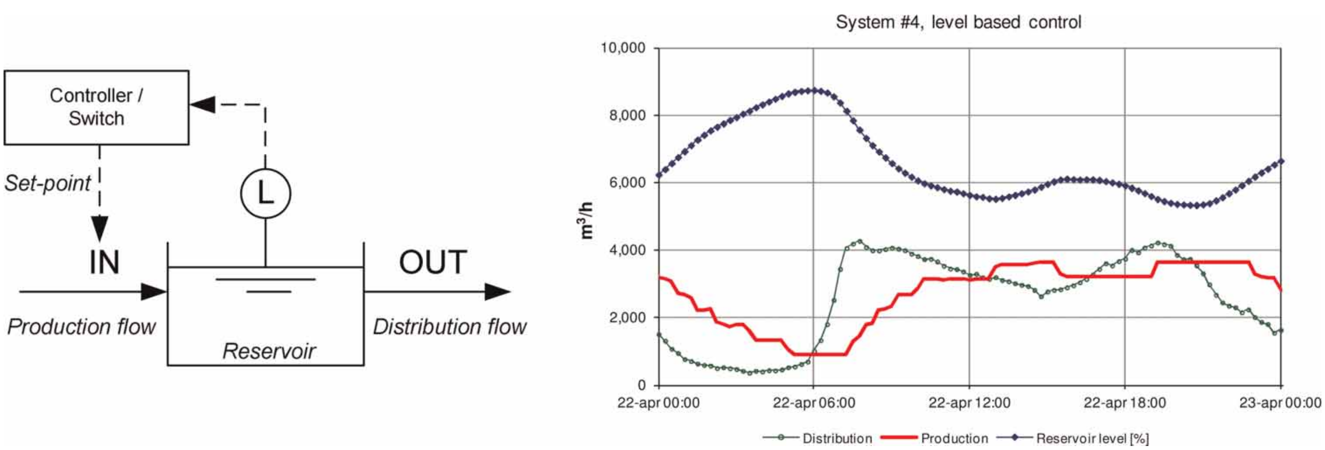

Figure 1 | Principles of level-based flow control and trends of production flow, distribution flow and level in the clear water reservoir on a day with level-based flow control.

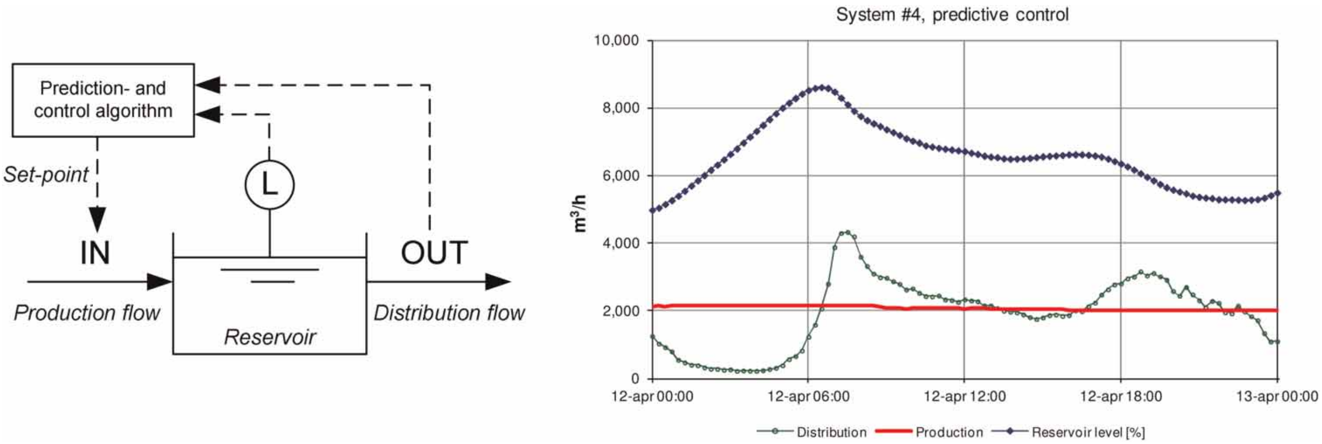

Figure 2 | Principles of model predictive flow control and trends of production flow, distribution flow and level in the clear water reservoir on a day with model predictive flow control.

control in the Netherlands. The result of the interviews is that, at present, 57% of the total production flow is controlled by predictive flow control. The production flow of the other 43% of the systems is controlled by level-based flow control (see Table 1).

Objectives for predictive flow control

There are two main reasons to apply predictive flow control rather than level-based flow control. The first reason is that drinking water treatment plants perform better at a constant production flow rate. Keuning *et al.* (1998) reported 20% lower values for turbidity and total hardness at a drinking water treatment plant, after the production flow control was changed from level-based control to predictive control. In studies by Gauthier *et al.* (2001) and Vreeburg *et al.* (2004, 2008), it was observed that the major part of the particle load in drinking water occurs as a result of peak flow and start-up procedures at the treatment plant. The occurrence of particles in the distribution network leads to discolouration events, which in England and Wales account for 80% of all customer complaints about drinking water quality (Husband & Boxall 2011). Particles in drinking water are therefore a dominant factor in customer satisfaction regarding water supply.

