Modeling and control of WRRF biogas production

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Abstract

Wastewater treatment sector uses about 1 percent of total energy consumption in European Union, hence development of energy-efficient digital technologies is an urgent challenge. The aim of this article is to develop energy-efficient control strategies for biogas production from sewage sludge at water resource recovery facilities (WRRF). The case study is developed in collaboration Veas WRRF, Norway. The Veas biogas plant is operated semi-continuously in mesophilic conditions. The process includes inlet sludge pumps, four anaerobic digesters, heat exchangers for sludge heating, pumps for sludge recirculation and a compressor for gas recirculation. The process has two controlled variables, biogas flowrate and digester temperature, the main disturbance is the inlet substrate composition. The manipulated variables are flowrates of the inlet sludge, heating medium, and sludge recirculation. The real semi-continuous operation approximated as continuous operation with two hour moving averaging. Transfer functions were identified from the pre-processed data. The accuracy of the models was sufficient $14-60\%$. The transfer functions were used to design control strategies with PID-controllers and model predictive controller (MPC). The results show that both control strategies can increase biogas production and decrease variability in controlled and manipulated variables compared to the plant operation. MPC gave the best results, increasing biogas production up to 10 % and decreasing variability in controlled variables by $50-80\%$ and by $92-99\%$ in manipulated variables. These results indicate that implementation of advanced control technologies can improve the energy efficiency of biogas production.

1 Introduction

Wastewater treatment sector uses about 1 percent of total energy consumption in European Union, generating a high energy bill covered by the taxpayers (EuropeanCommission, 2022). The EU has set a goal for energy-neutrality in the wastewater sector by 2040 with renewable energy production, carbon neutrality and a resource-efficient bioeconomy (EuropeanCommission, 2021b) (EuropeanCommission, 2021a). Norwegian wastewater industries have ambitious targets to reduce the environmental impact (NorskVann, 2017), therefore, investment in energy-efficient biogas production is essential. Biogas can replace diesel and other fossil energy carriers in transport industry increasing the income for WRRFs and reducing the environmental impacts associated with biogas production and use. In our previous work we have reviewed digital technologies that can improve energy-efficiency in water industry to meet these demands (Komulainen & Johansen, 2021).

Several complex models have been suggested and applied for biogas production from sewage sludge. Veas WRRF biogas production has previously been modeled with the anaerobic digestion model nr 1, ADM1, with complex influent characterization by (Bergland & Bakke, 2016). (Attar & Haugen, 2019) have continued the work adapting to a simpler AM2 model with two substrate types. The simplest first principles modeling approach is continuous stirred tank reactor, a chemostat, with only one substrate type (Seborg et al., 2017). In recent master thesis work in collaboration with Veas, Mukhtar (2023) used the AM2 model to identify transfer function models for the biogas production, and plant data to identify models of the heat exchanger and pumps. Using these transfer function models, Mukhtar (2023) developed PID and MPC control algorithms for the Veas biogas process.

As VEAS biogas process has only one online process measurements related to the substrate, total suspended solids, in this article, we continue Mukhtar's work by identifying transfer function models of the anaerobic digestion process directly from plant data. Further, we use the new transfer function models to develop and test energy-efficient control strategies. Our research question is "Which control algorithms can optimize energy consumption and maximize biogas production?"

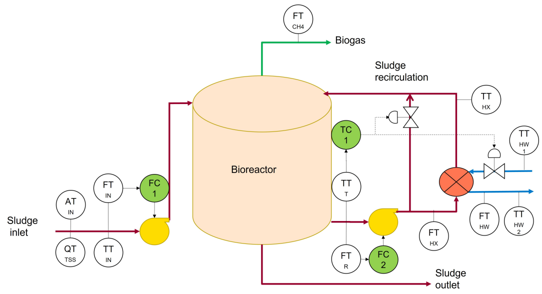

Figure 1. Simplified Veas biogas process with instrumentation

2 Materials and Methods

2.1 Software

Matlab software package version R2023a was used for the control experiments and System Identification Toolbox for estimation of the model parameters. Simulink solver algorithm was ode23s with automatic settings for the time step and error tolerance.

