# Statistical monitoring and dynamic simulation of a wastewater treatment plant: a combined approach to achieve model predictive control

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## Abstract

The on-line monitoring of Chemical oxygen demand (COD) and total phosphorus (TP) restrains wastewater treatment plants to achieve better control of aeration and chemical dosing. In this study, we applied principal components analysis (PCA) to find out significant variables for COD and TP prediction. Multiple regression method applied the variables suggested by PCA to predict influent COD and TP. Moreover, a model of full-scale wastewater treatment plant with moving bed bioreactor (MBBR) and ballasted separation process was developed to simulate the performance of wastewater treatment. The predicted COD and TP data by multiple regression served as model input for dynamic simulation. Besides, the wastewater characteristic of the wastewater treatment plant and MBBR model parameters were given for model calibration. As a result, $R^2$ of predicted COD and TP versus measured data are 81.6% and 77.2%, respectively. The model output in terms of sludge production and effluent COD based on predicted input data fitted measured data well, which provides possibility to enabled model predictive control of aeration and coagulant dosing in practice. This study provide a feasible and economical approach to overcome monitoring and modelling restrictions that limits model predictive control of wastewater treatment plant.

Keyword: Control; Dynamic simulation; MBBR; Multiple regression; Principal component analysis; Wastewater treatment

## 1. Introduction

Model predictive control (MPC) is considered as an advanced control scheme to optimize wastewater treatment plants (WWTPs) (Kim et al., 2014; Vega et al., 2014). The application of MPC has been reported that 25 % aeration cost can be saved in a activated sludge plant (O'Brien et al., 2011). For the successfully use of MPC, real time monitoring of the treatment process and appropriate models which can describe process behaviors are required. However, the application of model predictive control in full-scale WWTPs is limited due to unavailability of capable process model and reliable online analyzers for process monitoring, especially for chemical oxygen demand (COD) and total phosphorus (TP) online measurement. Present literature reports are mainly focus on the selection of control structure (Gutierrez et al., 2014; Stare et al., 2007) and cost function and set point optimization (Vega et al., 2014). Consequently, most control scheme developed in the past is tested using simulation, but much fewer controllers have been implemented in full scale WWTPs (Olsson et al., 2014; Åmand et al., 2013).

Moving Bed Biofilm Reactor (MBBR) is a fluidized biofilm wastewater treatment system, which was widely used during last decades due to its higher treatment efficiency and lower footprint (Di Trapani et al., 2011; Ødegaard, 2006). The separation of biomass produced by MBBR system usually requires coagulant dosing to enhance biomass separation. Therefore, aeration and coagulant dosing control is essential to the performance of wastewater treatment plant with MBBR. For the purpose of improving MBBR plant performance and reduce operation cost, a MBBR model and influent wastewater characteristics are necessary to achieve model predictive control.

Although there is no standard MBBR model available as activated sludge model 1- ASM1 (Henze et al., 1987), modelling and dynamic simulation of MBBR has been carried out based on ASM1 (Mannina et al., 2011; Plattes et al., 2006), which proved that the bio-kinetic model in ASM1 are able to serve as reference for the modelling of MBBR system. Nowadays, fluidized biofilm model are available in simulation tools for wastewater treatment, e.g. STOAT® (WRc, Wiltshire, England), BioWin® (EnviroSim Associates Ltd., Canada). Consequently, modelling and dynamic simulation of a MBBR plant are possible to carry out for model predictive control purpose.

Principal components analysis (PCA) is a multivariable statistical method for detecting data collinearity and reduce dataset dimensions, which plays an essential role in software sensor development (Cecil and Kozlowska, 2010; Haimi et al., 2015). Recently, researchers employed PCA to determine correlation between process variables (Avella et al., 2011) and characterize water quality (Huang et al., 2012). Moreover, multiple regression coupled with PCA was used to monitor WWTP operation and predict process performance (Avella et al., 2011; Liu et al., 2014; Martín de la Vega et al., 2012). Data collected from WWTPs contain useful information and are not always explicit. Therefore, with the application of modern statistical methods, process engineers are able to obtain real-time information without the corresponding online sensors.

The objective of this work was to provide an approach to optimize full-scale WWTP performance and reduce operation cost in practice. This is achieved by a combined approach to enable model predictive control. Furthermore, the study provides wastewater characteristics of a full scale WWTP in Norway, based on which a MBBR model was built. Statistical monitoring of influent wastewater and dynamic simulation of WWTP performance based on predicted influent data was carried out. By applying the approach presented in this work, full-scale WWTPs are able to achieve model predictive control easily and economically.

