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Industrial Electrical Engineering and Automation

Model predictive control in wastewater treatment plants – a literature review

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Advanced Urban Wastewater Treatment

Contents

1 Introduction

Automatic control of processes at wastewater treatment plants (WWTPs) is essential to achieve optimal treatment while minimizing use of resources such as chemicals and energy. The level of control ranges from simple feedback controllers (such as PI controllers which are most widely used today) to advanced methods like model predictive control (MPC). Advanced control such as MPC, where optimization algorithms and model predictions are used to solve control problems (Figure 1), have great potential since it allows control on a variety of objectives (e.g., operational costs, energy use, greenhouse gas emissions) and can consider complex systems that are hard to optimize with simpler methods (Åmand et al., 2013; Stare et al., 2007). It is possible to impose constraints on both the states and the control signal which makes it a powerful tool. The predictive controller can be used to directly control the process, or in a hierarchical control structure where a high level MPC feeds setpoints to controllers at lower level (e.g. Duzinkiewicz et al., 2009; Vega et al., 2014).

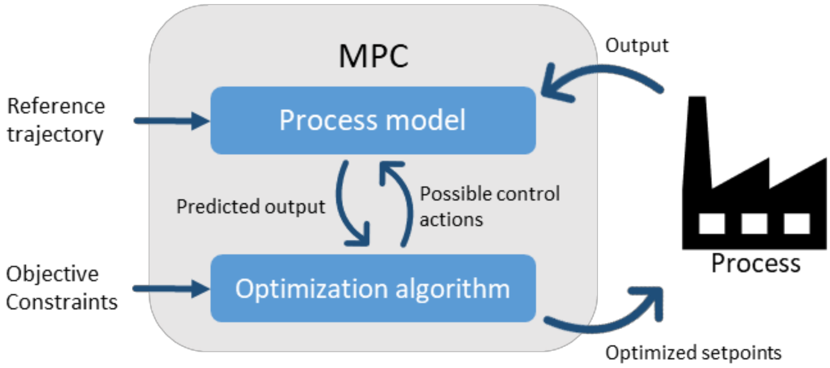

Figure 1. Schematic illustration of the concept of MPC. A process model and an optimization algorithm are used to decide optimal setpoints to control the process.

Compared to other process industries, such as chemical and pulp- and paper industries, the development of automatic control has been slower in the wastewater treatment sector (Olsson, 2008) and few examples of advanced methods are seen at WWTPs today. This could be attributed to several factors, e.g.: i) the influent wastewater (equivalent to raw material in other process industries) cannot be controlled in volume and quality, causing large disturbances to the processes; ii) the harsh environment at WWTPs with high concentrations of organic material, nutrients and bacteria makes measurements with sensors error prone and maintenance heavy; iii) economic incentives are lacking compared to other industries; iv) WWTP biological processes are highly non-linear and corresponding model based control strategies are computationally demanding.

In line with the ongoing digital transformation, computational capacity increases fast. At the same time new methods for data management and modelling are being developed that allow better control of data quality from sensors (Samuelsson, 2021). This means that methods such as MPC, which have great potential to increase sustainably operation of WWTPS, are becoming increasingly applicable in practice. This literature review aims to investigate previously used MPC applications at WWTPs with focus on different methods and benefits.

2 Method

Two different strings of words to be searched on Web of Science were defined: “model predictive control + wastewater treatment” and “model based control + wastewater treatment”. No time range or other filtration was applied. The newly adopted terms for WWTPs (i.e., resource recovery facilities) was not included as the term is fairly new and it was assumed that most authors include the old denotation among the keywords.

The resulting articles were sorted on date (newest to oldest) and most citations, from where the first 100 articles from each sortation was exported. Articles that did not contain “model predictive control” or “model based control” in its title or abstract was discarded. The remaining articles were read and categorized based on:

- Simulation / real plant case study;
- Type of models used in the predictive controller;
- Controlled variables;
- Manipulated variables

3 A brief introduction to wastewater treatment

The WWTP are designed to treat the wastewater in several steps, each specialized to reduce organic matter, nitrogen, phosphorous, and micropollutants such as pharmaceuticals to prevent them from causing environmental problems (e.g. eutrophication and oxygen depletion) in the receiving water body and its ecosystem. Mechanical, chemical, biochemical and biological processes are used depending on the plant’s layout, incoming loads, and effluent requirements. Phosphorous can either be reduced by precipitation and filtration/sedimentation, or biologically, where the latter is less common. Nitrogen and organic matter are reduced by biological processes and filtration/sedimentation (la Cour Jansen et al., 2019).

