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Towards Model Predictive Control on Anaerobic Digestion Process

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Abstract: Anaerobic digestion with biogas production has both economic and environmental benefits. 25% of all bioenergy in the future could potentially be sourced from biogas. Although anaerobic digesters have seen wide applicability, they typically perform below their optimum performance as a consequence of the complexity of the underlying process. This work involves the development of a generic advanced process control system to optimize the performance of anaerobic digesters. There is a requirement for a configurable monitoring and optimization system with associated sensors to optimize the production of biogas, combined with a degree of flexibility for quality and content of the digestate.

Keywords: Modeling, Automation, Inferential Sensors, Anaerobic Digestion, Nonlinear, Multivariable.

1. INTRODUCTION

In recent years, waste has been recognized as a significantly underutilized resource and hence the emphasis has now shifted from disposal-based solutions, such as landfill, to the process-based solutions of recovery and recycling. There is a new sense of direction and an increasing focus on utilizing organic waste for the generation of energy. One of the leading technologies to support this drive towards the exploitation of waste is that of anaerobic digestion (AD). The techniques behind AD have existed for over a century [1]. However, the dynamic nature, non-linear behaviour and lack of expert knowledge of the whole process, has resulted in AD processes performing less than optimally with only limited success in terms of the application of control strategies.

The primary reasons include limited online measurements, system uncertainties, constraints on manipulated and state variables, highly non-linear behaviour and load disturbances [2]. For the implementation of an efficient control system there is a strong requirement for increased robust instrumentation. For the implementation of an efficient control system there is a strong requirement for increased robust instrumentation. Steyer and co-workers [3] summarised the advantages and disadvantages of various control schemes applied on AD processes. This included limitations of traditional classical control and advanced controls to effectively control the AD process which are subject to large disturbances and large set-point changes.

In 2009 Newcastle University, Perceptive Engineering Ltd, Northumbrian Water, Yorkshire Water and United Utilities formed a consortium with the aim of improving the control of AD systems through the development and application of an advanced controller such as model predictive control. Following the benchmarking of four industrial AD systems from the consortium, it was evident that the main obstacle to the successful application of advanced control regimes is a lack of instrumentation and monitoring. This study looks into improving the monitoring of AD systems with the goal of providing better control of the process.

Traditionally, the objective of AD in wastewater treatment plants (WWTP) has been that of sludge stabilization and odour reduction. Biogas production, solids destruction and pathogen reduction are now key areas of interest with biogas being the main product. AD with biogas production has both economic and environmental benefits, with 25% of all future bioenergy production potentially being sourced from biogas and thus having a significant role in contributing to the EU target of increasing the amount of energy derived from renewable energy sources to at least 20% by 2020 [4].

Several reviews have concluded that in order to achieve optimum performance, advanced control systems are required. Advanced control strategies can offer an opportunity for optimisation of processes such as anaerobic digestion that operate under strict regulatory constraints. The complex nature of the process dynamics provides sufficient motivation for the use of a model based control strategy. With the use of mathematical simulation models the application of model based control can be investigated for the anaerobic digestion process.

2. INVENTORY SIMULATION

The benchmark study of the four industrial AD systems revealed significant findings with the top three being (1) Inventory and scheduling have an impact on both downstream and upstream processes and form the main bottleneck in the optimisation of the process, (2) There is a significant lack of online instrumentation and (3) There is limited monitoring of the processes in general, resulting in lack of understanding of the process.

Thus the key bottleneck for optimising industrial AD processes lies within sludge inventory levels at each site. Inventory and scheduling bottlenecks are the main issues for all the benchmark sites. It is understood at this stage that inventory and scheduling form the initial optimisation problem. This needs to be solved or their impacts reduced to enable optimisation of digestate quality, increase biogas yield and energy production, which form the next level with respect to optimising ADs. Constant feed is essential for the stability of the process as large changes in feed affects the process drastically. Therefore, large changes in inventory results in large fluctuations in feed rate causing instability in the process. Inventory and, therefore, feed rate variations acts as the main disturbance in the system. It is therefore critical to feed the digester with constant feed or to limit high changes to the system.

To overcome this problem a simulation was designed to evaluate the capability of a model predictive controller to control the inventory levels and reduce their disturbance on various downstream processes. Only by removing this bottleneck can the true capability of the advanced controller on optimising the system be achieved. A simulation model depicting the nature of the industrial processes and the effects of inventory on operating the process was built. A study was then conducted into testing the capability of model predictive control on removing or reducing the hindrance of inventory on the process.

