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Comparison of control strategies for multi-objective control of urban wastewater systems

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Abstract: In recent years much attention has been paid to integrated management and control of urban wastewater systems. With the application of integrated system modelling tools, overall system performance can be improved to a great extent in terms of receiving water quality, through development of optimal control strategies. Most studies to date, however, have used a single objective to demonstrate the potential benefits. Control of urban wastewater systems is actually a multiple objective optimisation problem, involving balancing different, possibly conflicting objectives required by stakeholders with different interests. This paper compares three different control strategies for multi-objective optimal control of the urban wastewater system, including one global control strategy and two integrated control strategies. A popular multiple objective evolutionary algorithm, NSGA II, is applied to derive the Pareto optimal solutions for the three strategies. The comparative results show the benefits of application of integrated control in achieving an improved system performance in terms of dissolved oxygen and ammonium concentrations in the receiving river. The simulation results also illustrate the effectiveness of NSGA II in deriving the optimal control strategies with different complexities.

Keywords: Evolutionary algorithms, Integrated control, Multi-objective optimisation, NSGA II, Urban wastewater system.

1. INTRODUCTION

There is growing recognition of the need for and benefits of integrated simulation of the sewer system, wastewater treatment plant, and receiving water body in order to achieve a better receiving water environment [Rauch et al., 2002; Schütze et al., 2002; Butler & Schütze, 2005; Vanrolleghem et al., 2005]. In recent years, several simulation tools and methods have been developed, for example, SYNOPSIS [Schütze et al., 2002], SIMBA [IFAK, 2005], WEST [Vanhooren et al., 2003], and CITY DRAIN [Achleitner et al., 2007], and this provides the opportunity to optimise the urban wastewater system as a whole. The benefits of integrated simulation and control include 1) simultaneous optimisation of various components in the three subsystems; 2) evaluation of the performance of the urban wastewater system directly using receiving water quality indicators, rather than by reference to surrogate criteria such as CSO discharge frequency/volume or treatment plant effluent quality, and 3) control of one subsystem based on the information from other subsystems, termed as ‘integrated control’, which makes the best use of potential interactions between subsystems to further improve system performance [Schütze et al., 1999].

In the context of integrated simulation of urban wastewater systems, the improvement in system performance has been demonstrated through development of optimal control strategies. Although most of the effort has been focused on a single objective in the receiving water (e.g. DO and Ammonium concentrations), there are a few studies considering multi-objectives to develop optimal control strategies for urban wastewater systems [e.g., Schütze et al., 2002; Fu et al., 2008]. This paper will describe the development of three different control strategies for multi-objective optimal control, including two integrated control strategies, and the parameter optimisation using a multi-objective evolutionary optimisation method.

2. MULTI-OBJECTIVE CONTROL

Control of urban wastewater systems is actually a multi-objective optimisation problem in practice, which has to balance different objectives in order to meet the requirements by stakeholders with different interests. Mathematically, the optimal control problem can be described as follows:

$$\text{Min } F(\mathbf{x}) = \{f_1(\mathbf{x}), \cdots, f_m(\mathbf{x})\} \tag{1}$$

where **x** is the variable vector which defines a specific control strategy in the feasible solution space, and $f_1, \cdots, f_m$ are the m objective functions to be simultaneously minimized. These objectives could arise from different parts of the system and possibly are conflicting with each other in nature. For example, avoiding and reducing sewer flooding and CSO discharges, ensuring treatment plant effluent quality complies with legislative requirements, maintaining or improving the water quality in receiving water bodies. In this paper, two water quality indicators for the receiving river are considered: minimum DO concentration (DO-M) and maximum ammonium concentration (AMM-M) for all the river reaches.

In general, different control strategies may achieve very different results for each of the objectives. Due to the non-linear, complex behaviours of urban wastewater systems, the objectives can only be evaluated through a simulation model. An existing model was used in this research to simulate various hydraulic and biochemical processes in the integrated system and thus to evaluate the chosen objectives [Fu et al., 2008]. This model was developed using the SIMBA tool, which is based on the SIMULINK® environment. This model allows a system dynamic modelling of the different processes in various subsystems and the interactions between them, which makes it possible to apply an integrated control with information interaction between different subsystems.

It is important to choose an appropriate optimisation method in order to reveal the whole trade-off relationship between objectives, which could help decision makers to make an informed decision. Evolutionary algorithms (EAs) have been regarded as promising to derive the optimal control strategies, in comparison with the conventional optimisation techniques [Rauch and Harremoës, 1999; Muschalla et al., 2006]. In this research, a state of the art multiobjective genetic algorithm, NSGA II [Deb et al., 2002], was chosen to derive the Pareto optimal control strategies.