## 2. Materials and methods

### 2.1 Description of the wastewater treatment plant

Solumstrand wastewater treatment plant locates in Drammen, in the south of Norway with the treatment capacity of serving 130 000 person equivalent. As is shown in Figure 1, the influent wastewater passes through the screen and grit trap to remove large solid and sand. The outlet of grit trap enters MBBR system for biological treatment. The biological treatment of this WWTP is consisted of four parallels, and each parallel has two aerobic MBBRs in series. The MBBR system is filled with bio-carriers with filling rate of 59%, and the specific surface area of bio-carriers is greater than 500 $m^2/m^3$. The MBBR system only has aerobic zone with short nominal hydraulic retention time (1.6 hours), which enables organic matter removal, but ammonia and soluble nitrogen removal are not required in this plant. The outlet of MBBR system carries detached biological particles and enters ballasted flocculation tank for solid separation. The ballasted flocculation and separation, also known as Actiflo (Plum et al., 1998), separates solid and water within a short period due to high settling velocity caused by micro-sand and coagulant dosing. Besides, coagulant dosing should secure phosphorus removal ratio larger than 94%.

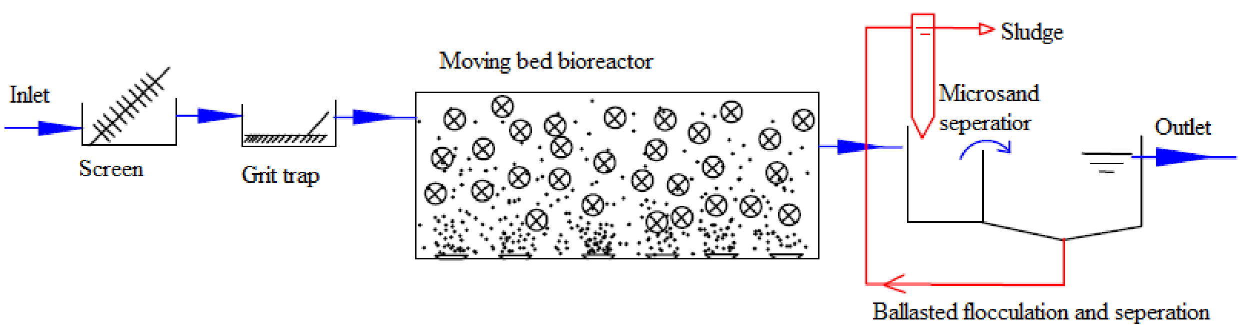


*Figure 1. Schematic diagram of the wastewater treatment plant*

### 2.2 Wastewater characteristics

Influent and effluent wastewater was continuously collected by automatic samplers and the wastewater characteristics was analyzed following Standard Methods for chemical oxygen demand (COD), ammonia, total nitrogen (TN), total phosphorus (TP), soluble phosphorus, and suspended solids (SS) (APHA, AWWA, 2012). The total sample collection period was 120 hours. Table 1 lists the average influent wastewater characteristic, which are also the input values of the steady state model.

*Table 1 Average influent wastewater characteristic, which serves as the input of steady state model*

| Symbol | Wastewater Composition | Values | Units |
|---|---|---|---|
| – | Total COD | 617 | mg COD $L^{-1}$ |
| – | Volatile fatty acids(VFA) | 10 | mg COD $L^{-1}$ |
| $S_s$ | Soluble biodegradable COD | 259 | mg COD $L^{-1}$ |
| $S_I$ | Soluble inert COD | 56 | mg COD $L^{-1}$ |
| $X_S$ | Particulate biodegradable COD (slowly biodegradable) | 218 | mg COD $L^{-1}$ |
| $X_I$ | Particulate inert COD | 73 | mg COD $L^{-1}$ |
| $X_{vi}$ | Influent volatile suspended solids | 190 | mg $L^{-1}$ |
| $X_{ni}$ | Influent non-volatile solids | 10 | mg $L^{-1}$ |
| $S_{NH}$ | Ammonia nitrogen in bulk liquid | 33.5 | mg N $L^{-1}$ |
| – | Soluble organic nitrogen | 2.88 | mg N $L^{-1}$ |
| $S_{NO}$ | Soluble nitrate and nitrite nitrogen | 0 | mg N $L^{-1}$ |
| – | Particulate organic nitrogen | 8.62 | mg N $L^{-1}$ |
| $S_{ND}$ | Soluble degradable organic nitrogen | 2.88 | mg N $L^{-1}$ |
| – | Soluble unbiodegradable organic nitrogen | 0 | mg N $L^{-1}$ |
| $X_{ND}$ | Particulate biodegradable organic nitrogen | 6.62 | mg N $L^{-1}$ |
| – | Particulate unbiodegradable organic nitrogen | 2 | mg N $L^{-1}$ |
| – | Soluble orthophosphate | 1.8 | mg P $L^{-1}$ |
| – | Soluble biodegradable phosphorus | 1.8 | mg P $L^{-1}$ |
| – | Soluble unbiodegradable phosphorus | 0 | mg P $L^{-1}$ |
| – | Particulate biodegradable phosphorus | 2.25 | mg P $L^{-1}$ |
| – | Particulate unbiodegradable phosphorus | 0.75 | mg P $L^{-1}$ |