Simulations give an alternative way of performing traditional experimental or theoretical research. The complex nature of the AD system provides difficulty for modelling the process and, consequently, there are several causes of inconsistency between the process model and real AD systems. This is mainly due to lack of in depth process knowledge as well as (1) Limited number of process interactions being modelled, (2) Models which do not take into account full indirect effects, (3) Selection of variables which mainly affect inventory, (4) Assumptions on the rate of change of some process effects, (5) Assumptions on the scale of some unmeasured parameters, (6) No sensitivity analysis conducted on numerical solutions, (7) and Hybrid models for model improvement.

The simulation model is validated and verified continuously to compare the model and its behaviour to real AD systems. This included an iterative calibration process to make adjustments to the revised model. These tests for comparison ensured that the model behaved closely as expected and observed on site and in the benchmark data.

Most processes are constructed without consideration of controllability and control at the design phase. Neglecting to consider controllability and control means that any proposed control scheme is restricted by the design, with the degree of controllability being a factor of the design, range of accepted values such as flexibility of the process and process stability. As such the simulation model is built with restrictions to enable it to behave more like industrial AD systems. The AD system is subject to considerable uncertainties and disturbances affecting operating conditions and product qualities such as biogas and sludge composition. To help achieve optimum dynamic performances and economic profits, assessment of the performance with respect to controllability is required at the design phase [5]. Measures such as separation of the different process phases for the digestion technology help improve the stability and controllability. This reduces the degree of non-linearity in the system yet there still remains an opportunity for improved control. This is an example of design criteria, which improves the controllability of the process.

In order to control a microbial process such as AD requires quantitative description of variables relevant for the systems kinetics. The availability of such information enables optimal process design for obtaining optimal control [6]. Nonetheless the non-linear nature of such processes does not permit this being possible; therefore approximations are made by developers aiming to choose the operating parameters that enable process improvement. Simulations are the typically employed as a test bed for attaining such parameters. The use of simulation tools enable real developments to be made without disturbing the process and/or reducing the cost associated with such activities.

Controllability analysis is concerned with determining the limitations for achievable dynamic performance [7], thus the AD process with varying dynamics makes the process highly uncontrollable. Improved measures need to be developed for the evaluation of process controllability and operability. As a result there is a need for further research into the development of simple criteria for controllability evaluation and clear understanding of their limitations to formulate an algorithmic synthesis technique to trade-off between controllability and economics [8].

The objective here is to reduce the disturbance in the process caused by sludge inventory levels through application of a model predictive advanced controller. The hypothesis is therefore that; the model predictive controller can effectively control the sludge inventory levels, thus improving the stability of the process and maximising biogas and energy production. This will be illustrated through reduction in the level of tank level trips, increasing the energy production and overall site efficiency. The aim of using the simulation in this manner to gain further understanding from the process and to utilise this during the plant testing or design of experiments on the industrial site. Thus changes made on the plant will be combination of results from the simulation results and improved process understanding.

2.1 The simulation model

In the study a hybrid model consisting of established relationships from industrial process data generated for the process benchmarking and empirical models was used to formulate a standard single phase mesophilic anaerobic digestion (MAD) simulation process as depicted in fig. 1.

Hybrid simulation models generally capture the better of the two different simulation paradigms of system dynamics and discrete event simulation models. The structured approach of design of experiment (DOE) and sensitivity analysis was used to evaluate the simulation model. Sensitivity analyses show the impact of parameter changes on the system. This dynamic model provides a platform for testing control and optimisation strategies primarily for assessing the capability of a model predictive control (MPC) controller for removing or reducing the scheduling and inventory bottleneck.

2.2 The simulator design

The simulation model consists of seven simulator auto regressive with exogenous inputs (ARX) model blocks. These form the underlying structures of the simulation which are recursive least squares (RLS) models. Together they provide the basis of controlling the tank levels, gas production and the heating and energy usage in the system. The simulator enables models identified within the PerceptiveAPC design system to act as a simulation of the AD plant behaviour. The models can be read into the online system to generated simulated data after model development in the design system.

The simulation is conducted in Perceptive engineering Ltd.'s PerceptiveAPC [9] development software. The software uses data driven algorithms to derive empirical models of the system. The AD system is typical bioprocess system and as such is subject to several pitfalls common for most bioprocesses. These include complexity which is often not measured and understood, long operating times, nonlinear systems and highly sensitive to environmental conditions with large variability and difficult to repeat results.