2.2 Biogas plant and instrumentation

A simplified illustration of the biogas plant and instrumentation is given in Figure 1. The Veas biogas plant has sequential operation with four bioreactors. The sequence for one bioreactor includes filling 5/6 of the tank with fresh sludge, heating the sludge until bioreactor temperature T reaches 37^oC. The anaerobic digestion process in mesophilic conditions is operated for about three weeks. The bioreactor is constantly fed with fresh sludge, flowrate F_{in} in and out of the bioreactor are the same, i.e. the bioreactor tank has constant hold-up. The sludge and biogas are semi-continuously recirculated in the bioreactor to avoid sedimentation. Measurements of all unit operations, except biogas recirculation rate are available, listed in Table 1.

2.3 Data collection and pre-processing

The online data set and laboratory data sets were collected for a period of one month 30.6.2022-30.7.2022. ABB Edge Insight was used to collect the online data from the SCADA system in .csv format. The laboratory data set was in .xlsx format.
The outliers in the online data set were first removed. Then, the missing values in the online data sets were filled.

2.4 Modeling

Transfer functions can be used for simplified modeling and control strategy design. These linear models can be developed following system identification procedure by (Ljung, 1999). The relationship between input variables $U_i(t)$ and output variable $Y(t)$ are assumed to be first order models with gain (K_p), time constant (T_p) and delay (T_d), presented in Equation 1:

Table 1. Online measurements

Symbol	Description	Unit
F_{in}	Flowrate sludge inlet	m^3/h
TSS_{in}	Total suspended solids in sludge at inlet	g/m^3
RPM_{in}	Pump speed inlet	rpm
T_{in}	Temperature sludge inlet	^oC
T_{HX}	Temperature sludge after HX	^oC
T	Temperature bioreactor	^oC
F_{HW}	Flowrate hot water in	m^3/h
T_{HW1}	Temperature hot water in	^oC
T_{HW2}	Temperature hot water out	^oC
R	Flowrate sludge recirculation	m^3/h
F_{HX}	Flowrate sludge via heat exchanger	m^3/h
RPM_R	Recycle pump speed	rpm
F_{CH4}	Biogas out	m^3/h

$$TF(s) = \frac{Y(s)}{U_i(s)} = \frac{K_p}{(T_p s + 1)} e^{-T_d s} \quad (1)$$

2.5 Control methods

The transfer function models identified from Veas data were used for parametrization and tuning of the PID controllers and the MPC controllers. Tuning rules were adapted from (Skogestad, 2003) and (Seborg et al., 2017).

2.6 Error indices

The data-driven models are compared with each other using the fitness index (FIT) and integral of absolute error (IAE) between the real measurements $y_{i,measurement}$ and the model calculated output $y_{i,model}$ over N samples. The fitness index is calculated with Equation 2, where norm is the Euclidean norm.

$$FIT = \left(1 - \frac{norm(y_{i,meas} - y_{i,model})}{norm(y_{i,meas} - y_{i,mean})}\right)100 \quad (2)$$

$$IAE = \int_0^N |y_{i,meas}(t) - y_{i,model}(t)|\, dt \quad (3)$$

The control results are evaluated using the integral of absolute error between the setpoint and measured value

$$IAE = \int_0^N |y_{sp}(t) - y(t)|\, dt \quad (4)$$

and integral of absolute movement in manipulated variables:

$$IAMV = \int_0^N |u_i(t) - u_i(t-1)|\, dt \quad (5)$$

Table 2. Mean, standard deviation and applied scaling of process variables.

Variable	Mean	St.Dev	Scaling
F_{IN}	7.049	0.8763	120 min MA
F_{HX}	42.2324	0.0541	120 min MA
T_{IN}	21.4041	0.8398	120 min MA
T_{HX}	38.3261	0.5049	120 min MA
TSS_{IN}	6.7175	0.7719	120 min MA
F_{HW}	12.2306	7.7764	120 min MA
T_{HW}	52.9991	0.8505	120 min MA
F_{CH4}	123.9211	13.7746	120 min MA
T	37.0662	0.0424	120 min MA

3 Results

3.1 Data description

For the modeling, online data from Veas WRRF were used for period 30.6.2022-30.7.2022 with 10 minutes sampling time. First half of the data was used for estimation and second half for validation of the transfer function models. As the size of the data set is limited, the same data set was used for the control experiments. The process variables with mean and standard deviation are presented in Table 2.

