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Model predictive control for the self-optimized operation in wastewater treatment plants: Analysis of dynamic issues

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ABSTRACT

This paper describes a procedure to find the best controlled variables in an economic sense for the activated sludge process in a wastewater treatment plant, despite the large load disturbances. A novel dynamic analysis of the closed loop control of these variables has been performed, considering a nonlinear model predictive controller (NMPC) and a particular distributed NMPC-PI control structure where the PI is devoted to control the process active constraints and the NMPC the self-optimizing variables. The well-known self-optimizing control methodology has been applied, considering the most important measurements of the process. This methodology provides the optimum combination of measurements to keep constant with minimum economic loss. In order to avoid nonfeasible dynamic operation, a preselection of the measurements has been performed, based on the nonlinear model of the process and evaluating the possibility of keeping their values constant in the presence of typical disturbances.

1. Introduction

The efficiency of most wastewater treatment plants (WWTP) is an important issue still to be improved. In order to fulfill the imposed legal effluent requirements for large load variations the operating costs are usually higher than the actually needed. Optimization of WWTP would provide a significant cost reduction, but it has not been extensively considered yet. There are some works in the literature, but most of them only consider the problem from a heuristic viewpoint or stating a particular optimization problem. In Stare et al. (2007), different control strategies are proposed and compared in terms of the operating costs, which are evaluated but not optimized. Other works, such as Ingildsen et al. (2002), Machado et al. (2009) and Samuelsson et al. (2007), tackle the problem of reducing costs, but not in a systematic way. Some of them (Francisco et al., 2011; Rivas et al., 2008) also include plant design, and others are only focused on tanks aeration (Amand and Carlsson, 2012). Only Araujo et al. (2011, 2013) provides a comprehensive approach, performing a sensitivity analysis of optimal operation for the selection of the best control structure in term of costs and effluent quality. The work of Cadet et al. (2004) is similar but without considering the economics of the system.

The aim is to satisfy effluent quality regulations with reasonable economic expenses. The WWTP influent variations are rather large making the plant to work away from the optimal operation point, with the subsequent economic loss. One possible approach to overcome this is the re-optimization of the plant when some disturbances occur by applying Real Time Optimization techniques (Darby et al., 2011), which can be very demanding computationally, or perform the set-point optimization off-line (Machado et al., 2009; Guerrero et al., 2011). In this work, the approach considered is the selection of some controlled variables that when kept constant, the economic loss is small with respect to costs when the operation is re-optimized. The methodology used to find these variables is the self-optimizing procedure of Skogestad (2000). The WWTP model considered for its application is the widely used Benchmark Simulation Model No. 1 (BSM1), described in Alex et al. (2008).

The appropriate control structure selection is crucial for the optimal operation of plants. The decisions on which variables should be controlled, which should be measured, and which inputs should be manipulated are part of the control structure selection. Generally, these decisions are based on heuristic methods that cannot guarantee optimality, but in this work, self-optimizing control (SOC) is applied, which is a methodology for the selection of the best controlled variables that minimize operating costs, considering a steady state of the process. The initial quantitative ideas related to self-optimizing control are presented in Morari et al. (1980), and later, Skogestad (2000) defined the problem more

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precisely, including also implementation error. The methodology is well-developed for linear models that generate quadratic optimization problems, and for that reason a nonlinear validation is needed. The "exact local method" (Halvorsen et al., 2003) provides the best controlled variables for both disturbances and implementation errors, and it was the first author that proposed linear combinations of measurements as controlled variables, determined by a matrix **H**. The problem of finding such combination may be reformulated as a quadratic optimization problem with linear constraints (Alstad et al., 2009), and the analytical solution to this problem provides a straightforward way to obtain the matrix **H** (Yelchuru and Skogestad, 2011). Specific worst-case and average loss minimization have been also proposed (Kariwala, 2007; Kariwala et al., 2008), and the use of branch and bound methods has been introduced to enable the application of the methodology to large-dimensional processes (Cao and Kariwala, 2008).

For processes with large load disturbances it is common that the steady state is difficult to reach. Then, the controlled variables can be determined and adapted on the basis of an algorithm that tracks the necessary conditions of optimality (NCO), making the SOC adaptive to operating conditions changes. Model-free NCO tracking procedure using finite perturbations to calculate the gradients has been developed in Srinivasan et al. (2008). The regression-based approach (Ye et al., 2013) and its extension to hierarchical control (Ye et al., 2014) provide a new methodology to determine CVs approximating the necessary conditions of optimality (NCO) in the whole operating region, achieving near-optimal operation globally, enlarging the operation region where the economic loss is acceptable. In Jäschke and Skogestad (2011), it is shown that NCO tracking in the optimization layer and SOC in the lower control layer are complementary methodologies because unexpected disturbances, which are not rejected by SOC, can be handled by the model free NCO tracking procedure. There are also other methodologies based on neighboring-extremal control (NEC) (Gros et al., 2009), where the gradients are evaluated by model based approaches, but eventually they are also local approximations. Another possibility to deal with large disturbances is the use of dynamic SOC, where the operational cost during transient response is taken into account. In Hu et al. (2012), a formulation of dynamic SOC which considers economic cost and set-point tracking cost at the same time has been developed, stating a multiobjective optimization problem equivalent to an optimal control problem.