Table 1 | Application of predictive control (MPC) for the production flow control at drinking water utilities in the Netherlands, based on interviews at the water supply companies (summer 2012)

Utility	Total production (million m^3 in 2009)	MPC controlled production (million m^3 per year)	%
Brabant Water	167	27	16
Dunea	69	69	100
Evides	176	176	100
Oasen	46	43	93
PWN	100	95	95
Vitens	329	68	21
Waternet	65	65	100
WBG	42	20	48
WMD	28	0	0
WML	72	62	86
Total	1,094	625	57

The second reason to apply predictive flow control is the reduction of energy consumption and energy costs. Since the late 1980s, the near optimal control of water supply systems (pump scheduling of distribution pumps) to reduce energy consumption and costs, has been a topic studied by many researchers. Ormsbee & Lansey (1994) and Brdys & Ulanicki (1994) give good overviews of developed algorithms until 1994 and report several successful implementations in Europe and Israel. More recent publications present newly developed optimization algorithms with new mathematical optimizing techniques (e.g., Jamieson *et al.* (2007); Martínez *et al.* (2007); Rao *et al.* (2007); Salomons *et al.* (2007); Ulanicki *et al.* (2007); Shamir & Salomons (2008); Cembrano *et al.* (2011); Savić *et al.* (2011)).

The dominant reason for most utilities in the Netherlands to implement predictive control, was the wish for a more constant operation of water treatment plants in order to get lower turbidity values. The implemented predictive control algorithms in the Netherlands therefore focus mainly on constant production flow set-points. Energy savings and energy cost savings are an important, though less dominant, second reason for the implementation of predictive control. Although predictive flow control is widely applied in the Netherlands, the effectiveness of this method of control has never been studied in detail. This paper describes the results of research that was carried out to quantify the differences between level-based flow control and predictive flow control at five full-scale water supply systems in the Netherlands. This research considers both water quality aspects, as well as energy consumption and costs.

MATERIALS AND METHODS

Experiments at five full-scale water supply systems

Five full-scale water supply systems were examined in the first half of 2011. Under normal operating circumstances, the selected systems are controlled with the predictive flow software OPIR (Bakker *et al.* 2003). In the experiments the predictive flow control was switched off for 1 week, during which the systems were controlled with level-based flow control loops. The OPIR algorithm optimizes constant production set-points, and controls both the production flow of the treatment plants, as well as the intake and distribution flows of the service reservoirs of the water supply system. The characteristics and the configurations of the systems are shown in Figure 3.

The research comprised examining the behaviour of the systems, during:

1. one week with predictive flow control;
2. one week with level-based flow control.

Water quality and production flow variation

The following water quality parameters were measured (sensors in the clear water main at the treatment plants):

- Turbidity (all systems), measured by Hach Lange 1720 turbidimeter/Endress + Hauser CUR22 turbidimeter.

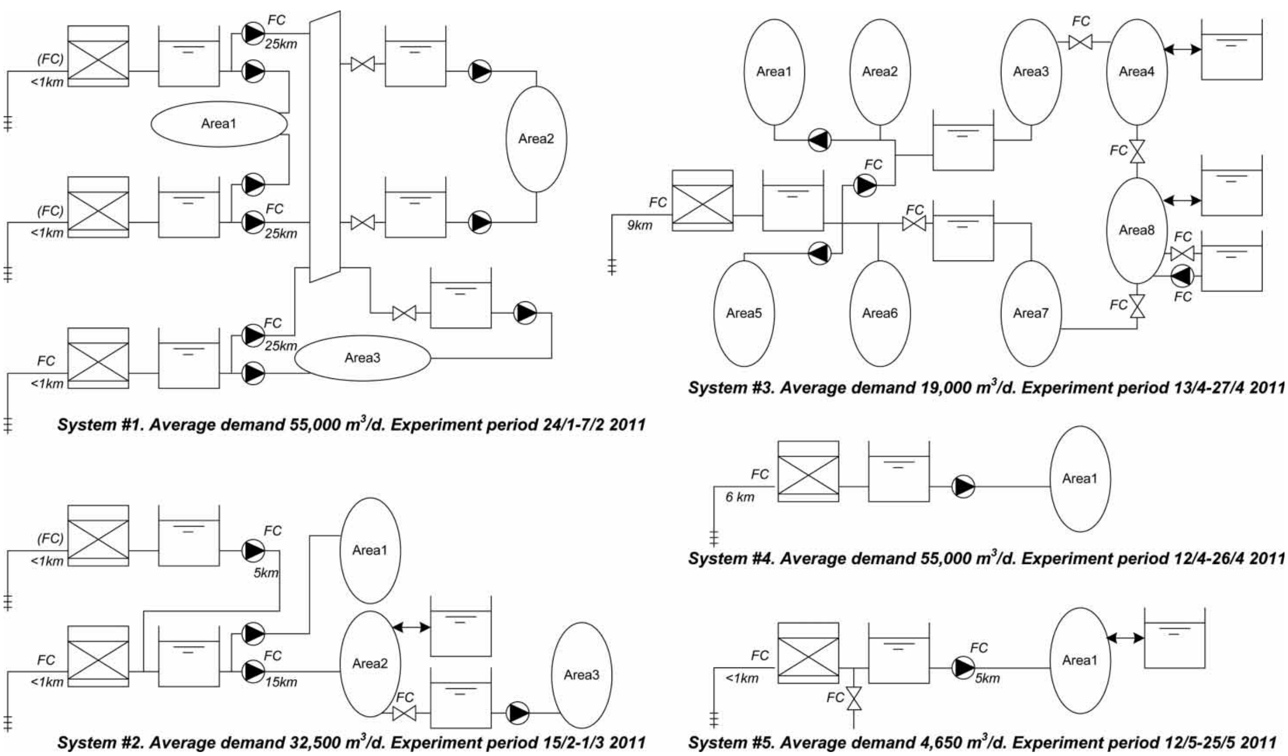

Figure 3 | Configurations of the five examined water supply systems. The flow controlled elements are indicated by '*FC*'. The elements indicated with '(*FC*)' are always level-based flow controlled (also when predictive flow control is active).

- Particles (systems #1 and #4), measured by Pamas Waterviewer system.

