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Control Strategies of Wastewater Treatment Plants

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Abstract: The objective of the current study is to investigate various control strategies implemented to wastewater treatment plants. The paper starts with discussion in modeling part of wastewater system and continues with designation of control objectives and control parameters. Subsequently, the implementations of common control structures including feedback, feedforward-feedback, supervisory and hierarchical controls are explained. The study is exclusively emphasized on four control techniques. Model predictive control performs superior control in optimizing nitrogen removal based on predictions of future behavior of wastewater systems. The performances of PID control in dissolve oxygen and nitrate control is improved significantly with multivariable configuration. Similar results achieved by data-driven approach compared to default PI simulation. Finally, artificial neural networks are commonly suggested for modeling and prediction purposes. A study is emphasized on Benchmark Simulation Model No. 1. The paper serve as a reference and for future research improvements in developing new advanced control techniques for wastewater field that aims in achieving stringent effluent quality standards.

Key words: Wastewater treatment plant, control strategies, BSM1 benchmark.

INTRODUCTION

Wastewater treatment plants (WWTPs) are mainly affected by large disturbances and uncertainties related to the influent wastewater's composition. The plants naturally aim to remove suspended substances, organic material and phosphate from the water before releasing it to the recipient. Generally, there are three different steps involve in the WWTPs include mechanical treatment, biological treatment and chemical treatment. The best technology available to control the discharge of pollutants proved in biological process. Activated sludge process (ASP) becomes a frequent concepts for biological process in which microorganism are oxidized to organic matter. The organic material is then transformed to carbon dioxide and some is incorporated into new cell mass. The new cell mass forms sludge that contains both living and death microorganisms and thus contains organic material, but also some phosphorous and nitrogen (Anders, 2000).

In wastewater, there are several forms of nitrogen components include ammonia (NH_3), ammonium (NH^{4+}), nitrate (NH^{3-}), nitrite (NO^{2-}) and organic matter (Wahab, 2009). Nitrogen is an essential nutrient for biological growth and acts as one of the main constituents in all living organisms. The presence of higher nitrogen in effluent wastewater invites a numbers of problems (Barnes and Bliss 1983). Initially, the increased numbers of aquatic plants and algae are originated from nitrogen and this leads to oxygen shortage because of degrading process. Next, high concentrations of ammonium in the effluent possible to reduce the oxygen stored in the recipient. It is noted that oxygen is heavily consumed to oxidize ammonia to nitrate. Thus, minimization of nitrogen level in the incoming wastewater is strongly demanded. As a result, two biological processes are proposed. The most common one is called a nitrification or ammonium removal, where ammonium in aerobic conditions is converted into nitrate by autotrophic bacteria. Secondy, a denitrification process or nitrate removal where nitrate is converted to nitrogen gas by heterotrophic bacteria under anoxic conditions with the aids of COD as reducing agent (Sotomayor *et al*., 2001).

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In conjunction, an advanced control strategies are highly demanded in improving or at least in maintaining the effluent quality where optimization of nitrate and/ or ammonium removal are stressed. Modeling and identification aspect besides selection on control variables, control structures and strategies play significant part in optimizing the control objectives and hence ensuring a good control performance. Numerous control strategies have been implemented by other researchers without addressing explicitly the performances of the controllers. This is due to the influent changeability, the biological and biochemical complexity, wide range of time constants and the lack standard of evaluation criteria. The study is highly focusing the control strategies applied on widely used standard simulation environment, Benchmark Simulation Model No. 1 (BSM1) as reported in (Copp, 2002; Alex *et al.,* 2008).

The Process on Control Strategies:

The present study outlined on two significant control schemes as indicated in Figure 1. It starts with modeling and/or identification approach where the physical aspects of the system are studied and the experimental input-output data are achieved in estimating the behavior of the wastewater plant. Controller design involves in the next procedure where designation of control aims, control variables and control structures are briefly explained. However, exclusive study on control strategies applied to Benchmark Simulation Model No. 1 (BSM1) is discussed.