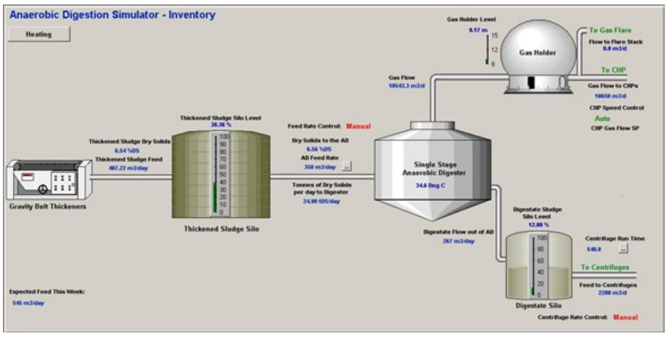


Fig.1. Schematic of AD Inventory Simulation

There are various model assumptions to include (1) Correlation of temperature, effects of % dry solids (%DS) and feed rate on biogas production, (2) %DS distribution in thickened sludge tank affecting the %DS into the digester, (3) The heating efficiency for digester, rate of heat change, (4) combined heat and power (CHP) efficiency with respect to % heat and energy production, (5) Cost penalties for process tank level trips to include the buffer tank, the digester, digestate tank and biogas holder, (6) Price of energy production used in the cost benefit analysis, (7) Tank sizes representation of true system affecting time taken to empty and fill and (8) Duration for each tank level trip to recover to the desired setpoints. These assumptions will form the basis of the validity of the results, thus the closely related the simulation is with true AD processes the greater the validity of the results from the simulation.

2.3 Model predictive control and quadratic programming

MPC involves the operation of multivariable controllers under process constraints [10]. These constraints may be 'hard' constraints of manipulated variable (MV) minimum and maximum limits, incremental move limits, as well as 'soft' constraints as controlled variable (CV) minimum and maximum limits. This makes MPC controller ideal for constraint optimisation problems such as the AD process. There are several methods available to manage such constraints, such as long range (LR), quadratic programming (QP) and a combination of these two; long range QP (LRQP). The PerceptiveAPC [9] MPC solution uses the QP constraint management method. The QP solver aims to optimise by minimising or maximising a quadratic function of multivariable, subject to linear equality and inequality constraints.

2.4 System understanding

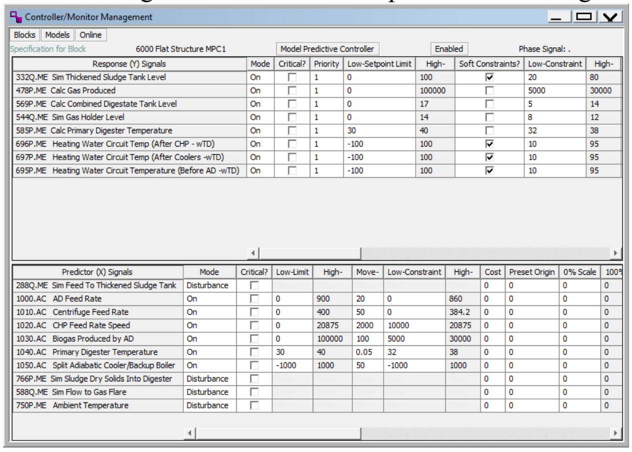
Step changes were made in manipulated inputs such as feed flow rate to observe the changes in measured outputs such as biogas production. These process excitations or step tests were conducted to generate data which captured the dynamics necessary for the modelling.
The data generated from the step tests were used to establish relationships within the system where comparisons were made to ensure the simulation results fitted with what has been observed on-site. This evaluation of system performance led to an iterative method where the model was continuously improved to make it behave close to the real system. Step tests were conducted to satisfy generate appropriate dataset for the modelling. The training data needed to satisfy various features to include richness, variability and consistency. This ensures that (1) The process moves around throughout the data range, (2) Data include all operating ranges of the process, to avoid the controller struggling if the process moves to a different region and (3) The dataset is together in sequence.