At all five systems, turbidity measuring devices were installed. The turbidity rate gives a good indication of the load of suspended solids in the water (Low Hui Xiang et al. 2011). At systems #1 and #4, particle measuring devices were installed. Measurements of particle numbers and sizes provide insight into the particle load of the clear water. The measured numbers and sizes of the particles are transformed in a 'particle volume concentration' in the units parts per billion ($10^{-9}\,m^3/m^3$) as described by Vreeburg et al. (2008).

To assess the variability of the production flow, the production variation per day (PV_d) is defined as the sum of the (absolute values of) the difference between subsequent hourly average production flow values ($P_{d,h}$) divided by the total daily production:

$$PV_d = \frac{\sum_{h=1:24} \left| P_{d,h} - P_{d,h-1} \right|}{\sum_{h=1:24} P_{d,h}} \cdot 100\%$$

A value of 10% indicates that, on average, the production flow changes on each hour with 10% of the average production flow of that day (d).

Energy consumption and costs

The specific energy consumption (kWh/m^3) as well as the percentage of the energy consumption during high tariff hours was analysed. In the Netherlands, the high tariff applies for each weekday from 7 am to 11 pm, the low tariff applies to all the other hours and at the weekends. At all the researched systems, one continuously measuring electricity meter was available at each water treatment plant and each service reservoir. Using measurements of flow, pressure and reservoir level, the measured energy consumption was divided into three main components: (1) abstraction/treatment, (2) transportation/distribution (clear water pumped in a transport main or towards a high reservoir) and (3) direct boosting (clear water pumped to customers in an area without a high reservoir):

$$E_{abst} = \frac{1}{\eta_{abst}} \cdot F_{abst} \cdot \frac{dH_{stat,abst} + C_{dyn,abst} \cdot F_{abst}^2}{g} + E_{base}\,[kW]$$

$$E_{pump} = \frac{1}{\eta_{pump}} \cdot F_{pump} \cdot \left(p_{pump} - \frac{L_{res}}{g} \right) [kW]$$

$$E_{boost} = \frac{1}{\eta_{boost}} \cdot F_{boost} \cdot \left(p_{boost} - \frac{L_{res}}{g} \right) [kW]$$

E_{abst}, E_{pump} and E_{boost} are the calculated values of the energy consumption (kW) for abstraction/treatment, transportation/distribution and direct boosting, respectively. The flows (F_{abst}, F_{pump}, F_{boost} [m^3/h]), pressures (p_{pump}, p_{boost} [kPa]) and the reservoir level (L_{res} [m]) are measured at the treatment plants and service reservoirs. The values for efficiency (η_{abst}, η_{pump}, η_{boost} [–]), the static and dynamic head loss parameters ($dH_{stat,abst}$ [m] and $C_{dyn,abst}$ [$m/(m^3/h)^2$] respectively), and the constant base energy consumption (E_{base} [kW]) were estimated. The values were estimated in a way that that the calculated energy consumption best fitted the measured energy consumption. By doing this, the total measured energy consumption was assigned to the individual 'components' of energy consumption, making it possible to evaluate the effect of the control on these components. Figure 4 gives an example of a trend with both the measured energy consumption and the calculated energy consumption. The figure shows that measured and calculated values resemble each other well ($R^2 = 0.92$), which indicates that the parameters were chosen well.

Figure 5 shows how the total energy consumption of each of the five examined water supply systems is divided over the components.

Energy costs were calculated by multiplying the calculated energy consumption with the average energy costs per kWh. The tariffs are 0.08229 €/kWh during high tariff hours, and 0.04849 €/kWh during low tariff hours.

RESULTS

Comparison

The differences between level-based control and predictive control were quantified by comparing average values of

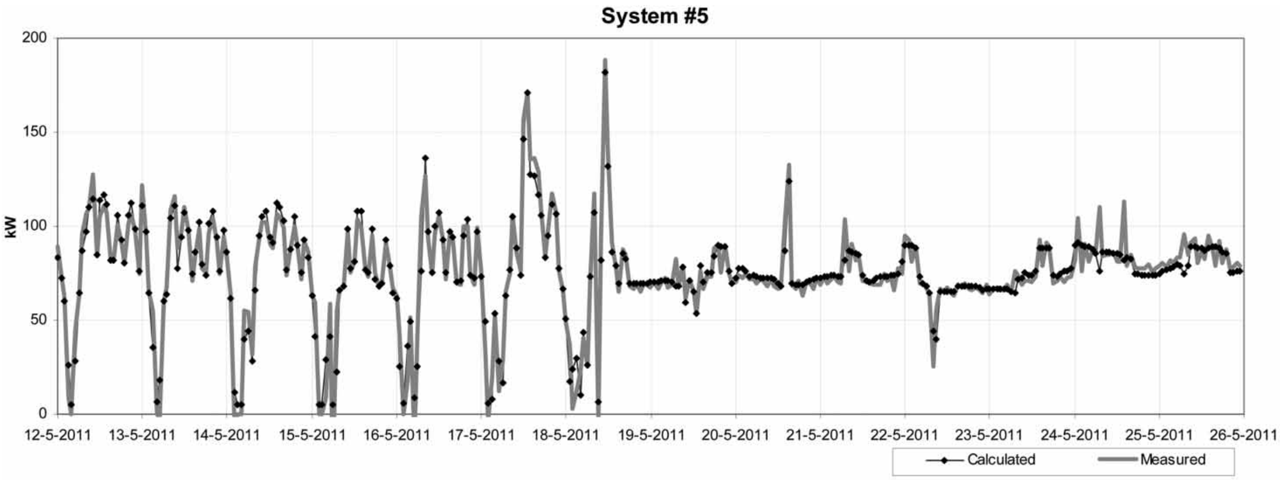

Figure 4 | Example of trend with calculated energy consumption and measured energy consumption.