## 2.3 Multivariate statistical analysis

Two multivariate statistical methods were applied to achieve statistical monitoring of the WWTP: Principal components analysis (PCA) and multiple regression. The mathematical procedure of PCA for statistical monitoring of WWTP was well explained in literature (Liu et al., 2014). In this work, we applied PCA to study the collinearity and correlation between influent variables, i.e., COD, soluble COD (SCOD), Flow, SS, ammonia ($NH_4$-N), PH, total nitrogen (TN), orthophosphate (OP) and total phosphorus (TP). The results of PCA were visualized in form of two types of plot: explained variances plot and loading plot. The explained variances plot indicates the proportion of total variance explained by each component, while the loading plot visualizes the correlation between original variables. In addition, if a small amount of principal components explains most variance of the data, it indicates high collinearity of original variables. Moreover, the original variables located closely on the loading plot indicates positive correlation, and variables are negatively correlated if they locate on the opposite of the origin. To verify the PCA model, cross validation method was applied.

Because it is expensive and slow to measure COD and total phosphorus by online analyzers, we applied multiple regression to predict influent COD and total phosphorus based on easily measured variables, e.g. flow rate and PH. Leverage correction method are used to validate the multiple regression model. The Unscrambler® software (Camo software company) was used for all the statistical analysis.

## 2.4 Model development

As stated above, a steady state model of the MBBR system was developed based on Activated Sludge Model 1 (Henze et al., 1987). The function of the steady state model was to determine model parameters. Average influent wastewater characteristic of 120 samples was applied as the model input. Table 2 lists the biological behavior of the MBBR system, based on activated sludge model 1 (ASM1). The full demonstration of process kinetics and stoichiometry can be found in ASM1 (Henze et al., 1987). In this study, we excluded anoxic growth of heterotrophs, because there is no anoxic zone in the MBBR system and only aerobic reaction was modelled. The notation of the state variables and process parameters are given in Table 3.

*Table 2 List of basic process model used to describe the biological behavior of MBBR system*

| j | Process | Process rate, $\rho_j$ |
|---|---|---|
| 1 | Aerobic growth of heterotrophs | $\rho_1 = \mu_H \left(\frac{S_S}{K_S+S_S}\right)\left(\frac{S_S}{K_{O,H}+S_S}\right) X_{B,H}$ |
| 2 | Aerobic growth of autotrophs | $\rho_2 = \mu_A \left(\frac{S_{NH}}{K_{NH}+S_{NH}}\right)\left(\frac{S_O}{K_{O,A}+S_O}\right) X_{B,A}$ |
| 3 | Decay of heterotrophs | $\rho_3 = b_H X_{B,H}$ |
| 4 | Decay of autotrophs | $\rho_4 = b_A X_{B,A}$ |
| 5 | Ammonification of soluble organic nitrogen | $\rho_5 = k_a S_{ND} X_{B,A}$ |
| 6 | Hydrolysis of entrapped | $\rho_6 = k_h \frac{X_h/X_{B,H}}{K_X+(X_S/X_{B,H})}\left[\left(\frac{S_O}{K_{O,A}+S_O}\right) + \eta_h \left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right] X_{B,H}$ |

| | | |
|---|---|---|
| 7 | Hydrolysis of entrapped organic nitrogen | $\rho_7 = k_h \frac{X_h/X_{B,H}}{K_X+(X_S/X_{B,H})}\left[\left(\frac{S_O}{K_{O,A}+S_O}\right)+\eta_h\left(\frac{K_{O,H}}{K_{O,H}+S_O}\right)\left(\frac{S_{NO}}{K_{NO}+S_{NO}}\right)\right]X_{B,H}(X_{ND}/X_S)$ |