The processes of importance when reducing nitrogen is the nitrification and denitrification processes. In the nitrification process, ammonia and ammonium nitrogen (NH_3-N+NH_4-N = NH_x-N) is oxidized to form nitrite (NO_2-N) and nitrate (NO_3-N) nitrogen, often measured by their summed concentration NO_x-N, in sequence by two types of autotrophic bacteria which requires oxygen. The dissolved oxygen (DO) concentration in the aerated reactors is important for the growth of autotrophic bacteria. Too low DO concentration will inhibit the growth and may also cause the growth of filamentous bacteria which can lead to foaming and deterioration of the sludge settleability (bulking), resulting in higher concentrations of biomass in the effluent and may risk emissions of nitrous oxide. Too high DO concentration is undesirable as it requires a lot of energy with only marginal improvement of the treatment (Kampschreur et al., 2009). In the denitrification process, heterotrophic bacteria use NO_2 or NO_3 as an electron acceptor in their metabolism which reduces NO_2 and NO_3 to nitrogen gas (N_2) and both are therefore important for the nitrogen removal (la Cour Jansen et al., 2019). The aeration is a costly and energy consuming part of the treatment process, and is of great importance for the treatment results, which both are incentives to optimize it (Åmand et al., 2013). This may explain the vast amount of research done on aeration control.

4 Simulation studies

Simulation is an effective tool to evaluate scenarios faster, cheaper and safer than with full scale test. Many simulation studies have been carried out over the years, in most studies the objective is to reduce the overall cost and energy consumption and improve the effluent quality by controlling the aeration at the WWTP. The Benchmark Simulation Models (BSM1, BSM1_LT and BSM2) and its underlying models (K. V. Gernaey et al., 2014) are commonly used as a simulation tool where the MPC algorithms are evaluated. Often compared metrics are the *operational costs index* (OCI) and *effluent quality index* (EQI), as computed in the BSM system. Many studies use the control loops in BSM1 with DO controlled by adjustment of aeration (through the oxygen transfer coefficient K_La) and NO_x-N by control of the internal recycle rate.

Wastewater models can generally be divided in two main groups: mechanistical and data-driven models. Mechanistical models, like the BSM, use physical and biochemical principles as a foundation to formulate model equations. Data is needed to calibrate the model to current conditions, but in comparison with data-driven models, the amount of data needed is often less. Data-driven models are derived using statistical methods to detect patterns and trends within a dataset. An important difference between the two groups is that the results from a mechanistical model are possible to interpret physically, while it is not always possible when it comes to data-driven models. Combination models, i.e. hybrid models, make use of the benefits from both types of models. The foundation of a hybrid model may be mechanistical, but specific functions or reactions are estimated from data (Gernaey et al., 2014). The following chapters are divided based on models used in the predictive controller.

4.1 Full or simplified mechanistic models

Biological wastewater treatment processes are in general non-linear. However, its dynamics can often be described by a linear model around an operating point. Using the prediction-error minimization method, Tejaswini et al. (2020) was able to identify a linear state-space model of the relation between DO, NO_x-N and the internal recycle flow and K_La. The developed MPC was compared to traditional PI controllers as well as a fuzzy logic controller and evaluated on the OCI and EQI, which were both improved with the MPC and the fuzzy logic controller. Holenda et al. (2008) developed a state-space model by linearizing the aeration process in the ASM1 model, which was used in a MPC for controlling the DO concentration. Aside K_La, all other inputs to the reactor were regarded as unmeasured disturbances. The results indicate that that the controller accurately can follow rapid changes in the DO setpoint. The error was reduced with a shorter prediction horizon but with the tradeoff of increased overshoot.