2.4 Disturbance profile modelling

The MPC controller enables disturbance profile modelling of expected sludge levels over the week and therefore a degree of the disturbance can be predicted. Although the profile varies greatly there is a general drop in the feed to the thickened sludge tank level over the weekend, this increases generally from Monday and by Wednesday inventory levels are in the high range through to Friday. Modelling of the disturbance profile into the system will help with reducing disturbances in the system as a whole as the sludge inventory level has a knock on effect for almost every process in the system.

2.5 Controller Design

Fig. 2 depicts the controller specification design page for which response and predictor variables are selected, setpoint limits, high/low constraints and mode for the variable defined. These settings are based on the simulator design restriction and results and conclusions drawn from the system understanding and disturbance profile modelling tests.



Response (Y) Signals	Mode	Critical?	Priority	Low-Setpoint Limit	High-	Soft Constraints?	Low-Constraint	High-
332Q.ME Sim Thickened Sludge Tank Level	On	☐	1	0	100	☑	20	80
478P.ME Calc Gas Produced	On	☐	1	0	100000	☐	5000	30000
569P.ME Calc Combined Digestate Tank Level	On	☐	1	0	17	☐	5	14
544Q.ME Sim Gas Holder Level	On	☐	1	0	14	☐	8	12
585P.ME Calc Primary Digester Temperature	On	☐	1	30	40	☐	32	38
696P.ME Heating Water Circuit Temp (After CHP - wTD)	On	☐	1	-100	100	☑	10	95
697P.ME Heating Water Circuit Temp (After Coolers -wTD)	On	☐	1	-100	100	☑	10	95
695P.ME Heating Water Circuit Temperature (Before AD -wTD)	On	☐	1	-100	100	☑	10	95

Predictor (X) Signals	Mode	Critical?	Low-Limit	High-	Move-	Low-Constraint	High-	Cost	Preset Origin	0% Scale	100%
288Q.ME Sim Feed To Thickened Sludge Tank	Disturbance	☐						0	0	0	0
1000.AC AD Feed Rate	On	☐	0	900	20	0	860	0	0	0	0
1010.AC Centrifuge Feed Rate	On	☐	0	400	50	0	384.2	0	0	0	0
1020.AC CHP Feed Rate Speed	On	☐	0	20875	2000	10000	20875	0	0	0	0
1030.AC Biogas Produced by AD	On	☐	0	100000	100	5000	30000	0	0	0	0
1040.AC Primary Digester Temperature	On	☐	30	40	0.05	32	38	0	0	0	0
1050.AC Split Adiabatic Cooler/Backup Boiler	On	☐	-1000	1000	50	-1000	1000	0	0	0	0
766P.ME Sim Sludge Dry Solids Into Digester	Disturbance	☐						0	0	0	0
588Q.ME Sim Flow to Gas Flare	Disturbance	☐						0	0	0	0
750P.ME Ambient Temperature	Disturbance	☐						0	0	0	0

Fig.2. Controller Specification Design page

3. RESULTS AND DISCUSIONS

3.1 Cost benefit analysis

Mesophilic digesters generally operate around 35˚C with a range between 25-45˚C. The optimum temperature varies dependent on the feedstock composition [11]. Overnight runs (7 hours of simulation time, equivalent to about 3 months of 'real life' time) of the simulation were conducted at temperatures between 25-38˚C. The aim was to evaluate best temperature condition for running of the simulation at set conditions with the hypothesis that the optimum to be around 35˚C.

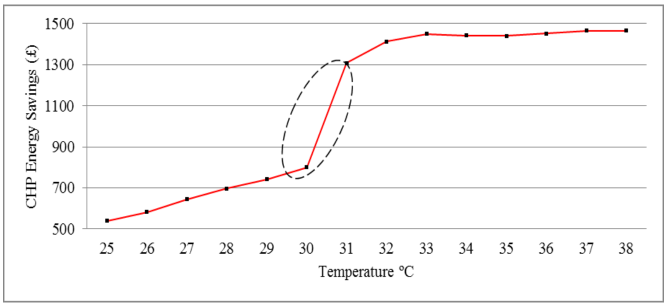


Fig. 3. CHP energy savings

Fig. 3 shows plot of CHP energy savings against temperature settings of 25 to 38˚C on the X axis. This shows a steady linear increase from 25 to 30˚C. There is then a large increase between 30 to 31˚C of about 510 savings. The plot illustrates that the peak energy saving is at 33˚C. The optimum is affected by gas flaring at high temperatures and therefore the energy savings for increasing temperature above what the gas holders and CHP units can handle results in the shift in the optimum.