*Table 3 Part of state variables and model parameters of biological model*

| Notation | Definition | Units |
|---|---|---|
| *State variables (other used state variables can be find from Table 1)* | | |
| $X_{B,H}$ | Active heterotrophic biomass | mg COD $L^{-1}$ |
| $X_{B,A}$ | Active autotrophic biomass | mg COD $L^{-1}$ |
| $S_O$ | Oxygen | mg COD $L^{-1}$ |
| *Kinetic parameters* | | |
| $\mu_H$ | Maximum specific growth rate for heterotrophic biomass | day $^{-1}$ |
| $K_S$ | COD half-saturation coefficient for heterotrophic biomass | mg COD $L^{-1}$ |
| $K_{O,H}$ | Oxygen half-saturation coefficient for heterotrophic biomass | mg COD $L^{-1}$ |
| $K_{NO}$ | Nitrate half-saturation coefficient for heterotrophic biomass | mg N $L^{-1}$ |
| $b_H$ | Decay coefficient for heterotrophic biomass | day $^{-1}$ |
| $\eta_H$ | Correction factor for hydrolysis under anoxic conditions | - |
| $k_h$ | Maximum specific hydrolysis rate | g COD (g COD · day)$^{-1}$ |
| $K_X$ | Half-saturation coefficient for hydrolysis of $X_S$ | g COD (g COD)$^{-1}$ |
| $\mu_A$ | Maximum specific growth rate of autotrophic biomass | day $^{-1}$ |
| $K_{NH}$ | Ammonia half-saturation coefficient for autotrophic biomass | mg N $L^{-1}$ |
| $b_A$ | Decay coefficient for autotrophic | day $^{-1}$ |
| $K_{O,A}$ | Oxygen half-saturation coefficient for autotrophic biomass | mg COD $L^{-1}$ |
| $k_a$ | Ammonification rate | L (mg COD · day)$^{-1}$ |
| $f_{bN}$ | Nitrogen content of biomass | g N (g COD)$^{-1}$ |

## 2.5 Model calibration

The model calibration has been carried out to minimize the difference between the measured and simulated values. As a simplified model for control purpose, the target model output are effluent COD, total phosphorus and ammonia concentration. The SS of MBBR outlet was also interested because it represents sludge production of MBBR system and determines the control of coagulant dosage for biomass separation. Thus, a steady state model with average influent data as input and default ASM1 values were assigned to the model. Latterly, model parameters related to interested variables were calibrated by comparing the steady state output and measured values.

## 2.6 Dynamic simulation of WWTP performance

We use STOAT to simulate the performance of WWTP. In detail, we employed the "Upflow biological aerated filter" to represent MBBR by setting medium surface area to 500 $m^2/m^3$. STOAT has no specific model for ballasted flocculation. We selected "chemical P removal" together with "Lamella separator" to represent ballasted flocculation section. Because micro-sand increases the settling velocity to more than 100 m/h, the sludge settling velocity coefficients were calibrated accordingly.

# 3. Results and discussion

## 3.1 Principal components analysis (PCA)

We applied PCA to summarize the collinearity and correlation of influent variables. Figure 2a shows the cumulative explained variance of PCA results, where the blue curve is the results of the fitted PCA model, and the red one shows the results of cross validation. As is shown in Figure 2a, the first principal component (PC-1) explains 50.1% of total variance of the data (calibrated), while the validated PC-1 explains 41.8% total variance. The first three principal components (PC-1, PC-2 and PC-3) of calibrated and validated results represent 88.9% and 81.9% of total variance, respectively. The results indicate high collinearity of WWTP influent data. Consequently, we can cluster the original variables into three groups and pick one variable from each group to represent the propagation trend of the corresponding group.

Figure 2b shows the loading of influent variables on the plane formed by PC-1 and PC-2. COD, SCOD, OP, Flow, TP and SS composite the first group with higher PC-1 loading. While PH has negative loading on both PC-1 and PC-2 coordinate, and locates on the opposite of the first group. It indicates that PH is negative correlated with the first group. Moreover, ammonia and total nitrogen forms the third group, which has high negative weight on PC-2. The third group and the first group are almost orthogonal with respect to the origin, which tells that ammonia and total nitrogen contain information that cannot be linearly expressed by variables in the first group. Overall, PCA proved the high collinearity of influent variables and suggested that three oringal varibles were sufficient to represent the variation of influent quality and quantity.