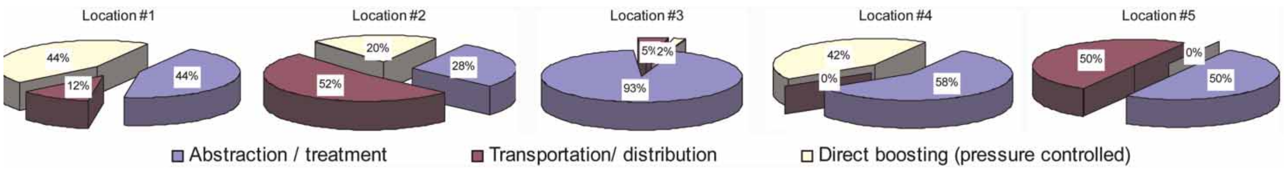

Figure 5 | Division of total energy consumption over the three components of energy consumption.

the measured parameters of both researched periods. The results for all water supply systems are summarized in Table 2. Examples of the differences at system #4 are shown in Figures 1 and 2, and for the other systems in Figure 6. The graphs show that predictive flow leads to a lower variation in the production flow and a higher production flow rate at night (during low energy tariff) compared to level-based control. The observed differences in flow patterns and the use of reservoirs during level-based control and predictive control were distinct and comparable for each of the five water supply systems.

Water quality

Table 2 shows that the production variation with predictive control (1.2–7.6%) was lower than with level-based control (11.7–37.7%). This resulted in lower turbidity values of on average 17% at all five systems. Figure 7 shows the relation between production flow changes and turbidity at all locations. At all systems a relation was found between flow changes and turbidity, though the correlation was weak (R^2 values between 0.25 and 0.6). Especially at systems #1, #2 and #5 lower turbidity rates are valuable, because those systems have rather high turbidity rates.

The experiments at the systems with particle counters installed (systems #1 and #4), showed that, on average, the values of particle volumes were 12–42% lower with predictive control compared to level-based control. This indicates that less variations in the production flow also results in lower particle volumes. The graphs of systems #1 and #4 in Figure 7 show a strong response of particle volume to production flow variations (high increase of particle volume after flow increase). However, the correlation of average values per day between production flow variation and particle volume is weak (R^2 values 0.13 and 0.37).

Energy consumption

Table 2 shows that the average specific energy consumption is 1.0–5.3% lower for predictive control compared to

Table 2 | Differences between level-based control and predictive control

	Level-based control	Predictive control	Difference %
System #1			
Production variation [%]	11.7%	4.1%	−65
Min/max production flow [m^3/h]	0/840	408/808	−52
Turbidity [NTU]	0.398	0.345	−13
Particle load [ppb]	30.8	17.9	−42
Specific energy consumption [kWh/m^3]	0.340	0.336	−1.0
Energy use at high tariff [%]	51.7%	51.0%	−1.4
Energy costs [€ per 1,000 m^3]	€ 22.47	€ 22.09	−1.7
System #2			
Production variation [%]	14.2%	2.9%	−80
Min/max production flow [m^3/h]	186/921	356/681	−56
Turbidity [NTU]	0.809	0.654	−19
Specific energy consumption [kWh/m^3]	0.733	0.694	−5.3
Energy use at high tariff [%]	55.5%	51.2%	−7.7
Energy costs [€ per 1,000 m^3]	€ 49.30	€ 45.65	−7.4
System #3			
Production variation [%]	12.5%	1.2%	−90
Min/max production flow [m^3/h]	250/1,260	430/933	−50
Turbidity [NTU]	0.078	0.056	−28
Specific energy consumption [kWh/m^3]	0.605	0.587	−3.0
Energy use at high tariff [%]	51.0%	48.6%	−4.8
Energy costs [€ per 1,000 m^3]	€ 39.77	€ 38.10	−4.2
System #4			
Production variation [%]	11.7%	2.8%	−76
Min/max production flow [m^3/h]	208/1,729	755/1,560	−47
Turbidity [NTU]	0.044	0.039	−12
Particle load [ppb]	5.43	4.78	−12
Specific energy consumption [kWh/m^3]	0.329	0.324	−1.4
Energy use at high tariff [%]	58.3%	54.5%	−6.5
Energy costs [€ per 1,000 m^3]	€ 22.38	€ 21.67	−3.2
System #5			
Production variation [%]	37.7%	7.6%	−80
Min/max production flow [m^3/h]	0/473	53/264	−55
Turbidity [NTU]	0.313	0.273	−13
Specific energy consumption [kWh/m^3]	0.399	0.389	−2.5
Energy use at high tariff [%]	57.3%	48.2%	−15.9
Energy costs [€ per 1,000 m^3]	€ 27.19	€ 25.29	−7.0