3. THE INTEGRATED CASE STUDY

The approach will be demonstrated by a semi-hypothetical case study, consisting of a combined sewer system, a treatment plant and receiving river. This integrated case study was originally defined by Schütze [1998] and has been studied in detail for real time control optimisation [Schütze et al., 2002; Butler and Schütze, 2005; Fu et al., 2008].

Figure 1 shows the schematic representation of the integrated system. The sewer system has seven sub-catchments with a total area of 725.8 ha, and four on-line pass-through storage tanks linked to sub-catchments SC2, 4, 6 and 7 respectively, which are controlled by a pump. The storage tanks have a total volume of 13,200 m^3. The wastewater treatment plant includes an off-line pass-through storm tank with a volume of 6750 m^3, a primary clarifier, aerator, and secondary clarifier. The storm tank is controlled as follows: filling starts when the inflow to the primary clarifier reaches its maximum value and emptying is triggered when the inflow drops below a threshold value. The treatment plant effluent and storm tank overflow are discharged to the river at Reach 10. The river is divided into 45 reaches, each 1km in length. For the detailed set-up of the case study, the reader is referred to Schütze [1998] and Schütze et al. [2002].

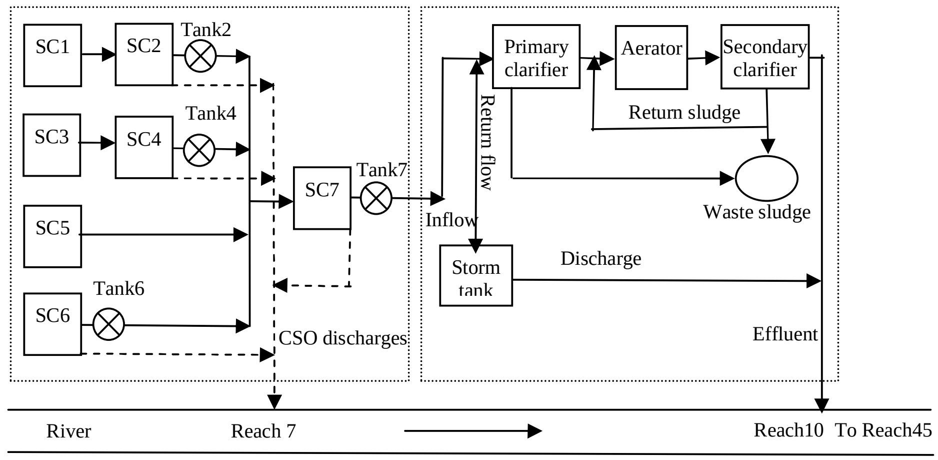

Figure 1. Schematic representation of the integrated urban wastewater system (adapted from Fu et al. [2008]. SCx represents the xth sub-catchment, and the dash lines show CSO discharges from the four storage tanks.

4. DEVELOPMENT OF CONTROL STRATEGIES

Development of control strategies for urban wastewater systems can be divided into two key stages: control strategy setup that determines what processes to be influenced by what measurements; and control strategy optimisation that aims to derive the optimal control parameters using an appropriate optimisation approach. In this research, three control strategies, originally developed by Schütze et al. [2002], were adapted here and compared for multi-objective control of the integrated system.

4.1 Global Control

A global control strategy was developed to control both of the sewer system and treatment plant, however, only local information was used in this control strategy setup, i.e., no information interaction between subsystems. According to the sensitivity analysis by Schütze et al. [2002], the most sensitive variables include the maximum outflow rate of Tank7 (x_1), maximum inflow rate to treatment plant (x_2), the threshold for emptying the storm tank (x_3) and its emptying flow rate (x_4). These variables were chosen in this global control strategy set up and are operated in the constant settings in which their optimal values are to be optimised. The feasible ranges used in this research is shown in Table 1, according to Schütze et al. [2002].

Table 1. Control variables and their ranges. The variables x_1 to x_4 are used for global control, x_1 to x_7 for integrated control (a), and x_1 to x_8 for integrated control (b).