Fig. 4 illustrates the various trips occurring for overnight runs at different temperatures. From the results it is clear that for all the various temperature levels studied, the trip on AD for low thickened sludge tank level and centrifuge trip on high digestate tank is totally eliminated by the controller. Therefore, the main issues for the overnight runs are the trips on high thickened sludge tank level and AD trip on high digestate tank level. This simply means that the level of inventory coming into the designed simulation site is higher for what the plant is capable of processing. The other level trips reflect temperature effect on gas production as at low temperature CHP trip on low has holder level occurs where at high temperatures, flare and AD trip on high gas holder level occurs. This is expected, nevertheless the level of trips are more erratic at high temperatures and should be avoided as the trips which occur at high temperatures may be of greater cost due to gas flaring and tripping the CHP.

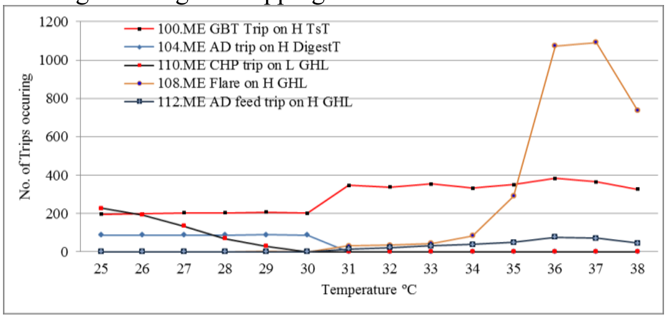


Fig. 4. Various numbers of trips occurring

Fig. 5 and 6 give number of trips occurring and the % of time trips occur in the overnight runs. There is high level of trips occurring around 36 to 37˚C due to the increase in high gas production to the high temperatures. This is, therefore, the sensitive point where the digester temperature should possibly be operated, provided that there is adequate capacity available for gas holder level and CHP units to avoid trips with gas flaring etc.

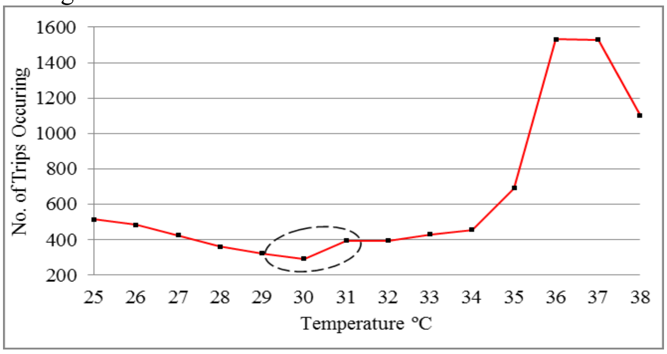


Fig.5. Number of trips occurring

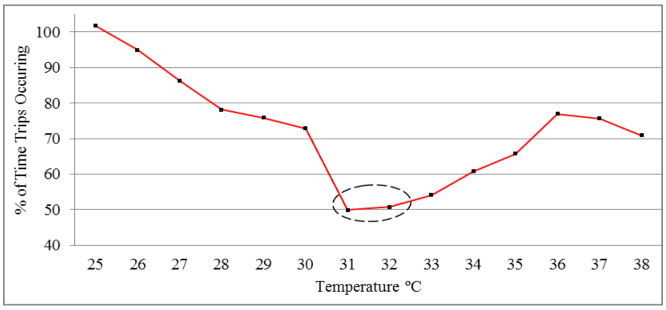


Fig. 6. % amount of simulation time that trips occur

The simulation cost/benefit analysis revealed the key variables for control and modifications required for industrial application are identified. However, due to the underlying assumptions some unexpected results have to be treated with care and therefore results here are to be validated through the industrial application. The main aim of the controller for improving inventory and scheduling is achieved; the cost/benefit relationships are questionable. Significant assumptions about the process are uncertain from the simulation results and have provided further insight into the complexity of the nonlinear relationships within the process.