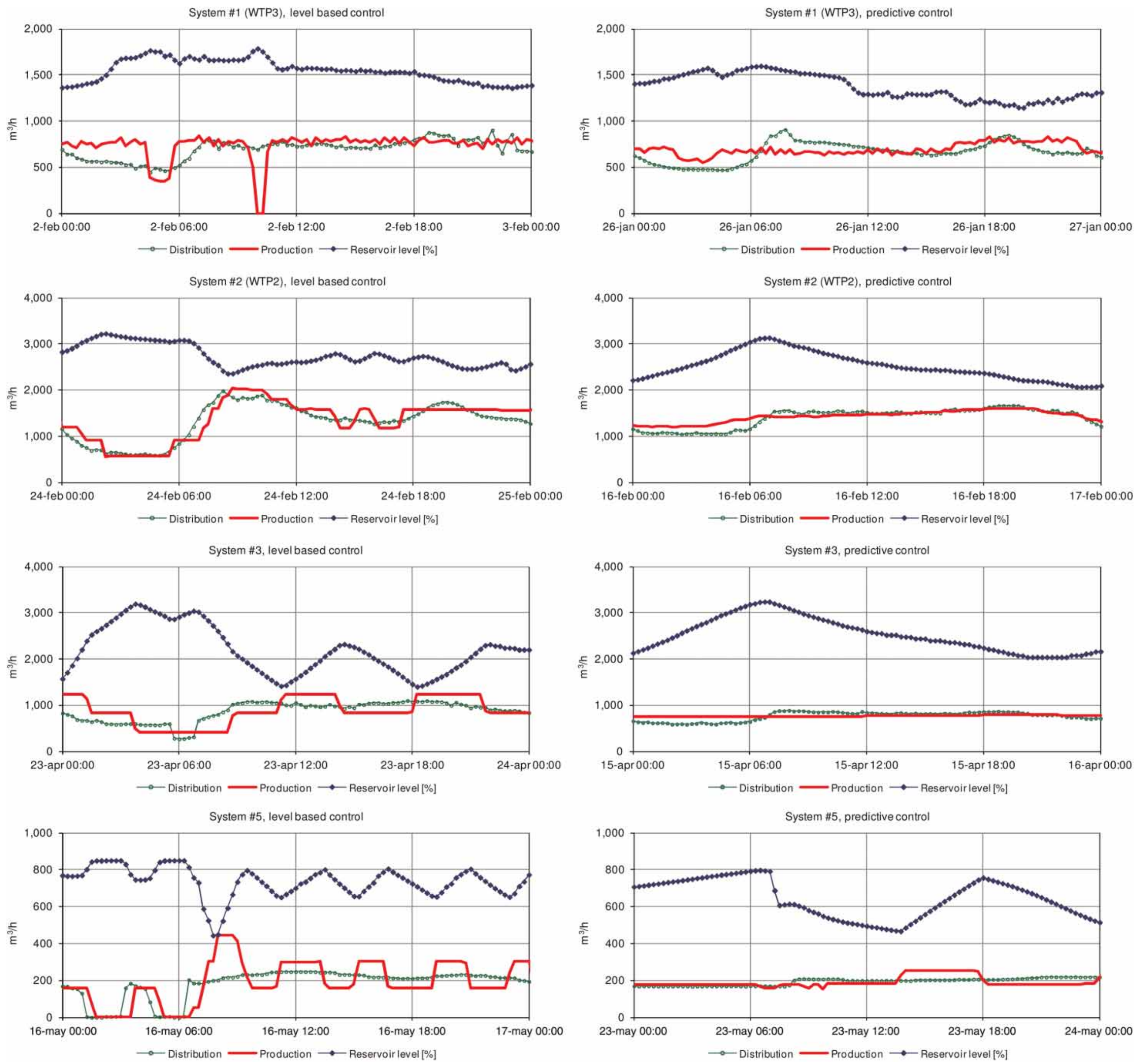

Figure 6 | Trends of level-based control (left) and model predictive control (right).

level-based control. This is the result of the fact that with level-based control the difference between minimum and maximum production flows is larger (see Table 2). The specific energy consumption (kWh/m^3) at high flows is relatively higher, because of the dynamic head loss components in the abstraction and treatment process, as well as in the transportation and distribution process. As a result, the average specific energy consumption is higher at varying flow rates. The hydraulic head loss occurs predominantly if the water is pumped over longer distances between abstraction and treatment plant, or for transportation. The distances in the examined water supply systems are indicated in Figure 3. Figure 8 shows the differences in specific energy consumption for the discerned components of energy consumption.

A second aspect is a shift of energy consumption from high tariff to low tariff hours at predictive control