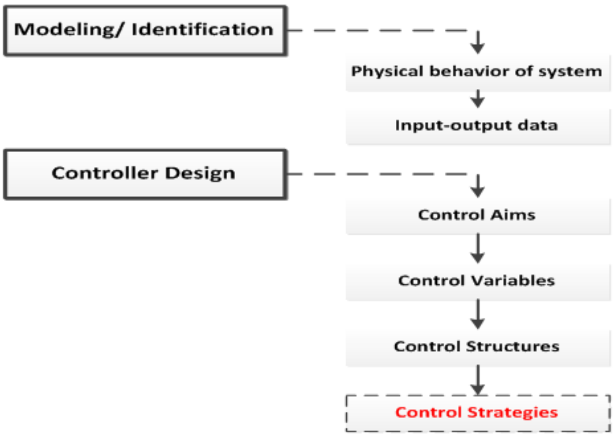

Fig. 1: Basic Scheme on Control Strategies.

A. Modeling / Identification on Wastewater Treatment Plants:

In general, modeling is a process that aims to represent the dynamic behavior of a system. A derivation on physical behavior of system is commonly being considered. No doubt, it offers interesting characteristics of the system but it is significantly difficult and time consuming when deal with a large systems. A wastewater treatment plants are strongly known with the complexity of the model structures and the large number of states and parameters. Due to the complexity factors besides inadequate online sensors available, an alternative modeling and identification approaches were explored. Thus, a model reduction methods proposed by Robertson and Cameron (1996) and identification based on input-output data of the system leads the implementation of a “black box” and “grey box” model.

There are various models that investigated the fundamental works related to the development of dynamic models for ASP. For example, (Ekama and Marais, 1979; Dold *et al*., 1980; Van Haandel *et al.,* 1981). In addition, the Activated Sludge Models (ASMs) family has been developed in the early 1980s. The most well-known and established activated sludge process model is ASM1 (Henze *et al.,* 1987). Eight dynamic processes with thirteen state variables and nineteen associated parameters were described. ASM2 models covers the biological phosphorus removal were then proposed by Henze *et. al.* (1995). This improvement offers well description of the dynamics behavior of phosphate and nitrate. Subsequently, ASM3 was proposed by Gujer *et al.* (1999). However, ASM1 that provide a very useful tool for plant design and control evaluation is highlighted in the study. Nevertheless, several researchers attempt to derive simple models based on ASM1 for control purposes. A set of reduced order nonlinear models based on ASM1 have been proposed by Jeppsson (1995). Anderson *et al.* (2000) introduces a simple model for nutrient control for an alternating aerobic-anoxic process.

Moreover, model reductions via linearisation are discussed in (Smets *et al.,* 2003). Meanwhile, Lindberg (1998) and Sotomayor *et al*., (2001, 2002, 2003) presents a multivariable model for describing nitrication and denitrication using "black box" parametric identification. It also been applied by Sánchez and Katebi that suggesting a linear identfication for DO and nutrient removal in (Sánchez and Katebi, 2003). The subspace identification with N4SID algorithm then been applied in benchmark simulation by (Wahab*,* 2007, 2009). Next, an AutoRegressive with eXogenous (ARX model) has been explored by Anders (2000) while Prediction Error Method (PEM) has been used in cascading control of nitrate removal in (Liu *et al.,* 2010; Liu and Yoo, 2011). Despite of that, "grey box model" that combine process equations with the "black box" models is also suggested in control application. See (Carstensen *et al.*, 1995 and Benchman, 1999).

B. Controller Design:

Control Objectives:

Most literatures were stress on satisfying a stricter effluent demands in optimizing the nitrate and/ or ammonium removal. Besides that, minimization on operating costs is always considered. Due to the large variations of influents, compensating the impact of process disturbances are addressed. It is noted that the biological nitrogen removal in an ASP is carried out by two biological processes, nitrification and denitrification where the control strategies are outlined significantly.

Selection on Control Variables:

The signals to be controlled and manipulated in WWTPs need to be identified in line with the control objectives. Common controlled variables such as the nitrate and dissolve oxygen control while an air flow rate, internal recirculation flow rate and additional carbon dosage are always been considered as the manipulated variables. The control of the DO concentration is addressed initially. In aerobic part, ammonium was converted to nitrate by microorganisms through the nitrification process where oxygen is strongly needed. The DO concentration should be sufficiently high to cover the microorganisms' oxygen demand. However, too high DO levels may deteriorate the sludge properties so that the denitrification might be less efficient due to highest DO concentration of the recirculated water. In addition, an appropriate DO concentration asks an appropriate aeration that significantly in relation with electrical consumption of the plant. As reported in (Zang, 2008), the control of DO concentration in the aerobic zone usually performed by three procedures. Firstly, a feedback control with respect to oxygen and/or ammonia measurement in the last aerobic reactor as applied in (Lindberg and Carlsson, 1996; Sahlmann *et al*., 2004; Holenda *et al.,* 2007; Wahab, *et al.,* 2007) are considered. Secondly, model-based feedforward control strategy is used. For both of control aims, the DO will be fixed at a constant value relating to the different biological processes. In contrast, the DO may be handled by time-varying DO set-point control. It is usually identified by a higher level controller that are driven by the ammonia concentration in the aerobic zone (Lindberg,1997; Holenda *et al.,* 2007).

Meanwhile, two possible approaches of nitrate control may be considered. Firstly, the nitrate concentration in the aerobic zone can be controlled by handling the internal recycling which is rich in nitrate that recirculated from the last aerobic zone to the last anoxic zone of the bioreactor (Anders, 2000; Sigman, 1999). However, in that case, a large recirculation rate increases the pumping costs, causes a larger leakage of substrate to the aerobic zones and recycles a larger amount of oxygen to the anoxic zone and hence affecting the denitrification process. Next, the nitrate control can be done and/or control of nitrate concentration in the anoxic zone by manipulating an external carbon source dosage *(PENG et al., 2007).* This purpose is to compensate the COD/N ratio deficiency of the influent, increasing the denitrification rate in order to ensure that the recirculated nitrate be fully removed from the anoxic zone. But, this strategy strongly possible to increase the operational costs due to the high rate of carbon required, increasing the sludge production, thus affecting the nitrification process, raising the oxygen demand and increasing the substrate concentration in the effluent.

Control Structures:

The implementations of control structures that are commonly used in WWTPs were considered. Control structures represent the way in which the model is used in solving the control problem. The basic control action covered in feedback control. Usually, the difference between the set-point and the measured output signal value will be used in calculating an appropriate value of the input signal (Doyle *et al.,* 1992; Gerksic *et al.,* 2008). Feedback control is used in many wastewater treatment applications, such as control of DO concentrations, nitrate concentrations and ammonium concentrations. At the same time, feedforward control capable to compensate the disturbances and hence increases the control performance. However, the combination of feedforward–feedback approach is strongly recommended.

There are many examples used to control the nitrogen removal described in the literature, see (Ekman *et al.,* 2002; Shen et al., 2009; Cristea *et al.*, 2008).

Meanwhile, a supervisory or cascaded control is addressed. The set-point of another controller will be calculated with a supervisory controller. This makes it possible to use information from intermediate signals in the control. This controller was highly recommended in controlling ammonium concentration in the ASP. See (Doyle *et al.,* 1992; Vilanova *et al*., 2011) for more detail. It was proved that the combination of feedforward and cascade capable to perform well in achieving the control objectives (Vilanova *et al.* 2011). In addition, a hierarchical structure is strongly recommended to the system with large time scale (Sotomayor *et al.* 2001).

Nevertheless, the process control may highly involve with multivariable control. In many cases, the multivariable method offers smaller overshoots to set-point changes, faster responses and minimal settling time. Example of multivariable control can be referred in (Pierre and Marie, 2004; Shen *et al.*, 2008; Wahab *et al.,* 2009). The process has several input and output signals where the changes in one of the input signals may cause a changes in several or in all output signals. In such a case, the controller calculates suitable input signal values based on all output signal values. If each input signal of a multivariable system mainly affects one output signal without perturbing the behaviour of other output signals too much, decentralised control might be used. Here, each input signal will control one specific output signal and the interactions in the different control loops are neglected. Thus, the multivariable control problem is reduced to a number of control problems with one input and one output signal. A decentralized PI control on BSM1 has been discussed in (Copp, 2002; Alex *et al*., 2008). Besides, architectures for distributed and hierarchical MPC were reviewed by (Scattolini, 2009). However, the degree of control performances for decentralised controller may need to be considered.