3.2 Data pre-processing

The outliers in the data set were identified based on the three standard deviation rule, and removed. Then, the missing values in the data sets were filled in using Matlab knnimpute function based on nearest-neighbor imputation method. The inlet temperature sensor T_{IN} is placed into a joint pipeline between inlet sludge and recirculated sludge, where recirculation is on 30 minutes and off 30 minutes. Hence, for T_{IN} before the moving averaging, the inlet temperature values over 20 ^oC were removed and replaced with previous temperature value under 20 ^oC.

Due to the sequential operation of the Veas biogas plant, all the variables exhibit high variation. The sampling interval is 10 minutes. Different moving average window sizes were tested, but considering the process time constants of 300-2800 minutes, 120 minutes (12 samples) window was chosen as a window of 60 minutes did not decrease significantly the high variation in the raw data.
A moving average of 120 minutes was applied to all input and output data. Without the moving average, the system identification did not work properly. Then, the mean values, given in Table 2, were removed.

3.3 Modeling

For control purposes, the process was to be modeled using transfer functions identified from plant data. To allow control strategy design, the process was divided into three subprocesses with one output variable each. The controlled variables are (1) biogas flowrate F_{CH4} out of the bioreactor, (2) temperature T in bioreactor and (3) recycled sludge outlet temperature T_{HX} after a heat exchanger. Different combinations of input variables were tested for the subprocesses. Some of the input variables were omitted if the parameter uncertainty got very high (thousand times larger than the parameter value) or if the time constant was very high (many thousands of minutes). For example, recycle rate R, is dependent on heated sludge flow rate F_{HX}, and omitting R improved the modeling results.

The biogas production F_{CH4} in the bioreactor is dependent on inlet sludge flowrate F, inlet suspended solids percentage TSS_{in}, inlet temperature T_{in} and recirculated and heated sludge flow rate F_{HX} and temperature T_{HX}. Surprisingly, inlet temperature T_{in} gave negative relationship to biogas production and was omitted as input variable. The model parameters and model fitness are given in Table 3. The model prediction and the measured value are illustrated in Figure 2. The model prediction is following the main trends of the biogas production. As an unmeasured part of the biogas is recirculated back to the digesters, the measured value has a rapid variation that the model cannot capture.

$$\begin{aligned} &F_{CH4}(s) = TF_{11}(s)F(s) + TF_{12}(s)TSS_{in}(s) \\ &+ TF_{13}(s)T_{in}(s) + TF_{14}(s)F_{HX}(s) + TF_{15}(s)T_{HX}(s) \end{aligned} \tag{6}$$

Temperature in the bioreactor T is dependent on the same input variables, except inlet suspended solids percentage TSS_{in}. The model parameters and model fitness are given in Table 4. The model prediction and the measured value are illustrated in Figure 3. The model prediction follows the main trends in the measurement, but the rapid variation in the data was not captured.

$$\begin{aligned} &T(s) = TF_{21}(s)F(s) + TF_{22}(s)TSS_{in}(s) \\ &+ TF_{23}(s)T_{in}(s) + TF_{24}(s)F_{HX}(s) + TF_{25}(s)T_{HX}(s) \end{aligned} \tag{7}$$

Further, the heat exchanger was modeled as first order transfer function between the HX outlet temperature T_{HX} and hot water variables F_{HW} and T_{HW1} and sludge flowrate F_{HX} and temperature $T(s)$. The model parameters and model fitness are given in Table 5.

The model prediction and the measured value are illustrated in Figure 4 . The model prediction follows the main trends in the measurement.

$$T_{HX}(s) = TF_{31}(s)F_{HW}(s) + TF_{32}(s)F_{HX}(s) + TF_{33}(s)T_{HW1}(s) + TF_{34}(s)T_(s) \tag{8}$$

Table 3. Transfer function parameters for between F_{CH4} and inputs.