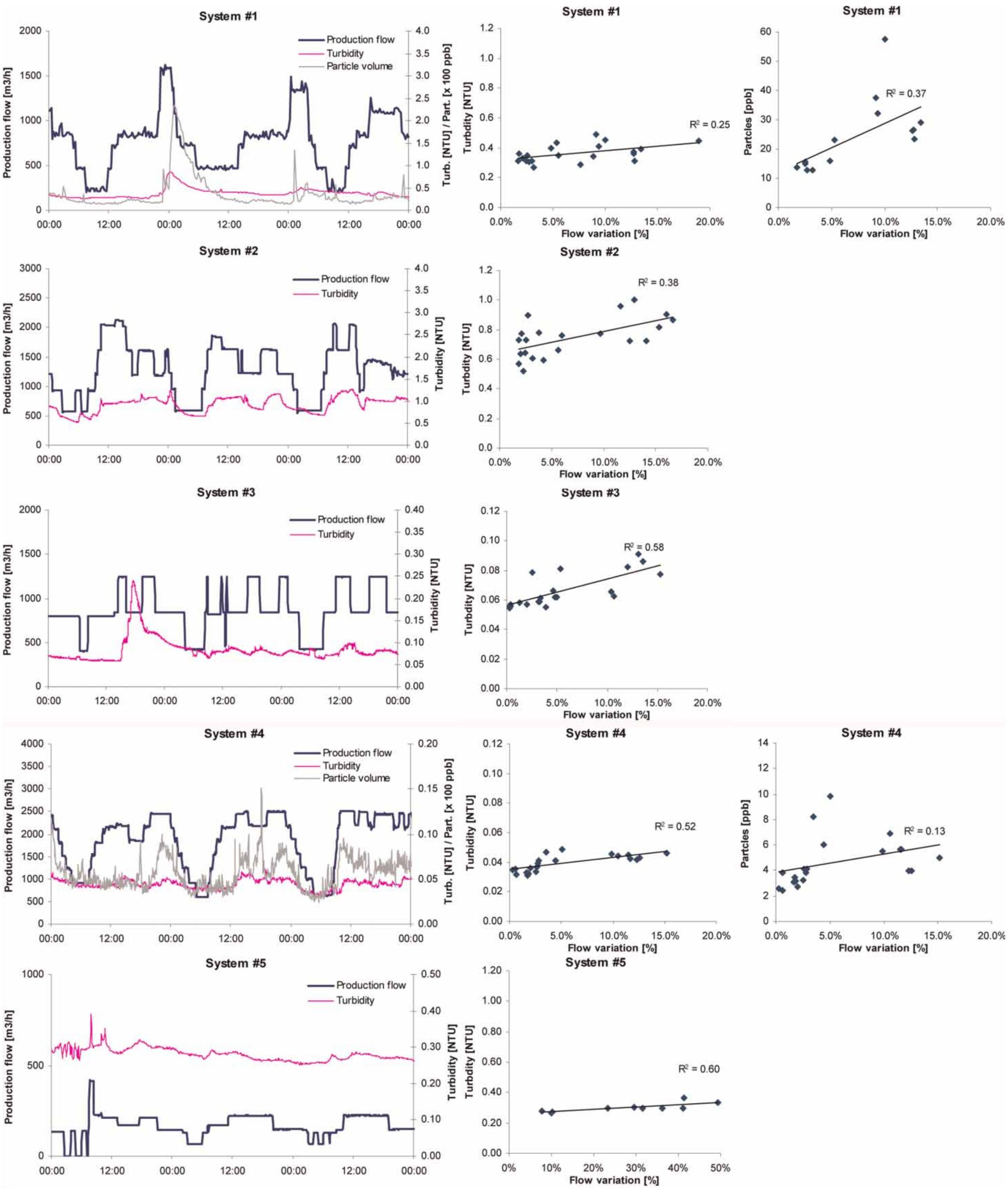

Figure 7 | Relation between production flow variations and turbidity/particle volume in clear water, at systems controlled with predictive control. The graphs on the left show the turbidity and the flow variations in time. The graphs on the right show the relation between average daily values of flow variations and average daily values of turbidity (middle graphs) or particle volume (right graphs).

compared to level-based control (shift varying from 1.4 to 15.9%). This is caused by the fact that with level-based control the reservoirs are filled with too high flow rates during the evening and night. As a result, the reservoir level becomes high early in the night, and the level-based control decreases the production flow. As a consequence, less water is produced or transported and therefore less energy is consumed during the period with low energy tariff (see also Figures 1 and 6). Figure 9 shows the shift in energy consumption for the different components of energy consumption for all five examined systems. The figure shows that the shift occurs especially in the Transportation and Distribution component, and to a lesser extent in Abstraction and Treatment. No shift is observed in the Direct Boosting component, which is the consequence of the fact that this component is pressure controlled and not influenced by the researched flow control.

The combination of the lower specific energy consumption and the shift from high tariff to low tariff results in lower energy costs of 1.7–7.4% for predictive control compared to level-based control. The results show a relatively large variation between the five examined water supply systems. This variation was caused by the fact that the five systems have quite different configurations, as can be seen in Figure 3. As observed in Figure 5, there are also large differences in the way the total energy consumption is divided over the components. The presented differences in

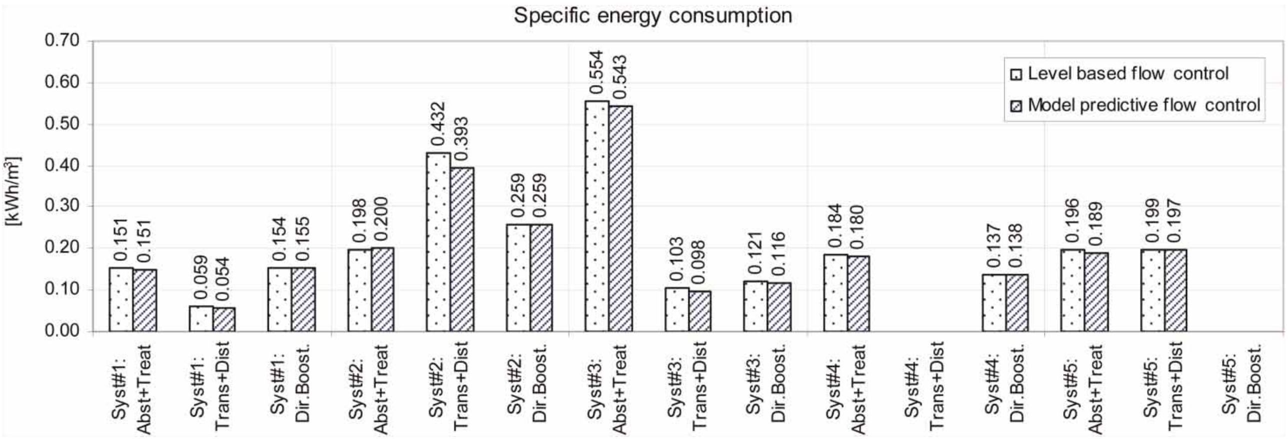

Figure 8 | Specific energy consumption per component of energy consumption for each system.