C. Control Strategies:

Benchmark Simulation Model No. 1:

The study on control techniques concentrates on Benchmark Simulation Model No. 1 (BSM1) that is developed by COST 264 and COST 682 Working Group No.2. The bioreactor consists of five reactors where the first two compartments are anoxic zones followed by three aerobic ones and a secondary settler. The plant is designed for an average influent dry-weather flow rate of 18,446 $m^3.d^{-1}$ and 300 $g.m^{-3}$ of average biodegradable COD in the influent. The biological reactor volume and the settler volume are both equal to 6,000 m^3. Based on the present amount of biomass, the wastage flow rate in the system equals to 385 $m^3.d^{-1}$. This relates to about 9 days of biomass sludge age. Meanwhile, there are 10 layers of non-reactive secondary settler unit with total height of 4 m. The settler area (A) is 1,500 m^2 which make the volume is 6,000 m^3. There are three dynamic input data files include dry, rain and storm for uniform testing and evaluation. Each input files comes with realistic variations of the influent flow rate and composition. More details on BSM1 development and control handle may be found in (Copp, 2002; Alex *et al.*, 2008).

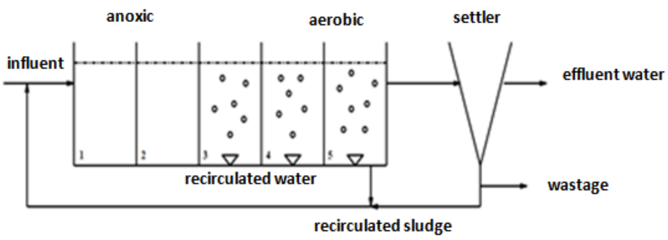

Fig. 2: The plant layout of the BSM1 with pre-denitrification.

Table 1 indicates the effluent quality limits that need to be satisfied for control design purposes. The total nitrogen (N_{tot}) is determined by addition of nitrate effluent ($SNO,_e$) and ($SNK_{j,e}$). It is noted that SNK_j is the Kjeldahl nitrogen concentration.

Table 1: Effluent Quality Limits.

Variable	Value
Total nitrogen (N_{tot})	<18 g N.m-3
Total carbon dioxcide (COD_t)	<100 g COD.m-3
Ammonia (S_{NH})	<4 g N.m-3
Total suspended solids (TSS)	<30 g SS.m-3
Biochemical oxygen demand (BOD_5)	<10 g BOD.m-3

Control Implementation:

It is difficult to attain a high performance control to the lowest possible cost. If the demands on effluent quality become stricter, the energy consumption and the use of chemicals will be increased and hence the lowest possible operational costs become harder. In addition, the chemicals used and the amount of energy consumed may excessively high in compensating the impact of process disturbances and necessitate the development of advance control strategies. The implementations of control strategies are discussed. Four controllers are addressed include the optimal control, PID techniques, data driven approach and artificial neutral network. With the purpose on developing recent control technique, the control strategies since 2003 are explored.

Model Predictive Controllers (MPC) is widely used and well accepted in process industries as reported in (Qin and Badgwell, 2003) Control of the WWTPs is not a trivial task since the unit is nonlinear, features large time constants and delays, and interaction between variables is most important. MPC algorithm is a good candidate for such demanding task. The main idea behind MPC is that the capability on predictions of advanced behavior of a process over an output prediction horizon referred on the current time measurements and the nominal model of the process. The MPC algorithm computes the manipulated variable sequence over an input horizon in order to minimize an error objective function. More information on MPC can be referred in (Michael 2010; Maciejowski 2002).