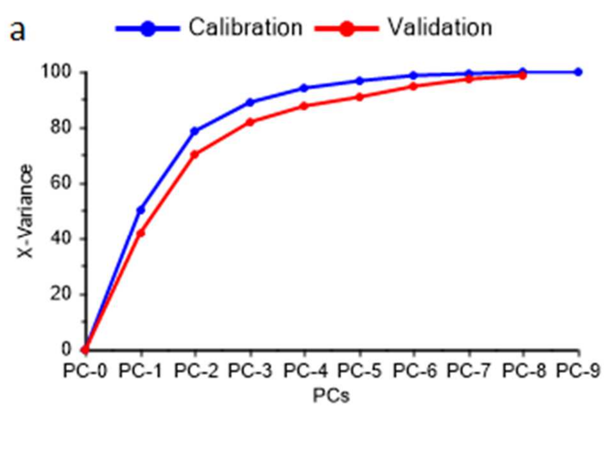


*Figure 2. Principal components analysis of influent flow and wastewater quality. a) Cumulative proportion of total variance of all PCs. The blue and red curve represent the results of PCA model and validated results based on cross-validation, respectively. b) Loading plot of influent variables on the plane of PC-1 and PC-2.The subscript in represent influent.*

## 3.2 Multiple regression

Online measurement of influent COD ($COD_{in}$) and influent TP ($TP_{in}$) is very important, because $COD_{in}$ and TP are two of the main input factors of the process model and determines whether model predictive control can be achieved or not. However, perspective from process online monitoring and control, COD and TP is slower and more expensive to measure by online analyzers. Therefore, we applied multiple regression method to use easy and fast responding variables (e.g. Flow, PH, ammonia) to predict slower and more expensive variables ($COD_{in}$, $TP_{in}$). Recent years multivariate prediction methods partial least squares (Amaral et al., 2013) and artificial neural network (Jing et al., 2015; Lou and Zhao, 2012; Nasr et al., 2012) are reported as useful prediction tools in the field of wastewater treatment. However, from the view of monitoring and control in practice, both partial least squares and artificial neural networks require continuously measurement of all the variables, which would increase the investment on online equipment and maintenance cost. Alternatively, a robust multivariate regression model with pre-selected variables based on PCA is preferred to predict real-time $COD_{in}$ and $TP_{in}$ values.

As is suggested by PCA results in Figure 2b, we picked one easier measured variable from each of the three groups to predict influent $COD_{in}$ and $TP_{in}$ to avoid overfitting. Therefore, influent flow, ammonia and PH were selected as predictor. Equation (1) and (2) are the multiple regression model for influent $COD_{in}$ and $TP_{in}$ respectively:

$$COD_{in} = 2708.2170 + 0.6806Flow + 11.4423Ammonia_{in} - 443.7516PH_{in} \quad (1)$$

$$TP_{in} = 0.5548 + 0.0067Flow + 0.0443Ammonia_{in} - 0.3926PH_{in} \quad (2)$$

The scatter plots of predicted $COD_{in}$ and $TP_{in}$ versus measured $COD_{in}$ and $TP_{in}$ are shown in Figure 3a and 3b respectively. The validated prediction based on leverage correction were evaluated in term of $R^2$. As is shown in Figure 3a, the linear expression of predicted $COD_{in}$ (Equation (1)) explains more than 81% of $COD_{in}$ variance. Meanwhile, the predicted $TP_{in}$ as linear expressed in Equation (2), descripts 77% total variance of measured $TP_{in}$. Considering the complexity of the full-scale WWTP, prediction accuracy of multiple regression with $R^2$ greater than 0.7 is acceptable. Thus, the multiple regression model is capable to predict influent COD and TP, which can serve as statistical monitoring tool to provide input values to the process model for model predictive control.