The work presented in this article is one of the first approaches to the SOC of the Benchmark Simulation Model No. 1 (BSM1) of a WWTP, which is a complicated nonlinear process benchmark, whose optimization is a difficult task. Therefore, the local SOC approximation has been chosen as a starting point, in order to find possible difficulties in the methodology and to propose the basis for implementing a more complex structure, particularly the one described in Jäschke and Skogestad (2011). With this approach, the SOC variables control decreases the operating costs with respect to the single active constraints control, which is the first step to improve the plant economy and safety (Maarleveld and Rijnsdorp, 1970). Moreover, in this article the focus is more on checking the controllability of the SOC variables and active constraints by using an advanced controller, particularly a NMPC.

Although there are plenty of successful works of SOC (see e.g. Umar et al., 2012) the dynamic validation of results is usually performed by means of decentralized PI controllers, making a previous pairing with variables (Larsson et al., 2001; Araujo and Skogestad, 2008). In Alstad (2005), the dynamic performance has been improved adding compensators on the measurements to avoid right half plane zeros, and the effect of the basis vectors for the null space method on poles and zeros has been studied. In Baldea et al. (2008), a singular perturbation-based framework has been employed, which accounts for the time scale separation present in the open loop dynamics of integrated plants, resulting in a controller design procedure that accounts for both economical optimality and dynamic performance. It is important to note that controllability can be improved by changing the matrix of combinations measurements **H** (Alstad, 2005), reducing the coupling and allowing for the implementation of decentralized PI controllers. Regarding to the active constraints control in SOC, only works dealing with dynamic validation of the control structures select a particular controller for that task. When there are active constraints only for manipulated variables, it is straightforward to keep constant the corresponding variable. For example, in Araujo and Skogestad (2008) the operation is optimal for maximum cooling in the heat exchangers for the ammonia synthesis process. In other situations, when constraints are active for some measurements, decoupled PI controllers based on the RGA matrix study are proposed (Alstad, 2005; Gera et al., 2013). In addition, if the set of active constraints changes depending on the disturbances affecting the process, the self-optimizing variables have to be recalculated following a systematic procedure, as in Manum and Skogestad (2012), that determines the different regions using a parametric program, based on a link with explicit model predictive control. Another approach is the implementation of a cascade control structure to satisfy both optimality and constraint requirements (Cao, 2003). In Jacobsen and Skogestad (2011), a methodology for finding active constraints regions is also proposed.

For the case of the WWTP, it has been proved that the set of active constraints does not change with the disturbances, but there is some coupling between active constraints control and the control of the self-optimizing variables. This coupling cannot be fully removed only by changing the matrix **H** of measurements combinations, and therefore in this work, a multivariable NMPC controller is considered as a novelty. The NMPC is a mature control strategy, and in this case an offset free formulation is considered to tackle the plant model mismatch and unknown disturbances based on Pannocchia and Rawlings (2003) and the extension to nonlinear MPC in Morari and Maeder (2012), using an augmented model with an additional integrating disturbance vector and adapting the MPC reference to the current disturbance estimate.

The first objective of this work is to find the self-optimized variables for the BSM1 following the simple procedure of Yelchuru and Skogestad (2011), which considers set-point and implementation errors and provides a set of optimal controlled variables as combination of the available measurements. The second objective is to evaluate the dynamic behavior of those variables by implementing a multivariable constrained nonlinear model predictive controller (NMPC). In particular, two approaches have been considered: one centralized MPC controlling the active constraints and self-optimized variables, and a distributed control structure with an NMPC controlling the self-optimized variables and local PI controllers for the active constraints control.

This article is structured as follows. First, the WWTP is described, in particular the activated sludge process. Then, the controlled variables selection methodology is explained, and the local methods for self-optimizing control. In the next section the methodology is applied to the BSM1, followed by the process controllability analysis with the description of the NMPC formulations and the distributed control structure. The article ends with a dynamic analysis and conclusions.

2. Description of the process

The purpose of a wastewater treatment plant (WWTP) is to process sewage and return clean water to the river. Activated sludge process (ASP) is a very important part of the cleaning procedure, and the Benchmark Simulation Model No. 1 (BSM1) (Alex et al.,