Input	Kp [-]	Tp1 [min]	Td [min]
F_{in}	12.76	1350	0
TSS_{in}	11.80	101	167
Tin_{in}	0	0	0
F_{HX}	-21.15	29	266
T_{HX}	4.77	432	0
Error index	FITest %	FITval %	
	59.57	18.52	

Table 4. Transfer function parameters for bioreactor temperature T and inputs.

Input	Kp [-]	Tp1 [min]	Td [min]
F_{in}	$1.549 \cdot 10^{-}3$	0	298
TSS_{in}	0	0	0
Tin_{in}	$31.05 \cdot 10^{-}3$	853	233
F_{HX}	$-171.6 \cdot 10^{-}3$	20	87
T_{HX}	$111.9 \cdot 10^{-}3$	379	300
Error index	FITest %	FITval %	
	17.00	14.24	

Table 5. Transfer function parameters between heat exchanger outlet sludge temperature T_{HX} and inputs.

Input	Kp [-]	Tp1 [min]	Td [min]
F_{HX}	-0.19072	0	0
T	0	0	0
F_{HW}	0.059157	0	0
T_{HW1}	0.650889	0	0
Error index	FITest %	FITval %	
	47.04	48.27	

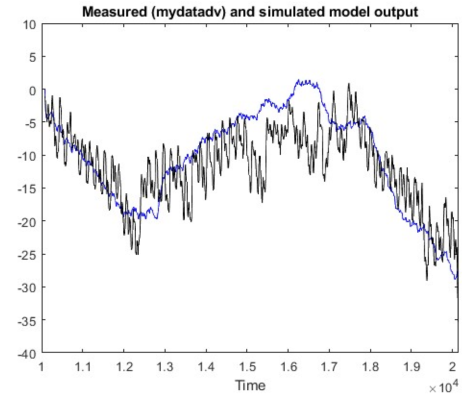

Figure 2. Scaled biogas flowrate F_{CH4} data (black) and model (blue), time in minutes.

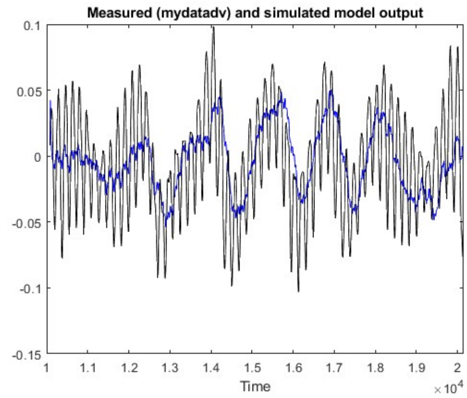

Figure 3. Scaled bioreactor temperature T data (black) and model (blue), time in minutes.

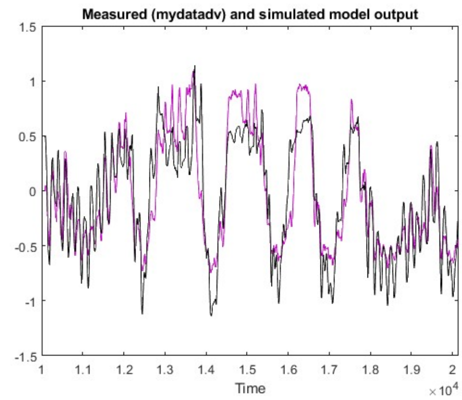

Figure 4. Scaled recycled sludge temperature out of heat exchanger T_{HX} data (black) and model (magenta), time in minutes.

3.4 Control

The control aim is to maximize biogas production F_{CH4} and minimize costs for pumping inlet sludge F_{in}, pumping recirculated sludge F_{HX} and heating sludge T_{HX}, while maintaining optimal temperature T in the bioreactor. Controlled variables are biogas production F_{CH4}, bioreactor temperature T and recirculated sludge temperature T_{HX}. The manipulated variables are flowrate of sludge in F_{HX}, flowrate of recycled and heated sludge F_{HX}, and flowrate of hot water F_{HW}. The disturbance variables of the system are total suspended solids in TSS_{in}, inlet sludge temperature T_{in} and hot water temperature T_{HW1} into the heat exchanger Two control strategies were designed based on the existing control strategy at Veas WRRF and a recent master thesis work (Mukhtar, 2023). The first control strategy with three PID controllers is illustrated in Figure 5 and, the second control strategy with one model predictive controller is presented in Figure 6.