MPC has been introduced to BSM1 by Jean-Pierre Corriou and Marie-Noelle Pons. A Linear Quadratic Dynamic Matrix Control (QDMC) has been applied in maintaining the effluent quality within regulations-specified limits. The manipulated inputs, controlled output and disturbance are reported in (Pierre and Marie, 2004). A feed-forward controller which is based on the measurement of the influent flow rate has been added to the MPC as to improve the performance of multivariable controller. It was proved that the influence of disturbances was attenuated even without tuning the controller parameters specifically related to steady state influent characteristics. On the other hand, the performances was less satisfactory in the presence of influent disturbances. The project was extended in (Shen *et al.*, 2008) where previous control objectives, control and manipulated variables were maintained. Two approaches have been studied. Firstly, it covers the addition of a feed-forward action based on the measurement of the influent flow rate. Next, the uses of a nonlinear MPC with addition of a penalty function. It was noted that the parameters were tuned based on experience and rules presented by Maciejowski (Maciejowski, 2002). Finally, from the result there is insignificant change of energy consumption with regards to the performances of the QDMC for feed-forward control action. In contrast, there was slightly improvement on quality of effluents and significant decreases on the aeration energy for nonlinear MPC with penalty function. However, the increment of pumping energy needs to be avoided. The nonlinear MPC strategy with penalty function demonstrates best with small effluent quality index and acceptable aeration and pumping energy consumption. The result on previous study leads the development of MPC with feed-forward compensation (Shen *et al.,* 2009). Three MPC strategies suggested include Dynamic Matrix Control (DMC) algorithm without constraints, a QDMC version with hard linear constraints and nonlinear MPC (NLMPC) version with hard constraints on the inputs and soft constraints on the outputs. Moreover, the influent flow rate and ammonium concentration were added as measured as disturbances. A feed-forward structure was added to previous feedback MPC controls so that the large influents of time variations were compensated. The oxygen mass transfer coefficient corresponds to the efficiency of aeration in a given aerated tank. The prediction horizon, control horizon, and model horizon are tuned for one to three days to meet the best of control performance. Again, the simulation results proved a good performance under steady-state influent characteristics. Meanwhile, the best performance was achieved by combining both feed-forward controllers with respect to the influent ammonium concentration and flow rate. NLMPC with penalty function offers slight improvement compared to DMC and QDMC. On the other hand, more aeration energy was consumed in all simulated cases. To enhance the control performance, MPC multivariable controller and MPC feedforward-feedback control structure has been proposed by Vasile-Mircea Cristea, Cristian Pop and Paul Serban Agachi. The control variables and control structures proposed were represented in (Cristea et al., 2008). No doubt, the multivariable feedback MPC controller provides an effective improvement of the WWTPs compared to PI control, proved in the presence of the dry weather disturbances. Subsequently, the combined feedback-feedforward MPC strategy succeeds to accomplish superior control performance, shown by its short setting time and reduced overshoot and small offset. To further extend, the DO control of activated sludge wastewater treatment process has been proposed by Holenda *et al*. The aeration process in ASM1 model at steady-state operating point of the WWTPs was linearized. Two cases have been identified. The first case aims to control the DO level at desired point in the third aerobic basin whilst the DO level was alternated as to be kept up with alternating ASP in the second case.

The variables selection and control approaches can be referred in (Holenda *et al.,* 2007) and (Holenda, 2007).

Next, Proportional, Integral and Derivative (PID) control is the most common control algorithm used in process industry and wastewater treatment. An error which is the difference between measured process variable and desired set point is calculated. The PID controller attempts to minimize the error by adjusting the process control inputs. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the set point and the degree of system oscillation. In WWTPs, a multivariable PID (MPID) and PID in advance control structures are highly interested.

A MPID control has been implemented in (Wahab. *et al.,* 2007). Four MPID control were investigated covers the schemes proposed by Davison, Penttinen- Koivo, and Maciejowski. Besides, a new method retains some of the properties of Maciejowski (Maciejowski, 2002), but eliminate the needs of frequency analysis has been suggested. The proportional and integral feedback gain of proposed controller was blend between the inverse of the plant dynamics at zero frequency and the inverse of the plant dynamics at high frequency. The outputs controlled were focused on DO concentrations in all aerated tanks. The three air flow rates were manipulated while the influent flow rate (Q_{in}) and influent ammonium (S_{NH}) concentration were considered as disturbances. All four PID design methods were successfully applied to the COST simulation benchmark with the best performances resulted by the new tuning method proposed. The investigation on MPID was extended by the same authors. The MPID was tested on nitrate (SNO) control instead of DO with influent substrate (SS) as an additional disturbance compared to previous strategies. More details on control implementation may be referred in (Wahab *et al.,* 2009).

Nevertheless, a feedforward-cascade controller for DO concentration in ASP has been proposed by Zhang *et al.* A reduced model of ASM1 and reduced IWA simulation benchmark were used in Proportional and Integral (PI) DO set-point control and feedforward–cascade DO set-point control that aims to control the DO setpoint from on-line measurements of the influent and effluent ammonia concentration. Basically, a higher level controller will selects the set-point of the lower level controller and hence directly control the DO concentration. A feed-forward control was introduced in the control system for preventing the influent loading from influencing the system. The outer ammonia loop was set to act slower than the inner DO loop. The simple model of ammonia removal rate and the master controller for oxygen set-point were discussed. A good performance recorded where the average effluent nitrate and aeration energy of controlled plant are significantly reduced in all-weather compared to PI control. However, the average effluent ammonia was slightly increased in rainy weather and it asks for more future improvement. More explanation may refer to (Zhang *et al.,* 2008).