Revollar et al. (2017) used a simplified version of BSM1, reduced to one anoxic and one aerated tank as well as only including four state variables and three processes, for MPC to optimize operational costs in the full BSM1 model. A penalty term was included for effluent NH_x-N to avoid excessively high ammonia concentration. The economic MPC showed increased benefit both for the standard PI control scheme in BSM1 as well as an MPC with only focus on setpoint tracking. Zhang et al. (2019) used the full BSM1 as well as a decomposed version with two separate subsystems to minimize the OCI and EQI of the BSM1. The decomposed version achieved considerably better computational efficiency while the control performance was slightly decreased. Boruah & Roy (2019) also used the full BSM1 for MPC to optimize operational costs, but used triggering conditions to update the optimization problem instead of running the optimization at each controller time step. This resulted in nearly 50% reduction in computation time while improving both EQI and OCI compared to the default PI controller scheme. In Francisco et al. (2011) a linearized version of BSM1 was used for MPC of DO and NO_x-N which improved control of disturbances compared to the default control scheme. Francisco et al. (2015) used the full BSM1 with self-optimizing algorithms for MPC for steady state conditions, but since the method assumes steady state the performance was not improved from the default case under dynamic conditions. Moliner-Heredia et al. (2019) used a simplified linear model with a nonlinear term (so called Wiener model) for NH_x-N prediction in combination with a influent flow prediction model and dynamic energy tariffs to optimize cost and evaluated on the full BSM1 system. Significant cost reductions were seen compared to default controls. Attar & Haugen (2017) used MPC to optimize methane production in a biogas reactor, using a simplified version of the ADM1 model and the input flow rate as manipulated variable, in a pure simulation study.

4.2 Data driven models

4.2.1 Artificial neural networks

Artificial neural network models (ANN) are purely data-driven models that consist of several layers of linear regression models and nonlinear activation functions. ANNs can be used to model non-linear and complex relationships, like the processes within a WWTP, and make predictions. Caraman et al. (2007) used a predictive controller with a neural network as the internal model. The MPC was designed to control the DO concentration by manipulating the dilution rate (air flow divided by volume). The control scheme was evaluated in BSM1. Results showed that the predictions made by the MPC followed the dynamics of the simulated WWTP and that the controller was able to control the DO concentration. Han et al. (2020) developed a self-organizing radial basis function (RBF) neural network MPC (SORBF-MPC) method to control the DO concentration in an activated sludge WWTP. The SORBF-MPC was applied to the BSM1 WWTP to maintain a specific DO concentration in the last aeration tank, while manipulating the internal flow recirculation and K_La. The performance of the control system was evaluated on effluent quality and aeration energy consumption. A comparison was also made with other control strategies. The results show that the aeration energy consumption was lowered by 8.4% compared to the default control scheme and that the proposed strategy gives accurate control of the DO concentration, as well as better quality of the effluent. Han et al. (2020) extended their work and created a four-layer adaptive fuzzy neural network (ANFF), including a RBF layer, to approximate nonlinearities in a WWTP. The developed ANFF updates the model parameters using an adaptive learning rate. The optimization problem was solved using a gradient method which decreased the computational cost. The proposed method was applied to BSM2 to control the DO concentration by manipulating the internal recycle rate and K_La. Compared to the previously proposed SORBF-MPC, the effluent quality was improved, and the aeration energy consumption was decreased. Sadeghassadi et al. (2018) used a neural network ARX model to predict DO and NO_x-N concentrations one controller step ahead, combining several predictions in series to gain longer prediction horizon. They used this for MPC of the DO and NO_x-N setpoints to optimize OCI and EQI in BSM1 which improved OCI as well EQI.