Variables	Description	Ranges
x_1 (×DWF)	The maximum outflow rate of Tank7	[3, 8]
x_2 (×DWF)	The maximum inflow rate to treatment plant	[2, 5]
x_3 (m3/s)	Threshold triggering emptying the storm tank	[0.19, 0.36]
x_4 (m3/s)	The emptying flow rate of storm tank (m3/s)	[0.08, 0.28]
x_5 (%)	The threshold of filling degree for ‘heavily loaded Tank 7’	[50, 100]
x_6 (×DWF)	The threshold of influent for ‘heavily loaded treatment plant’	[3, 5]
x_7 (%)	The threshold of filling degree for ‘heavily loaded storm tank’	[50, 100]
x_8 (×DWF)	The threshold of flow rate for ‘heavily loaded river’	[4, 5]

4.2 Integrated Control (a)

This strategy is defined as integrated control because it uses measured information from one subsystem to control another subsystem [Schütze et al., 2002]. This can make the best of the available capacity to achieve a better overall system performance. This control strategy is an extension of the global control strategy defined above, through further exploration of the spare capacity of tanks in sewer system or treatment plant when one subsystem is heavily loaded.

Only the sewer system and treatment plant's states are considered in this control strategy set up. As different state variables can be used to indicate each subsystem's states, and the choice could have a major impact on system performance. In this research, the state of sewer system is measured by the filling degree of Tank7 (s_1), and the state of treatment plant measured by the flow rate of treatment plant influent (s_2). The storm tank is regarded as a separate component here in order to explore its potential in retaining wastewater for treatment, and its state is indicated by its filling degree (s_3). For simplicity's sake, only two states are considered for each of the components, i.e., 'heavily loaded' and 'not heavily loaded'. A threshold value is used to determine which state each component lies in, i.e., the component is regarded as 'heavily loaded' if the value of its state variable is bigger than its threshold. In this research, the optimal thresholds x_5 to x_7 are derived by NSGA II, and its feasible ranges are listed in Table 1.

Considering all the possible combinations of the states, there are 8 if-then rules in total of which the control strategy set up is comprised, as shown in Table 2. For example, Rule 1 for the case that all the three components are not heavily loaded, is interpreted as

IF $s_1 < x_5$ and $s_2 < x_6$ and $s_3 < x_7$ THEN $x'_1 = x_1$ and $x'_2 = x_2$

x'_1 and x'_2 will override x_1 and x_2, respectively. The other control variable x_3 and x_4 keep the same for the rules but will also be optimised.

4.3 Integrated Control (b)

On the basis of integrated control (a), this control strategy setup further considers the state of river to improve the river water quality. The river state is also regarded as 'heavily overloaded' if its flow rate is bigger than its defined threshold x_8, otherwise, not heavily overloaded. There are totally 16 rules defined for this control strategy setup. The 8 rules in which the river is 'not heavily overload', are defined as the same as integrated control (a), (b) in Table 2 shows the other 8 rules with the 'heavily overloaded' river.

Table 2. The rules for the integrated control strategies (a) and (b).

Rule number	Sewer system over-loaded?	Storm tank over-loaded?	Treatment plant over-loaded?	$[x'_1, x'_2]$ for (a)	$[x'_1, x'_2]$ for (b)*
1	No	No	No	$[x_1, x_2]$	$[x_1, x_2]$
2	No	No	Yes	$[x_1, x_2]$	$[x_1, x_2]$
3	No	Yes	No	$[x_1, x_2]$	$[x_1, x_2]$
4	No	Yes	Yes	$[x_1-1, x_2]$	$[x_1-1, x_2+1]$
5	Yes	No	No	$[x_1+1, x_2]$	$[x_1+1, x_2]$
6	Yes	No	Yes	$[x_1-1, x_2]$	$[x_1-1, 2]$
7	Yes	Yes	No	$[x_1+1, x_2+1]$	$[x_1+1, x_2+1]$
8	Yes	Yes	Yes	$[8, x_2+1]$	$[8, x_2+1]$

*These 8 rules are for the river state of 'heavily overloaded', and the other 8 rules for 'not heavily overloaded' are defined as the same as control (a).

5. RESULTS AND DISCUSSION

5.1 Runtime convergence

A runtime convergence indicator was used to measure the algorithm's performance [Deb and Jain, 2002]. This indicator measure the average Euclidean distance between a solution set S and a reference set $P = \{p_1, \quad p_2, \quad \cdots \quad p_n\}$ and is calculated as follows

$$C = \frac{1}{|S|}\sum_{i=1}^{|S|} d_i \tag{2}$$

where the smallest Euclidean distance d_i of each solution s_i in S to P is calculated as

$$d_i = \min_{j=1}^{n} \sqrt{\sum_{k=1}^{m}\left(\frac{s_i(k) - p_j(k)}{p_{\max}(k) - p_{\min}(k)}\right)^2} \tag{3}$$

$p_{\max}(k)$ and $p_{\min}(k)$ are the maximum and minimum objective values of k-th objective in the reference set. The reference set is made up of the non-dominated solutions from all the solutions visited in a simulation run. The obtained indicator is normalized to the range between 0 and 1, which represent a poor and perfect performance, respectively.