Meanwhile, a process control oriented strategy for nitrogen removal has been proposed in (Vilanova *et al.* 2011). The performance of one-parameter tuning approaches; Analytic Tuning (AT) and Internal Model Control (IMC) design were explored. The control strategy based on PI/PID type controller was considered. The main target in control proposed was DO control loop in the last aerated tank. The time-varying DO set-point was provided by an outer nitrate control loop based on the nitrate concentration in the second anoxic tank. A cascade configuration was developed and improved effluent quality was recorded. The effluent quality index and the aeration energy were reduced with AT tuning approach. On the other hand, the cascade control was incapable to retain the concentration below the limit. The problem was solved by feed-forward control. The results proved a good performance of nitrogen removal for the three dynamic influents recorded by combination of cascade and feed-forward control configuration.

Furthermore, a cascaded of MPC and PID control strategy has been introduced (Liu *et al.*, 2010.). Primary MPC controller acts to control the nitrate concentration in the effluent while the nitrate concentration in the final anoxic compartment was controlled by a secondary PID controller. To satisfy the quality of effluents, an external carbon dosage is manipulated. A relay feedback method has been applied in for automatic tuning of a PID controller. Certain variables were fixed such as the internal recycle flow rate, the effluent of suspended solids, the wastage stream flow rate and the concentration of external carbon source. The proposed controller offers smaller overshoot and faster response with respect to the set-point. The closed-loop response for a set-point change was satisfied. To assess the cascade control performance, the Control Performance Assessment (CPA) technique has been applied. It was observed that the PID controller in the inner-loop performs well under the dry weather influent distribution condition. Average nitrate, ammonia and total nitrate in the effluent significantly decreased compared with the default open-loop and closed-loop cases. On the other hand, slight increases were recorded on the sludge production, the aeration energy and pumping energy. However, the performances of proposed control strategy have been improved in (Liu and Yoo, 2011).

Subsequently, a data-driven strategy aims to maintain the effluent quality to WWTPs has been proposed. Generally, data-driven control never attempts to find the model of the plant. It uses the data of the plant directly to find a controller.

It leads the minimization of some control performance criterions compared to model based control. Here, Virtual Reference Feedback Tuning (VRFT) has been applied in (Rojas *et al.,* 2010). Two basic loops were considered including the nitrate (SNO) in the second anoxic tank and the DO controlled of the fifth tank. The data obtained by performing a test on the plant in steady state with constant disturbances. Here, the oxygen transfer coefficient and DO were used as input and output for oxygen control loop while the internal recycle flow rate (Q_{intr}) and the SNO for the nitrate control respectively. The transfer functions were selected upon the settling time on each of the control loop. The VRFT method was applied in two degrees of freedom Proportional-Integral (PI) control with a constraint in the optimization problem. The simulated effluent components and the performance index by VRFT control with respect to default PI controller are compared. It was observed that the effluent components obtained were always under the maximum values and closely with the default controlled values. On the other hand, there was slight increased on effluent quality and percentage of violation in SNO and SNH. The DO control performs a good response however; the changes of nitrate-nitrogen's reference are required in nitrate control. Similar results were achieved with the data from the direct simulation of the process with simpler control methodologies compared to model based control.