4.2.2 Dynamic matrix control

Dynamic matrix control (DMC) is one of the earliest examples of MPC, and is based on a model of the step response of the system (Camacho & Bordons, 1999). It can be used with measurable disturbances as input to the system (i.e., feedforward terms), and the method has had industrial success related to its applicability in multivariate systems. Shen et al. (2008) compared quadratic DMC (QDMC), QDMC with feed-forward, and nonlinear MPC to control the effluent quality (NH_x-N, TN, TSS, BOD_5 and COD) by manipulating the internal recycle, external recycle, waste activated sludge flow, carbon source flow rate and k_La in the aeration tanks in presence of disturbances in the incoming flow rate. The nonlinear MPC handled disturbances best, while still having acceptable energy consumption. Shen et al. (2009) later compared linear DMC, QDMC and nonlinear MPC, all with feedforward terms of influent flow rate or NH_x-N concentration, for control of effluent quality (NH_x-N, TN, TSS, BOD_5 and COD) in the BSM1 system. They concluded that nonlinear MCP only gave small benefits over linear DMC and quadratic DMC and that performance was highest with combined influent NH_x-N and flow rate as feedforward terms but that the NH_x-N concentration had the highest impact. In reality, influent flow rate is often measured while NH_x-N is not. The control worked well under steady influent conditions but deteriorated under dynamic conditions with increased energy consumption.

4.3 Fuzzy control

Fuzzy control is not a MPC method per se but used in conjunction with MPC in many cases and therefore given a separate section here. The method is based on logic expressions, but unlike Boolean logic (true or false) fuzzy logic is based on continuous function expressions with values between 0 and 1, which make them less sharp than Boolean logic (Åström & Hägglund, 2006). Compared to other advanced methods for control it has the benefit that the rule-based expressions can be readily interpreted by humans in the control room. Tejaswini et al. (2020) implemented a hierarchical control scheme with fuzzy control or linear MPC at the high level (effluent NH_x-N) and fractional PI-controllers at the low level (DO and NO_x-N). Fuzzy control was found more efficient that linear MPC and performed better for EQI during storm conditions, while linear MCP performed better regarding OCI during storm conditions. Santín et al. (2014) used fuzzy control for high level objectives (DO setpoint, based on effluent NH_x-N) while using a continuous time state space model feedforward MPC for low level control (DO and NO_x-N concentration). They reported substantial improvement in setpoint tracking at different conditions compared to PI control, as well as significant reduction in EQI and OCI for the combined fuzzy control and MPC. Santín et al. (2015) later presented a two-level hierarchical control structure to improve effluent quality and lower operational costs, evaluated as EQI and OCI in BSM1. The high-level control layer consisted of one fuzzy controller that feed DO setpoints to the low-level control layer, and two fuzzy controllers that eliminates violations of total nitrogen and NH_x-N effluent requirements respectively. The low-level control layer consisted of three MPCs with feedforward compensation used to control NO_x-N and DO. Compared to the default control strategy of BSM1, an improvement in the number of violations of effluent requirements as well as the EQI was reported, but only with a slightly lower OCI.

5 Real case studies

Few examples of MPC used at real WWTPs are found in the literature. The examples that have been found in the literature are presented below.

As with the simulation studies presented above, most articles focus on aeration control. O'Brien (2011) implemented MPC on a WWTP in England. They used UV based BOD sensors for feedforward control with an incremental ARX model for MPC of the DO profile over the basin by adjusting the aeration rate and achieved 25 % reduction in power usage as well as smoother operation of the plant. Ekster et al. (2019) used adaptive heuristics models for control of DO and model based sludge retention time (SRT) control at the Chico WWTP (California, USA). It was included in a cascade control scheme with feedforward and feedback control of NH_x-N which decides DO setpoints for different zones. The authors report aeration energy savings of 47 % compared to the previous DO control scheme, as well as increased process stability with decreased bulking.

Han & Qiao (2014) used self-organizing radial basis function neural networks for MPC of a nitrifying pilot plant with pre-denitrification for setpoint tracking for DO and NO_x-N, with air flow and internal recycle flow as manipulated variables. Good setpoint tracking was achieved in this setup, but a drawback was that optimization of the setpoints was not possible. Bernardelli et al. (2020) combined machine learning with fuzzy techniques (Artificial Neuro-Fuzzy Inference System) for control of effluent TN as well as energy consumption, also by manipulation of aeration rate and internal recycle flow rate but also including set point determination. They measured DO, ORP, T, NH_x-N and NO_x-N in the aeration tank as well as N_{tot} in the effluent as input to the controller. They alternated between MPC and regular control on a weekly basis and concluded that the MPC achieved better effluent quality and energy savings.