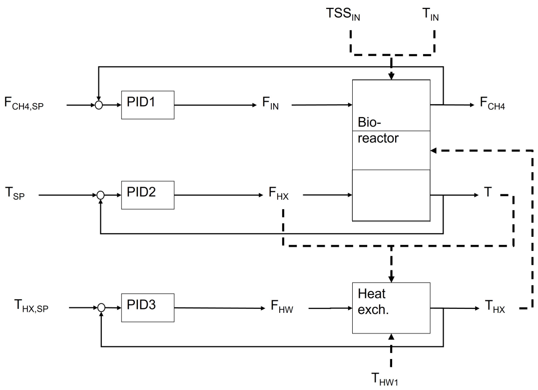

Figure 5. Suggested PID control strategy.

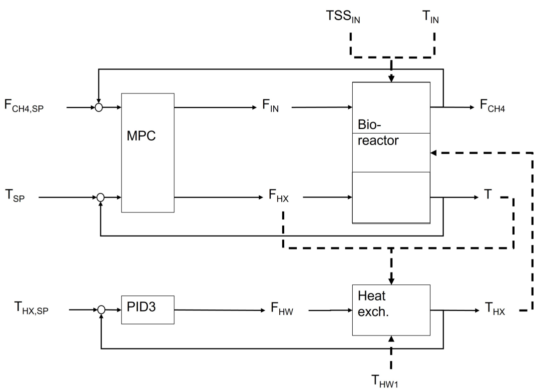

Figure 6. Suggested MPC strategy.

3.4.1 *PID controllers*

The PID controllers were parametrized using Skogestad tuning rules for first order system, the parameters are given in Table 6. The minimum and maximum limits for the PID controller outputs were minimum and maximum values from the scaled data of the manipulated variables.

Table 6. PID parameters.

Controller	Kc	Ti	tauc	min	max
PID1	0.5289	800	200	-2.03	1.45
PID2	-0.3998	19.7209	200	-0.14	0.19
PID3	0.0845	-	200	-12.00	15.48

3.4.2 *Model Predictive Controller*

The MPC controller tuning parameters are given in Table 7. The settling time was calculated as average between TFa and TFb. The MPC sampling time was chosen to keep the model horizon N, a ratio between settling time and sampling time under 120. Control horizon M was chosen between 1/3 and 1/2 of N. The prediction horizon was a sum of model horizon N and control horizon M. The output variables biogas flowrate F_{CH4} and bioreactor temperature T were weighed 10:1 (Q) to give more importance for the biogas production. Saturation limits for manipulated variables were the same as for PID controllers. Movements in the manipulated variables, F_{in}, F_{HX}, were restricted with Rd values. Tested Rd values included 1-1, 5-15, 10-60, 35-210, 50-300, 100-500. Through extensive simulation tests 35-210 gave lowest values on flowrate of inlet sludge F_{in}, reduced oscillations in both flowrates, and avoided flowrates to remain at saturation limits.

Table 7. MPC parameters.

MPC controller			
MPC sampling time	Ts	10	
Model horizon	N	$22 \cdot Ts$	
Control horizon	M	$11 \cdot Ts$	
Prediction horizon	P	$33 \cdot Ts$	
CV weights	Q	F_{CH4}	T
		2	1
MV saturation limits		F_{in}	F_{HX}
	min	-2.03	-0.14
	max	1.45	0.19
MV rate	Rd	F_{in}	F_{HX}
weights		35	210