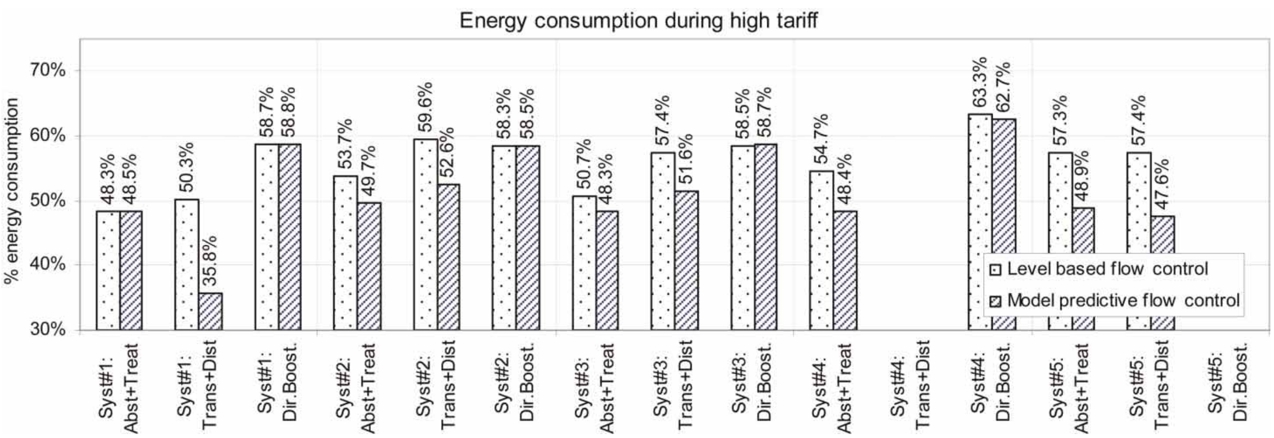

Figure 9 | Percentage of energy consumption during high tariff per component of energy consumption for each system.

Table 2 are related to the energy consumption of all three components, including the energy consumed for (pressure controlled) direct boosting. Direct boosting is not influenced by the control, and therefore the numbers in Table 2 (of specific energy consumption, energy use during high tariff and energy costs) are not fully representative for the real difference between the control of the systems. Table 3 shows for each of the water supply systems which part of the energy consumption is influenced by the method of control, and how the differences in energy costs are related to the influenced energy consumption. The table shows that the observed differences between predictive control and level-based control are relatively larger when the differences are related to the influenced energy consumption.

DISCUSSION

Relation production variation–turbidity

In comparison to the period with level-based control, in the period with predictive control at all five systems lower turbidity values (and particle volumes) and lower production variation values were observed. However, the relation between production variation and turbidity is weak (see Figure 7, R^2 values between 0.25 and 0.6). This indicates that the production variation is not the only factor which influences the turbidity. Other disturbances in the treatment process (like filter backwashing, Vreeburg *et al.* (2004), Bakker *et al.* (1998)) might also be responsible for variations in the turbidity. However, backwashing and other disturbing events were not monitored in this study.

Limited energy savings

The observed energy cost savings in this study (5.2% on average) were smaller than reported energy cost savings in other studies, such as Bunn & Reynolds (2009): 12% measured savings; or Martínez *et al.* (2007): 17% simulated savings. This difference can be explained by a number of reasons. The effectiveness of changing the control of a water supply system depends on three main factors: (1) the effectiveness of the optimal control in relation to the existing control; (2) flexibility in the system to change the control; (3) influence of control on operational costs. In the first factor the existing control particularly plays a dominant role: if the existing control is rather bad, then the potential savings can be quite large. However, if the existing control is already rather good, the potential savings are limited.

The second factor relates to the flexibility of the system. If there are large buffers in the network and pump and treatment capacity largely exceeds the average demands, a large range of operational control strategies is possible without violating the boundary conditions. Among the very different control strategies, the most efficient can be selected by the optimal control algorithm. In systems with less flexibility, the range of possible control strategies is smaller, and therefore the potential savings are smaller.

The third aspect relates to how much the energy consumption and costs are influenced by the control. If pump efficiencies or pump heads change dramatically depending on the control of the system, or if there are large differences in energy tariffs, potential savings can be very high. In systems where the control hardly influences energy

Table 3 | Energy consumption influenced by the type of control, and differences in energy costs. (Note that the influenced energy consumption in system #1 is rather low, because the abstraction and treatment flow control of two of the three treatment plants are always level-based controlled)

		Difference in energy costs between predictive control compared to level-based control	
	Energy consumption influenced by control (%)	**Related to total energy consumption (%)**	**Related to influenced energy consumption (%)**
System #1	26.3	−1.7	−6.4
System #2	80.4	−7.4	−9.2
System #3	98.0	−4.2	−4.3
System #4	57.9	−3.2	−5.5
System #5	100.0	−7.0	−7.0

consumption and where tariff differences are small, the potential savings are much smaller.

In this study, there was quite a large difference between the examined controls (factor 1). However, in the investigated predictive control algorithm, a constant production flow was the main goal, and not the energy and cost reduction. This limited the energy and cost savings of the investigated predictive control systems. The flexibility of the systems was limited due to relatively small buffers in the system (factor 2), which also limited the energy savings. The dominant factor that the energy savings in this study were limited, is that the control did not influence the energy to a large extent (factor 3). This is quite different from other studies, where the water supply systems have large high reservoirs (which can be filled during low energy tariff) and where pump efficiencies are highly influenced by the control strategy. Bunn & Reynolds (2009) show examples where the pump efficiencies vary up to 20%.

Other aspects

The experiments were carried out in a relatively short time and a limited number of parameters was studied. Therefore this study describes not all differences between the level-based control and the predictive control of a water supply system. Some differences can only be measured over a longer period of time. Two factors which were not highlighted in this study are wear of pumps and valves, and the occurrence of process alarms and alerts. Both of these are reported by Keuning *et al.* (1998), who studied the effects of the implementation of predictive control at one location in less detail, but over a longer period of time. Keuning reported that predictive control resulted in less wear, because of less variation in the operation, and therefore less starts and stops of pumps occurred. The value of the production variation in Table 2 is a measure for the number of starts/stops of pumps. As can be observed in the table, the values for level-based control were some three to eight times higher than for predictive control. Keuning also reported that failures and alarms occurred less frequently when using predictive control, because processes switched on and off less often. At each switch there is a small risk of a failure in the installation, resulting in a process alert or alarm.