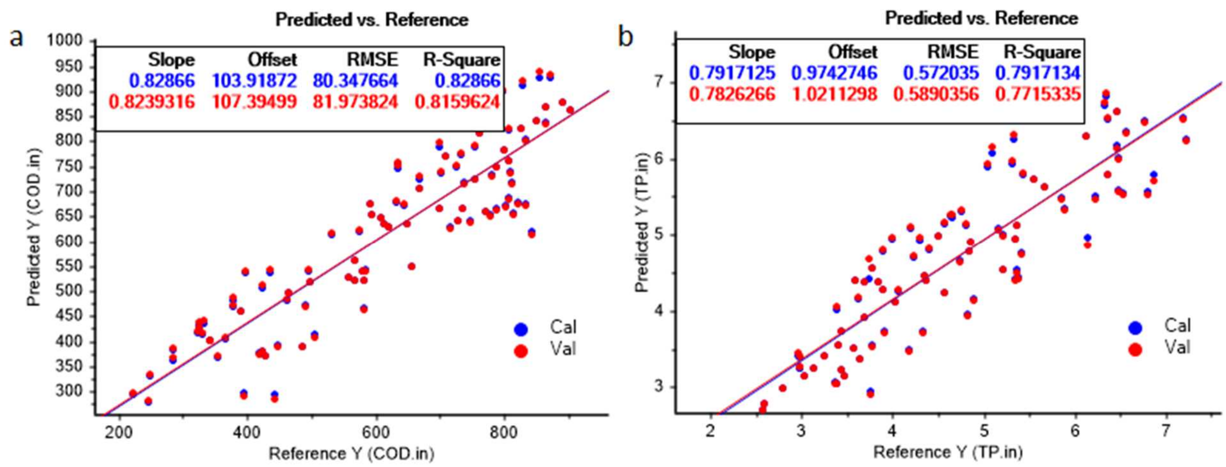


*Figure 3. a) Predicted $COD_{in}$ versus measured $COD_{in}$; b) Predicted $TP_{in}$ versus measured $TP_{in}$. The blue values are results of model output, while red values are validated model output based on Leverage Correction.*

### 3.3 Process model calibration

As mentioned previously, the model calibration has been carried out to minimize the error of steady state model output and measured data. More specifically, effluent COD, ammonia and the suspended solids (SS) of MBBR outlet were considered as state variables for the seeking of biological kinetic parameters. In addition, the effluent SS was used as state variable to determine setting velocity parameters of the separation tanks. The parameters obtained from calibration step are listed in Table 4. Typical values of model kinetic parameters in ASM1 are given in 10℃ and 20℃ (Henze et al., 1987), but the kinetic parameters in STOAT simulation environment are based on 15℃. To provide compared modelling result, the equivalent parameter values at 20 ℃ are calculated. Calibration of temperature dependency of bio-kinetic parameters was based on activated sludge model No. 2 - ASM2 (Henze et al., 1994). However, ASM2 applied Equation (3) for the calculation of bio-kinetic parameters under different temperature, while Equation (4) is used in STOAT. To find the equivalent model parameters at 20℃, the temperature coefficient "$\theta$" in STOAT was calculated from temperature coefficient "$a$" in ASM2, $\theta = ln a$ (Table 5).

$ASM2$: $$\mu = \mu_{max} \cdot a^{(T-T_{ref})} \quad (3)$$

STOAT: $\mu = \mu_{max} \cdot e^{\theta(T-15)}$ (4)

The adopted parameters have been compared with reference values in ASM1. The heterotrophs growth rate ( $\mu_H$ ) and decay rate ( $b_H$ ) are almost consistent with reference values. However, parameters related to ammonia removal are significantly different with reference values. As the MBBR system is not used to remove ammonia, much lower autotrophic bacteria growth rate ( $\mu_A$ ) was adopted in this model. Besides, a relative higher ammonification rate ($k_a$) was used to achieve nitrogen balance. However, the reason of higher ammonification in this system is unknown, and further study is necessary to figure out the ammonification mechanism. Overall, the coefficients related to ammonia removal have a higher influence on the model output than those related to COD removal.

*Table 4 Calibrated process model parameters and reference values from ASM1.*

| Parameters | Values in STOAT at 15℃ | Parameter unit in STOAT | Equivalent values at 20℃ | Reference values at 20℃ | Parameter unit at 20℃ |
|---|---|---|---|---|---|
| $\mu_H$ | 0.19 | $h^{-1}$ | 6.40 | 6 | $day^{-1}$ |
| $\mu_A$ | 0.008 | $h^{-1}$ | 0.34 | 0.8 | $day^{-1}$ |
| $b_H$ | 0.0147 | $h^{-1}$ | 0.50 | 0.62 | $day^{-1}$ |
| $b_A$ | 0.0036 | $h^{-1}$ | 0.15 | - | $day^{-1}$ |
| $k_h$ | 0.07 | $h^{-1}$ | 2.04 | 3 | $day^{-1}$ |
| $k_a$ | 0.004 | $h^{-1}$ | 0.12 | 0.05 | $day^{-1}$ |
| $Y_H$ | 0.67 | mg COD $(mg\ COD)^{-1}$ | 0.67 | 0.67 | mg COD $(mg\ COD)^{-1}$ |
| $Y_A$ | 0.24 | mg COD$(mg\ N)^{-1}$ | 0.24 | 0.24 | mg COD$(mg\ N)^{-1}$ |
| $f_{bN}$ | 0.005 | g N$(g\ COD)^{-1}$ | 0.005 | - | g N$(g\ COD)^{-1}$ |
| K | 4000 | Settling coefficients K and h for the settling velocity equation: $= C^h$ , where C | | | |
| h | 1 | represents suspended solids concentration. | | | |