3.4.3 *Controller testing*

The controllers were tested using the transfer functions as process model. The testing was performed using the plant data as disturbance variables (inlet sludge temperature T_{IN}, inlet sludge total suspended solids TSS_{IN} and hot water inlet temperature T_{HW1}). Setpoint for bioreactor temperature T and for recycled and heated sludge T_{HX} to follow a 240 sample moving mean of the original data. As the aim is to improve biogas production, setpoint for biogas flowrate $FCH4$ was created as 240 sample moving mean multiplied by 1.00, 1.03, 1.05 and 1.10. Multiplication by 1.00 allows fair comparison between the real operation (orig.) and the proposed control strategies, whereas the increased biogas flowrate setpoint can show how much increase production will affect the manipulated variables. The integral of absolute error was calculated between setpoint and measurement for the controlled variables biogas flowrate $FCH4$ and bioreactor temperature T . Recycled and heated sludge T_{HX} is an intermittent variable between the bioreactor and heat exchanger, and therefore not added to the results table. Integral of absolute movement in the manipulated variables was calculated for inlet sludge flowrate F_{IN}, sludge recirculation rate F_{HX} and hot water flowrate F_{HW}.

The results for controlled variables in Table 8 show that biogas production $FCH4$ can be increased up to 10 % and variability (IAE) in controlled variables decreased with both PID and MPC strategies. The results for manipulated variables in Table 9 show that the MPC controller gives $92-99\%$ lower variability (IAMV) in the manipulated variables than the original control strategy, where as the PID strategy gives much higher variablity (IAMV) in the inlet sludge flowrate but $25-76\%$ lower for the other manipulated variables than the original control strategy. The integral of the scaled inlet sludge flowrate F_{in} and hot water flowrate F_{HW} have lowest values for the MPC controller without setpoint increase. When the biogas production setpoint is increased, naturally also inlet sludge flowrate F_{in} is increased.

Hence, the best control results for both controlled and manipulated variables are achieved with the MPC controller. The visual results for the scenario without setpoint increase are shown in Figures 7 - 11 .

Table 8. Control results CV

Control strategy	Int F_{CH4}	IAE F_{CH4}	IAE T	IAE T_{HX}
	$\cdot 10^6$	$\cdot 10^4$	$\cdot 10^2$	$\cdot 10^3$
Orig.	2.50	6.51	7.06	8.17
PID	2.50	1.85	0.92	1.62
PID 3%	2.57	1.90	0.92	1.62
PID 5%	2.62	1.94	0.92	1.62
PID 10%	2.75	2.04	0.93	1.62
MPC	2.50	1.89	2.86	1.61
MPC 3%	2.58	2.06	3.05	1.61
MPC 5%	2.62	2.21	3.10	1.61
MPC 10%	2.73	3.31	3.71	1.61

Table 9. Control results MV

Control strategy	Int F_{IN}	Int F_{HW}	IAMV F_{IN}	IAMV F_{HX}	IAMV F_{HW}
	$\cdot 10^3$	$\cdot 10^3$	$\cdot 10^3$	$\cdot 10^3$	$\cdot 10^3$
Orig.	-0.018	-0.003	5.85	1.06	185.7
PID	-1.626	1.21	19.45	0.80	43.95
PID 3%	4.642	2.50	20.35	0.80	43.93
PID 5%	8.816	2.61	20.95	0.80	43.94
PID 10%	19.26	2.92	22.59	0.79	43.94
MPC	-3.000	-1.32	0.46	0.040	1.92
MPC 3%	2.933	-1.60	0.45	0.039	1.91
MPC 5%	6.297	-2.92	0.45	0.037	1.92
MPC 10%	14.31	-5.21	0.31	0.025	1.93

4 Discussion and Summary

Development of energy-efficient control methods is crucial to reach the EU waste water directive target of energy-neutral of WRRF operation. Therefore, continuous efforts should be made to implement novel control technologies at municipal and industrial WRRFs. The work on modeling and control strategy development has been done in collaboration with Veas municipal WRRF in Norway. One of the main challenges on for control strategy development is availability of industrial measurements necessary to parametrise a state-of-the-art anaerobic digestion model. Hence, in this work a simplified approach with linear dynamic models was chosen. Three transfer function models were identified to model the biogas production in a bioreactor, temperature in the bioreactor and outlet temperature of the recirculation heat exchanger. The modeling results show sufficient fit $14\%-60\%$ to the industrial data.

