Environmental Modelling & Software 46 (2013) 240–249

Contents lists available at SciVerse ScienceDirect

Environmental Modelling & Software

journal homepage: www.elsevier.com/locate/envsoft

Wastewater treatment plant design and operation under multiple conflicting objective functions

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A R T I C L E I N F O

Article history:
Received 29 June 2012
Received in revised form
21 February 2013
Accepted 5 March 2013
Available online 28 April 2013

Keywords:
Multiobjective optimization
Interactive methods
Pareto optimality
Nitrogen removal
Primary sludge fermentation
Anaerobic digestion

A B S T R A C T

Wastewater treatment plant design and operation involve multiple objective functions, which are often in conflict with each other. Traditional optimization tools convert all objective functions to a single objective optimization problem (usually minimization of a total cost function by using weights for the objective functions), hiding the interdependencies between different objective functions. We present an interactive approach that is able to handle multiple objective functions simultaneously. As an illustration of our approach, we consider a case study of plant-wide operational optimization where we apply an interactive optimization tool. In this tool, a commercial wastewater treatment simulation software is combined with an interactive multiobjective optimization software, providing an entirely new approach in wastewater treatment. We compare our approach to a traditional approach by solving the case study also as a single objective optimization problem to demonstrate the advantages of interactive multiobjective optimization in wastewater treatment plant design and operation.

1. Introduction

Design and operation of a wastewater treatment plant (WWTP) are complex tasks, which involve trade-offs between a number of conflicting economic and operational objective functions, and for these problems mathematical modelling and simulation combined with optimization (using engineering judgement and/or mathematical tools) can be of great help. The most obvious example of conflicting demands is the trade-off between treatment results and operational costs, e.g., reaching low BOD, ammonium nitrogen and phosphate levels in effluent implies high consumption of aeration energy and precipitation chemicals. Another example is the goal to avoid washout of sludge by operating with shortest possible sludge retention time, thus, securing treatment results in terms of suspended solids and BOD, but at the same time risking the stability of nitrification and producing a lot of excess sludge. However, optimization tools included in commercial simulation software as well as most of the published cases of mathematical optimization of WWTP design and operation (e.g., Ayesa et al., 1998; Espírito-Santo et al., 2005; Guerrero et al., 2011; Hernández-Suárez et al., 2004; Holenda et al., 2007; Rivas et al., 2008) are based on optimizing only one objective function, into which the objective functions of interest are lumped up to form some kind of a total cost index. The most common way in WWTP optimization is to use weights describing the importance of each objective function and use their weighted sum as an objective function to be optimized (e.g., Espírito-Santo et al., 2005; Guerrero et al., 2011; Hernández-Suárez et al., 2004; Holenda et al., 2007).

Typically in the modelling phase of an optimization problem for a real world application, it is not always clear what should be chosen as objective function(s) to be optimized and what should be used as constraints. For example, if the optimization tool familiar to the user can solve problems having only a single objective function, then the problem will be formulated in a way that conflicting objective functions are not necessarily recognized (e.g., a single total cost index is formulated). In other words, the optimization method is chosen first and the optimization problem is formulated only after that. In order to take into account all the relevant aspects of the problem, it is important to identify the relevant conflicting objective functions as early as possible when formulating the optimization problem. When the optimization problem has been formulated according to the best knowledge about the phenomena involved, then the attention should be turned into how that optimization problem can be solved.

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http://dx.doi.org/10.1016/j.envsoft.2013.03.016

WWTP design and operation are and always have been multiobjective by their nature. This means in practice that there exist several (possibly infinitely many) alternative compromises between the conflicting objective functions involving different trade-offs instead of a single solution resulting in optimal performance. A compromise known as a Pareto optimal (PO) solution (or nondominated solution) is a solution where none of the objective functions can be improved without impairing some other objective function (Miettinen, 1999). This aspect has not been explicitly emphasized in WWTP design and operation because the optimization techniques used have been suitable for only one objective function. This has resulted in forcing all the objective functions into a single function to be optimized and hides the real nature of the problem making it difficult to assess the true optimality of a solution.

Usually, the single objective function has been a total cost function that has been minimized in order to find the best (that is, the cheapest) design. This approach, however, has drawbacks that may result in loss of information about the relevant characteristics of the problem and about the interdependencies between different cost factors as well as includes unnecessary uncertainties. Therefore, multiobjective optimization (MOO, see e.g., Miettinen, 1999; Miettinen et al., 2008; Rangaiah, 2009), where an objective function is used for describing each relevant aspect to be optimized separately, should be applied to WWTP design and operation. Note that a MOO approach supports the idea of formulating the optimization problem first without limitations from the optimization method used. Optimizing the weighted sum of the objective functions is called the weighting method and it is one of the earliest methods in MOO. One of its widely known drawbacks is that the solution obtained does not obey the weights selected, in other words, it does not necessarily emphasize the objective functions that are given the biggest weights (Nakayama, 1995).