Stentoft et al. (2019) developed a hybrid data driven/mechanistic model based on stochastic differential equations which incorporates parts of the well-established ASM1 model (see Henze et al. (2000)). The model was used to predict NH_x-N and NO_x-N in an intermittent aeration activated sludge process in Denmark and showed excellent predictive quality, although it was not used for control. The methodology was extended in Stentoft et al. (2021) to include dynamic electricity prices and greenhouse gas emissions to allow control of aeration time over a day. The article was only a proof of concept, the model was not used for control of the plant, but predicted significant cost savings or lowered greenhouse gas emissions depending on chosen evaluation criteria.

6 Outlook and conclusions

MPC has great potential to help reduce energy usage, greenhouse gas emissions and costs for WWTPs, though most studies of the use of MPC found in the literature are still only tested in ideal simulated environments. This presents a problem in evaluating the efficacy of the methods since the (very) real problems that occur at WWTPs, e.g. faulty data and equipment failure, are often neglected in simulation studies but must be taken into account for proper evaluation of benefits and robustness of the methods. This also means that there are many opportunities for more research in this area as more case studies of real systems are needed. While predictive power and computational demand of the models has been a problem in the past, recent additions (Bernardelli et al., 2020; Stentoft et al., 2019) show very promising results in these regards. More research is needed to evaluate where MPC is most efficient. Should it only be used as a high-level controller in a cascade scheme (e.g. to decide set points) or is it efficient also as a low-level controller? During evaluation of the benefits of MPC increased costs for additional sensors and maintenance should also be included. The interpretability of the model structure can also be important to achieve operator trust, which is an important part of the implementation process.

Efforts to improve wastewater treatment are often focused at optimization of the WWTP. However, there is also potential to improve the effluent quality and the operation of WWTPs by measures in the sewer network. MPC could facilitate the control of the whole urban water cycle. With more advanced methods on both the modelling and the control side, in combination with an increase in computational capacity as well as higher demands on the WWTPs, MPC can help to improve the control of both the sewer network and WWTP. In a recent study Sun et al. (2020) used MPC for a combined sewer system to mitigate the environmental impact of combined sewer overflows (CSOs). A discrete-time state-space model was used in the MPC. The multi-objective cost function accounted for minimization of CSO volume, maximation of the usage of the WWTP, control smoothness, and minimization of the pollutant load to the environment. In comparison with rule-based local control the proposed method can reduce the CSO volume and pollutant load to the environment. Integrating the WWTP capacity in the control strategy reduced the CSO volume which indicates that there are possibilities to find a better balance between the sewer network and the WWTP by considering the whole urban water cycle. Predicting flows to control inlets pump is also a possible area of use for MPC. Aakre Haugen (2018) implemented a simple MPC to control the pumps at a simulated WWTP. The system consisted of a long tunnel that discharged in an inlet basin from where the wastewater was pumped to the WWTP. The model used in the predictive controller was based on a simple mass balance of the inlet basin and was used to control the pumps. The results were promising, yet only tested in a simulated system. Ongoing project *Future City Flow* aims to develop a decision support system to help cities control wastewater flows and reduce the risk of CSOs. Implementation of full MPC will be done in the final stage of the project (Valverde-Pérez et al., 2021).

Another possible application of MPC at WWTPs is for control of the sludge dewatering. The process is often hard to control as the sludge quality differs depending on current operation and conditions. It is also a process where there are economic incitements for optimization as both the flocculation chemical consumption and the amount of dewatered sludge (and subsequent transportation needs) are costly. The dewatering unit and the sludge flow are difficult to model mechanistically and have therefore not been given much attention. Recent advances in e.g. machine learning and other data driven technologies opens up possibilities to develop accurate models of the dewatering units. As accurate models are important for MPC, improvement in the modelling of this part of the WWTP may create opportunities to also create more sophisticated control strategies.

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