Based on the transfer functions, two control strategies with PID and MPC controllers were designed. The control results show that both PID and MPC strategies decrease the variablity in the controlled and manipulated variables. MPC gave the best results, increasing biogas production up to 10 % and decreasing variability in controlled variables by $50-80\%$ and $92-99\%$ in manipulated variables. The answer to our research question is both PID and MPC control algorithms can optimize energy consumption and maximize biogas production. Best results can be achieved with MPC algorithm. Our results indicate that implementation of advanced control technologies can improve the energy-efficiency of biogas production at WRRFs.

We suggest future modeling work estimate the biogas recirculation rate, for example using a Kalman filter and research on modeling methods feasible for sequential operation. Other data-driven modeling methods could be tested for example using time-series

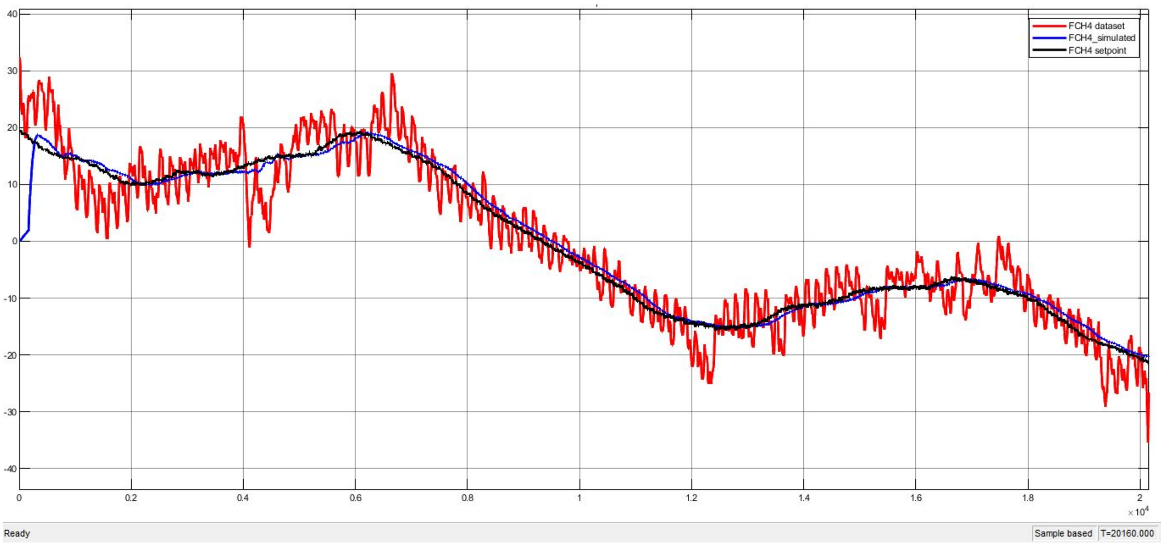

Figure 7. Biogas flowrate F_{CH4} original data (red), 24sample-moving average setpoint (black) and MPC simuled value (blue). Data is scaled, time in minutes.