Generally, artificial neural networks (ANN) have been suggested for modeling and prediction purposes. The design and training of ANN models for the dynamic simulation of the controlled BSM1 was presented by Cristea et al. in 2009. Moving window approach was applied in generating ANN training data. Control configurations have been investigated where the DO mass concentration in the third aerated reactor and the SNO mass concentration in the second anoxic reactor were controlled using PID and MPC. See (Cristea *et al.,* 2009) for variables and ANN structures. Good correlation between targets and ANN outputs with respect to testing data set for both PID and MPC controls. In addition, smaller differences recorded between analytical and ANN simulator results for the WWTP with PID and MPC controlled DO and nitrate concentration. As a result, the process variables well predicted and simulation time was reduced with ANN based simulators. Meanwhile, a prediction of the sludge recycling flow rate (Q_R) has been modeled with Radial Basis Function (RBF) Neural Network (Luolong et al., 2010). It was observed that Q_R significantly affects the sludge recycling process. Sludge return was required to ensure the bioreactor sludge concentration, and the balance between the secondary clarifier and the bioreactor sludge concentration. There were five input variables declared as RBF input nodes includes influent flow rate (Q_{in}), return sludge concentration (RSS), Sludge Concentration in the aeration tank (MLSS), sludge residence time (SRT) and DO. 200 groups-sample of two weeks data was used in training and also 200 samples in validating the RBF prediction function. It was shown that the neural network models provide good estimates for the sludge recycling flow rate, which covers a range of data for training and testing purposes. Simulation proved a good estimation for the sludge recycling flow rate and hence been an alternative way for the sludge recycle flow rate control.

Despite of that, there are several researchers that investigate the performances of different control structures and strategies as presented in (Yong *et al.,* 2006). The control strategies involve is PID control actions that concerned on external carbon dosage and nitrate recirculation flow rate. Simulated results revealed the improvement of effluent quality, the reduction on average nitrate and the total nitrogen concentrations in the effluent. However, the increment of effluent ammonium concentration was recorded. Overall, the control strategy (a) was concluded to be the best for external carbon dosage and nitrate recirculation flow rate with respect to external carbon consumption and plant performance criteria. This is due to maximizes usage of influent COD in denitrification process.

Furthermore, the different control strategies for BSM1 with reactive secondary settler model were proposed in (Ostace *et al.*, 2010). The MPC architectures deployed at supervisory and/or regulatory levels, the PI and PID control schemes and ANN with NARMA-L2 controller were investigated. The IAE, ISE and the maximal deviation from set point (DEVmax) were assessed. For all investigated control structures the tuning has been performed for minimizing the ISE criterion and was achieved by repeated simulations. Performance evaluation of the different investigated control strategies, for the two controlled variables, was concisely presented. It can be seen that the conventional PI and PID controllers have good control performance for the DO control but less effective for the nitrate (NO) control. Next, the MPC controllers implemented directly at the regulatory control level have better performance compared to the conventional controllers. Furthermore, the simple supervisory MPC schemes prove to have good performance for both control loops but they are inferior to the regulatory MPC architectures. The supervisory/regulatory MPC schemes show best control performance in rejecting the influent disturbances with reduced overshoot and in shorter time.

Nevertheless, the comparison of control strategies for nitrogen removal in ASP in terms of operating costs was studied in (Stare *et al.,* 2007). It was aims to investigate various control strategy that capable to perform well with considering the plant operating costs.

Here, constant manipulated variables and numerous PI and feed-forward control strategies were tested and compared with predictive control. The control strategies were distinguished with respect to the complexity of the control algorithms besides in the number and location of sensors. Here, each of control strategy was accompanied with operational map in determining the set-points that yield the optimal operating costs. It was proved that there is a slight differ on optimal operating costs of PI, feed-forward controllers and more advanced MPC algorithms under various plant operating conditions. However, an advanced control algorithms may highly beneficial when the plant is strongly loaded. In addition, concentration on minimizing the operational cost in wastewater system was addressed too in (Ostace *et al.,* 2011).

Conclusion:

The main control objectives of wastewater treatment plants are addressed on effluent quality standard and reduction of operating cost in an activated sludge process. Modeling and identification aspect besides selection on control variables, control structures and strategies play significant part in optimizing the control objectives and hence ensuring overall good control performance. Between all four control structures being discussed, none of them could claim as the best all-round control strategies for wastewater systems, as there are deficiencies, as well as significant advantages, with respect to different application and performance parameters in evaluation.

Model predictive control works well in optimizing nitrogen removal based on predictions of future behavior of wastewater treatment plants. Moreover, MPC schemes show best control performance in rejecting the influent disturbances with reduced overshoot and in shorter time. It was proved that the performance of dissolve oxygen and nitrate control improved significantly with multivariable PID control that strongly demanded in highly nonlinear system. In addition, similar results were observed by data-driven approach with Virtual Reference Feedback Tuning compared to default PI simulation. It was revealed too that artificial neural networks are commonly suggested in modeling and prediction purposes of wastewater plant. The discussion of various control approaches highly motivates the development of new advanced control strategies in wastewater application.

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