Figure 2 shows the runtime convergence for each of the control strategy setups. The parameters of NSGA II are set to the same values for each run, amongst them the population size and number of generations are set to 100. For the global control setup, the algorithm can converge rapidly within 30 generations and it converges slower for the other control strategy setups. For all the three setups, this algorithm reaches its ultimate convergence after 60 generations.

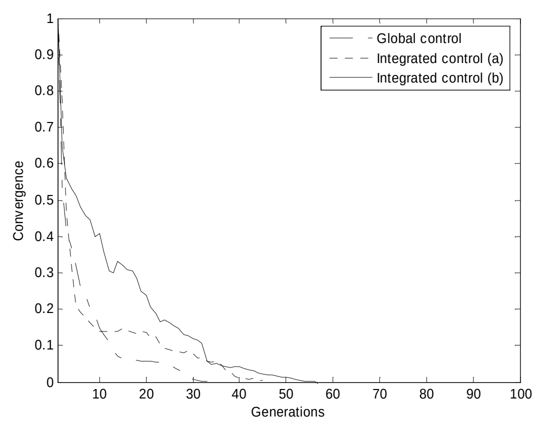

Figure 2. The run time convergence for the three control strategy set-ups.

Comparing the three setups, NSGA II attains the best for the global control in approaching the true Pareto front, and performs the poorest for the integrated control (b). The performance here is probably related to the complexity of control strategy setups, i.e., only 4 parameters were used for the global control in total, however, 7 and 8 parameters for the two integrated controls, respectively.

5.2 The Pareto solutions

Figure 3 shows the sets of Pareto optimal solutions from the three control strategy set-ups derived by NSGA II. For each set-up, a clear trade-off curve can be observed between DO-

M and AMM-M, in which a solution cannot be improved upon without deteriorating either of the objectives. Understanding the trade-off relationship between these two objectives will give decision makers an insight into the implications of different control strategies and thus help them make an informed decision.

Comparing the global control and two integrated control strategies, Figure 3 shows that the set of Pareto solutions from the global control is completely dominated by those of the integrated control strategies, which means that the integrated controls can achieve a better system performance in terms of both river DO and ammonium concentrations. This confirms the benefit of considering information interaction in system control. It can also be seen that the set from integrated control (b) dominates that of integrated control (a). This shows the importance of choosing the right sensors and controllers in the control strategy setup process. If the critical control variables or measures are not included in control strategies, it might be not able to achieve the best system performance. As shown in this case study, in addition to the states of components in sewer system and treatment plant, the real time river information plays a significant role in improving system performance.

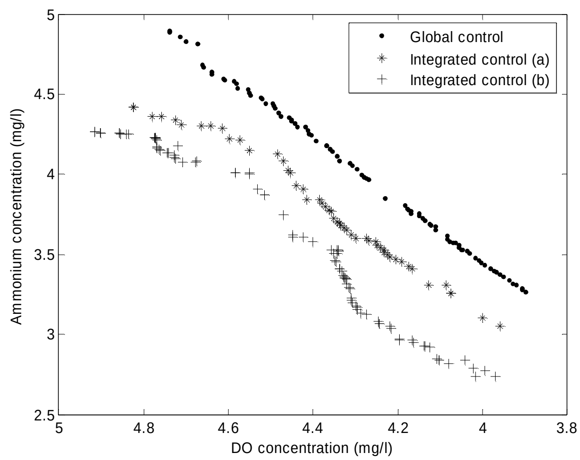

Figure 3. The Pareto optimal solutions from the three control strategy set-ups.

6. CONCLUSIONS

Recent advances in integrated modelling of the urban wastewater system make it possible to apply integrated control to achieve better overall system performance in terms of receiving water quality. While the receiving water quality can be measured by different determinants, there are also other objectives that might need to be considered to address interests from different stakeholders. So there is a real need to apply multi-objective optimisation methods to reveal any possible trade-offs between the objectives. This paper discussed three control strategy setups based on different levels of information interactions between the subsystems. A popular multiple objective evolutionary algorithm, NSGA II, was applied to derive the Pareto optimal solutions for the three strategies. Optimisation results from this research show the necessity for the use of multi-objective optimisation to derive Pareto optimal solutions. This provides decision makers a detailed understanding of the trade-off relationships when balancing the control objectives to meet various needs in practice. Further, the potential benefits of integrated control can be illustrated in comparison with global control in terms of both DO and ammonium concentrations. The simulation results also illustrate the effectiveness of NSGA II in deriving the optimal control strategies with different complexities.

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