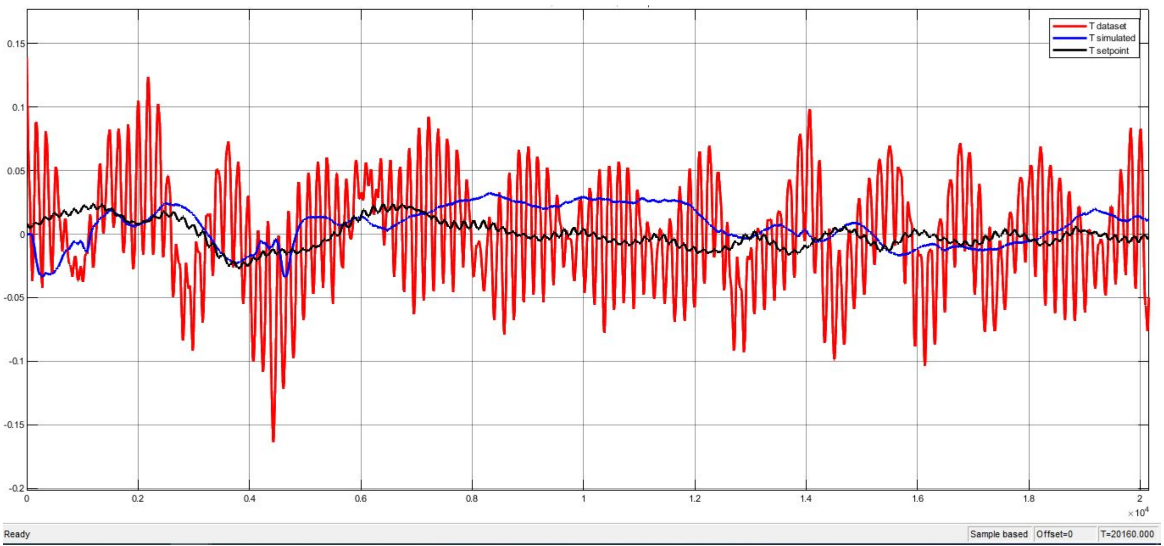

Figure 8. Bioreactor temperature T original data (red), 24sample-moving average setpoint (black) and MPC simuled value (blue). Data is scaled, time in minutes.

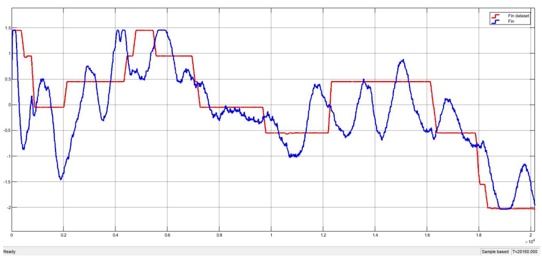

Figure 9. Inlet sludge flowrate F_{in} original data (red) and MPC simuled value (blue). Data is scaled, time in minutes.

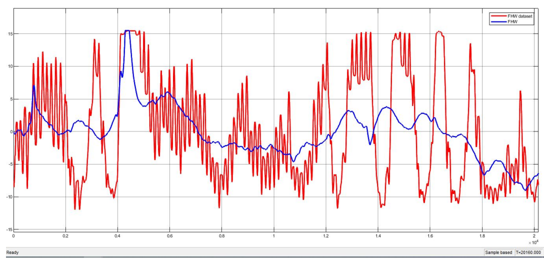

Figure 10. Hot water flowrate F_{HW} original data (red) and MPC simuled value (blue). Data is scaled, time in minutes.

models or Long-Short-Term-Memory networks could be tested. Future work on control should include predictive control algorithms that can account for sludge variations based on seasonality and weather progno-

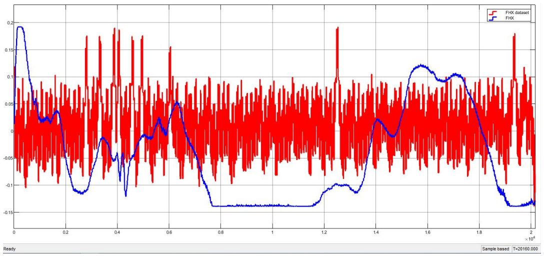

Figure 11. Sludge recirculation flowrate F_{HX} original data (red) and MPC simuled value (blue). Data is scaled, time in minutes.

sis. Adaptive control with AI approach could be explored.

5 Acknowledgements and Contributions

OsloMet is greatfully acknowledged for funding the MaxBiogas pre-project. Contributions:
Kristine Haualand, Kjell Rune Jonassen and Hilde Johansen have contributed to idea development and data collection from Veas wastewater resource recovery facility. Professor Tiina Komulainen is the principal investigator of the project. She has supervised modeling work and provided the initial ideas on modeling and control design and TF model structures. Master student Bilal Mukhtar has done initial work on identifying the transfer functions from Veas data, and setting together bioreactor model and control strategy. Research assistant Truls Ødegaard and Professor Komulainen have revised the biogas production model and control strategy based on Bilal Mukhtar's findings.
Head of studies Simen Antonsen has co-supervised Bilal Mukhtar's master project and done critical review of this article.

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