Another factor is the ease of operation. The process operators of system #1 and system #3 stated that the most valuable aspect for predictive control for them was the ease of operation. With level-based control, the operation demanded much more attention, especially during high demand periods. The predictive control was better able to cope with changing demand situations and to adjust the control accordingly.

CONCLUSIONS

Experiments at five full-scale water supply systems prove that predictive control will lead to a better water quality and a more energy-efficient water supply compared to level-based control:

- The production variation was three to eight times lower.
- Turbidity values were 12–28% lower.
- Particle volume values were 12–42% lower.
- The overall energy consumption was 1.0–5.3% lower.
- The overall energy costs were 1.7–7.4% lower.

The quality improvements were the result of the fact that the variations in the production flow were on average some three to eight times lower for predictive control compared to level-based control. Variations in production flow resulted in peaks in the turbidity values of the clear water. The observed higher energy efficiency was the result of more constant production flows which lead to a lower average energy consumption. Moreover, relatively less energy was consumed during high tariff, resulting in a lower energy bill. Both quality improvements and higher energy efficiency make predictive control a valuable asset for water supply companies.

ACKNOWLEDGEMENTS

This study was carried out in the DisConTO project (Distribution Control Training & Operation). The project is a cooperation between four water supply companies (Vitens, Dunea, PWN and Brabant Water), Delft University of Technology, the National Institute for Public Health and the Environment (RIVM), Royal Haskoning DHV

Consultancy and Engineering and UReason. The project is financially supported by the Dutch government through the 'Innowater' programme. We thank water supply company WML for their cooperation in this research.

REFERENCES

Bakker, M., Verberne, A. J. P. & Van Schagen, K. M. 1998 The benefits of demand forecasting and modelling. *Water Qual. Int.* **May–June**, 20–22.

Bakker, M., Van Schagen, K. M. & Timmer, J. L. 2003 Flow control by prediction of water demand. *J. Water Supply Res. T* **52** (6), 417–424.

Brdys, M. A. & Ulanicki, B. 1994 *Operational Control of Water Systems: Structures, Algorithms and Applications*. Prentice-Hall International, London.

Bunn, S. 2007 Closing the loop in water supply optimisation. Paper presented at the IET Seminar Digest 2007(11804), Coventry.

Bunn, S. M. & Reynolds, L. 2009 The energy-efficiency benefits of pump scheduling optimization for potable water supplies. *IBM J. Res. Dev.* **53** (3), 1–13.

Cembrano, G., Quevedo, J., Puig, V., Pérez, R., Figueras, J., Verdejo, J. M., Escaler, I., Ramon, G., Barnet, G., Rodriguez, P. & Casas, M. 2011 PLIO: a generic tool for real-time operational predictive optimal control of water networks. *Water Sci. Technol.* **64** (2), 448–459.

Gauthier, V., Barbeau, B., Millette, R., Block, J.-C. & Prévost, M. 2001 Suspended particles in the drinking water of two distribution systems. *WST: Water Supply* **1** (4), 237–245.

House-Peters, L. A. & Chang, H. 2011 Urban water demand modeling: review of concepts, methods, and organizing principles. *Water Resour. Res.* **47** (5), W05401.

Husband, P. S. & Boxall, J. B. 2011 Asset deterioration and discolouration in water distribution systems. *Water Res.* **45** (1), 113–124.

Jamieson, D. G., Shamir, U., Martinez, F. & Franchini, M. 2007 Conceptual design of a generic, real-time, near-optimal control system for water-distribution networks. *J. Hydroinformat.* **9** (1), 3–14.

Keuning, J., Mense, P., Van Schagen, K. M. & De Moel, P. J. 1998 Reduction of hardness by production control. *H_2O* **19**, 73–75 (in Dutch).

Low Hui Xiang, D., Handojo, D. U. & Lim Zhi Hao, K. 2011 Correlation between turbidity and total suspended solids in Singapore rivers. *J. Water Sustain.* **1** (3), 313–322.

Martínez, F., Hernández, V., Alonso, J. M., Rao, Z. & Alvisi, S. 2007 Optimizing the operation of the Valencia water-distribution network. *J. Hydroinformat.* **9** (1), 65–78.

Ormsbee, L. E. & Lansey, K. E. 1994 Optimal control of water-supply pumping systems. *J. Water Resour. Plan. Manage. – ASCE* **120** (2), 237–252.

Rao, Z. F., Wicks, J. & West, S. 2007 Optimising water supply and distribution operations. *Proc. Inst. Civ. Eng.: Water Manage.* **160** (2), 95–101.

Salomons, E., Goryashko, A., Shamir, U., Rao, Z. & Alvisi, S. 2007 Optimizing the operation of the Haifa-A water-distribution network. *J. Hydroinformat.* **9** (1), 51–64.

Savić, D. A., Bicik, J. & Morley, M. S. 2011 A DSS generator for multiobjective optimisation of spreadsheet-based models. *Environ. Modell. Softw.* **26** (5), 551–561.

Shamir, U. & Salomons, E. 2008 Optimal real-time operation of urban water distribution systems using reduced models. *J. Water Resour. Plan. Manage.* **134** (2), 181–185.

Ulanicki, B., Kahler, J. & See, H. 2007 Dynamic optimization approach for solving an optimal scheduling problem in water distribution systems. *J. Water Resour. Plan. Manage.* **133** (1), 23–32.

Vreeburg, J. H. G., Schaap, P. G. & Van Dijk, J. C. 2004 Particles in the drinking water system: from source to discolouration. *WST: Water Supply* **4** (5–6), 431–438.

Vreeburg, J. H. G., Schippers, D., Verberk, J. Q. J. C. & Van Dijk, J. C. 2008 Impact of particles on sediment accumulation in a drinking water distribution system. *Water Res.* **42** (16), 4233–4242.

First received 26 June 2012; accepted in revised form 30 November 2012