*Table 5 Temperature coefficients used for the calculation of equivalent MBBR model parameters at* 20℃.

| Process | $\theta$ | a | Degree of dependency |
|---|---|---|---|
| Hydrolysis | 0.0392 | 1.04 | Low |
| Heterotrophs, fermentation | 0.0677 | 1.07 | Medium |
| Nitrification | 0.1133 | 1.12 | High |

## 3.4 Dynamic simulation

To test the possibility of achieving model predictive control, both predicted influent (multiple regression output) and measured influent data were used as input of wastewater treatment process model to simulate the WWTP. Figure 4 shows the dynamic simulation results of plant effluent COD, ammonia, TP and suspended solids of MBBR outlet (before separation). SS of MBBR outlet represents sludge production of MBBR. The goodness of fitting in terms of $R^2$ are given in Table 6. Generally, the model output of SS (Figure 4a), COD (Figure 4b) and ammonia (Figure 4c) are well fitted to the measured data. In particular, the model output based on measured input have higher $R^2$ values than those based on predicted values. This is reasonable because the predicted influent COD and TP had some errors to real values. The output values of ammonia based on measured influent ammonia overlapped with those based on predicted values (Figure 4c), because influent ammonia are regarded as easier measured data which is not predicted by multiple regression. However, the simulated phosphorus results were quite higher than measured data (Figure 4d). Microorganism in MBBR system assimilated more than 1.7 mg/L, but the biological model based on ASM does not contain any anabolism functions related to phosphorus removal. For that reason, the MBBR model passed all the phosphorus content to the separation tank without removal and resulted in higher model output of total phosphorus. On the other hand, the results indicate that phosphorus removal by chemical precipitation requires negligible coagulant in this WWTP, because soluble phosphorus was already transformed to particulate phosphorus in biomass. In other words, only the SS of MBBR outlet determines coagulant dosage into separation tanks.

As is given in Table 6, the $R^2$ of model output of MBBR suspended solids, effluent COD and ammonia based on predicted influent are 0.507, 0.504 and 0.659, respectively. According to literature report (Avella et al., 2011), correlation coefficients $R^2$ greater than 0.5 were acceptable to say that model output match measured data well. Furthermore, the SS of MBBR outlet can be used to determine coagulant dosage into the ballasted separation tank, while the model output of effluent COD and ammonia can be used to control real-time airflow to the MBBR system. Therefore, the combined approach of statistical monitoring of influent constituent and process modelling is capable to provide input data for model predictive control of airflow and coagulant dosage.