In this paper, we propose to use interactive MOO methods in WWTP design and operation. In interactive methods, the solution process utilizes continuous interaction between a decision maker (DM, that is, a designer or an operator in practice) and the method. Once the DM has expressed preferences on how the current solution should be improved, the method computes new (more preferred) PO solutions. This continues iteratively. This kind of an approach enables the DM learning about the interdependencies between the conflicting objective functions, e.g., how different operational decisions of certain unit processes influence the performance of other processes and the plant as a whole. Therefore, the DM's own preferences may evolve along the way due to learning and (s)he can indicate that by changing the preference information given to the method. Due to this interaction, the method can utilize the experience of the DM about WWTP design who guides the search towards preferred solutions. Therefore, only PO solutions that are of interest to the DM are computed.

We have found few cases in the literature where multiple objective functions have been utilized in WWTP design and operation. Biswas et al. (2007) used multiple objective functions in determining an optimal choice of wastewater treatment train and they produced a representative set of the PO solutions to a MOO problem without using process simulation. Béraud et al. (2007) applied multiobjective genetic algorithm to produce a representative set of PO solutions for optimizing simultaneously two objective functions, namely effluent quality and energy consumption. A multiobjective genetic algorithm was also used in the same way by Liu et al. (2012) to simultaneously maximize an effluent quality index and minimize energy consumption in MOO of cascade controller in combined biological nitrogen and phosphorus removal WWTP. Fu et al. (2008) studied multiple objective functions in controlling integrated urban wastewater systems consisting of a sewer system, a WWTP and a river model. They considered two and three objective functions using water quality indicators in the river as objective functions and the aim was to compute a representative set of PO solutions by using multiobjective genetic algorithm.

On the other hand, Flores et al. (2007) considered multiple objective functions in a conceptual design of activated sludge systems. A multiobjective methodology was used to evaluate and compare a small number of alternatives resulting from conceptual design. Flores-Alsina et al. (2008) studied the effect of input uncertainty by using Monte Carlo simulations in selecting control strategies for WWTPs. They considered environmental, economical, technical and legal objective functions in comparing six different control strategies by using multiple criteria decision analysis techniques. Guerrero et al. (2012) utilized random sampling and selection of nondominated solutions while considering operating cost, effluent quality and microbiological risks as objective functions in selecting optimal WWTP control setpoints. In addition, they compared the approach with their earlier work (Guerrero et al., 2011) for optimizing only total costs. Benedetti et al. (2010) considered five objective functions in WWTP design and control under uncertainty, namely the effluent quality, the fraction of time during which the effluent exceeds the ammonium limit set, the operating costs, the investment costs and the total costs of the plant. Their methodology consisted of Monte Carlo sampling yielding five nondominated solutions that were compared based on uncertainty analysis related to the objective functions mentioned. However, none of these approaches in the literature considers interactive MOO methods that enable the DM to actively participate in the optimization process.

In this paper, we illustrate our interactive approach by describing an application of the tool developed for interactive MOO of WWTP design and operation, which combines the commercial Hydromantis GPS-X wastewater treatment process simulator and the interactive IND-NIMBUS software for MOO (Miettinen, 2006). We call this tool GPS-X-NIMBUS. This is an entirely new approach in wastewater treatment, although corresponding tools are successfully utilized in other fields, see e.g., Miettinen et al., 2008. The basic functionality of the GPS-X-NIMBUS tool is described in Hakanen et al. (2011). Preliminary results of multiobjective WWTP operation and design were presented in Sahlstedt et al. (2010). In this paper, we describe the results obtained and the interactive solution process used in more detail as well as emphasize the benefits that GPS-X-NIMBUS has when compared to approaches described earlier.

To show the benefits of interactive MOO and the applicability of GPS-X-NIMBUS in practice, we consider a case study of plant-wide optimization of a municipal WWTP. The problem deals with simultaneous optimization of effluent quality as well as different operating cost factors leading to a problem with five conflicting objective functions. In addition to this case study, other use cases can be identified where the GPS-X-NIMBUS tool can be utilized. For example, an operator may have noticed through practical experience that a certain unit process at the WWTP is exceptionally difficult or risky to use, and funds for its renewal are not available in the near future. Therefore, (s)he may want to minimize the use of that process unit or otherwise seek to minimize operational risks. In such a situation, it is important to know the trade-offs inherent in the form of treated water quality and/or operational costs.

The paper is organized as follows. Section 2 describes interactive MOO as a way of handling conflicting objective functions simultaneously and shortly introduces the IND-NIMBUS software. The process modelling and optimization problem formulation of our case study as well as the basic operation principle of GPS-X-