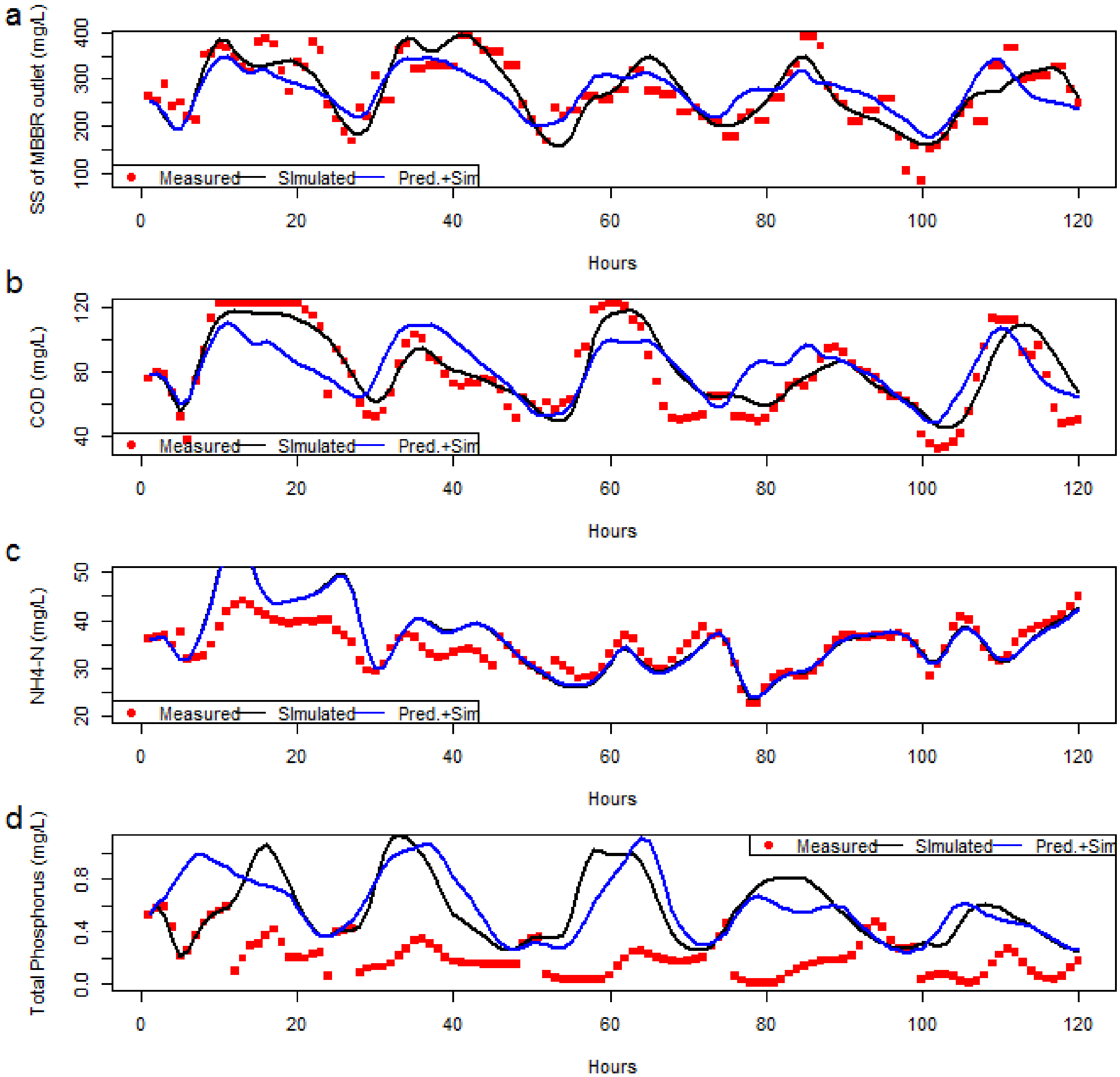


*Figure 4 Dynamic simulation results of a) SS of MBBR outlet; b) effluent COD; c) effluent ammonia; d) effluent total phosphorus. The red, black and blue values represent measured data, simulated data based on measured influent and simulated data based on predicted influent data, respectively.*

*Table 6 Goodness of fitting in terms of $R^2$ of dynamic simulation*

| Variables | $R^2$ | | |
|---|---|---|---|
| | Measured VS. Simulated | Measured VS. Pred.+Sim. | Simulated VS. Pred.+Sim. |
| $SS_{MBBR}$ | 0.711 | 0.507 | 0.713 |
| $COD_{outlet}$ | 0.798 | 0.504 | 0.527 |
| $Ammonia_{outlet}$ | 0.666 | 0.659 | 0.999 |
| $TP_{outlet}$ | 0.003 | 0.038 | 0.490 |

## 4. Conclusion

Model predictive control in full-scale wastewater treatment plant has been limited due to on-line monitoring and capable process models. This study provide a combined approach of statistical monitoring and process modelling to achieve model predictive control of the WWTP.

The statistical monitoring of influent COD and total phosphorus (TP) were achevied by combining principle components analysis (PCA) and multiple regression. PCA suggested influent flow, ammonia and PH as predictor variables for COD and TP. Multiple regression shows that the predicted COD and TP allowed description of 81.6% and 77.2% variance of influent COD and TP. A WWTP process model contains MBBR and ballasted separation was built to simulate the performance of a full-scale WWTP. The predicted influent wastewater was used as the input of the process model to simulate the dymamic performance of the treatment process. The results shown that the model was capable to predict sludge production and outlet COD concentration, which determines coagulant dosage and air flow of MBBR system. Therefore, it is possible to apply MPC to control aeration and chemical dosage by applying statistical monitoring of the WWTP. This study provide an convienent and economic approach to achieve better control of wastewater treatment plant.

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