Due to the degree of variation on inventory levels and the rate at which changes occur, it is practically impossible not to trip any of the level controls. This may require increased capacity or flexibility and prediction on the incoming feed stocks. The controller however is able to limit trips by almost 85%. This has enabled increased biogas production and energy production, whilst reducing cost.
The main bottleneck in the process is shifted from the thickened sludge tank level to the gas holder as the feed rate increases due to high tank level. This is further alleviated by reducing the temperature setpoint in the system and, therefore, continuous maximum feed can be observed whilst producing less biogas and therefore limits gas flaring and gas holder trips. The feedforward information from the AD process enables the digestate tank and centrifuge to be controlled effectively to avoid both systems from tripping. It is thus evident that a feedforward control on the digestate tank and centrifuge feedrate can easily be achieved with digester feed information.
The key findings from the simulation assessment can be summarised as follows:
1. Significant reduction in level trips, with total elimination on the AD trip on low thickened sludge tank level and centrifuge trip on low digestate tank level which were possible because sludge inventory levels are mostly at high levels;
2. Optimum temperature for total simulation cost/benefit gain found to be around 33˚C instead of the predicted optimum of 35˚C. This is typical of the simulation conditions, as sludge inventory is high, high temperature operations incur more trips and the cost element associated with these within the simulation makes operation at high levels of temperature not so cost effective. The optimum is therefore process dependent as at different capacities, the optimum will change;
3. A key turning point in the process is around 31˚C: level trips are at zero, or stable within 25˚-31˚C and above 31˚C, there is a general erratic behaviour within the system. Total simulation cost/benefit and CHP energy savings increase significantly above 31˚C;
4. The feed to thickened sludge tank level i.e. the sludge inventory on site changes to quickly and is very unpredictable, therefore prediction of incoming feed is not possible. The aim was to implement disturbance profile modelling into the controller design to help the controller better predict changes;
5. Temperature is best controlled by the feed rate for cooling with cold sludge feed making heating more difficult as cold sludge is continuously added. The next factor affecting temperature is the cooler/boiler settings followed by ambient temperature and CHP speed respectively;
6. The best set-points are identified to best control the process with constraints settings based on system dynamics and process understanding;

3.2 Controller evaluation

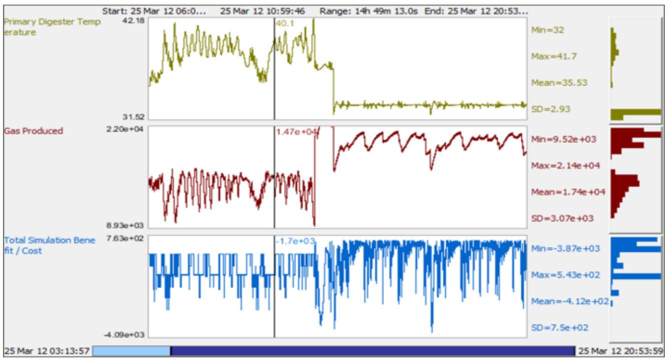


Fig.7. Process improvement through advanced control in simulation

The model predictive controller has also been shown to significantly improve the process. Best temperature settings for various scenarios are identified as shown in Fig 2-5. An advanced controller such as MPC can be used to effectively control the multi-constraint, nonlinear nature of the process. The MPC calculates a future set of moves to avoid the constraint violation. This has been shown to improve the process in simulation environment as shown in Fig 7; where about 40% increase in biogas production can be achieved at 13% lower average temperatures.

3.3 System dynamics

The AD system has varying dynamics; there are some parameters which change very quickly (the fast dynamics) and others such as biogas production which is very slow. Therefore a one level model structure to capture all the varying dynamics is difficult and not a true representation of the system. Simulation analysis were carried out to test if by separating the AD system into two model structures with split of fast and slow dynamics parameters. The findings from the split dynamics structure included (1) Reduction in the number of level trips in general and % of time trips occurring, (2) Temperature setpoint less controlled, (3) Process more erratic and therefore further tuning may be required to smooth the controller (4) gravity belt thickener (GBT) trip on high thickened sludge tank tripped above 197 times for all overnight runs for the flat structure, however for the dynamics split model; this is reduced to 77. This is over 60% reduction in the number of trips occurring for the GBT system and (5) the overall simulation cost/benefit did not improved for the current settings and tuning of the split dynamics modelling. Although the findings show that the simulation system is less controlled smoothly in comparison to the flat structure, there is a significant reduction in the number of level trips occurring in the system. There is therefore further assessment to be conducted on this model to ascertain whether any further improvements can be made.

3.4 Controller Optimisation

The QP optimiser is applied and evaluated to test the capability of improving the process through further optimisation. The first objective of the QP is to keep the process within bounds of its constraints followed by cost minimisation. The QP is designed to handle soft constraints such as the thickened sludge tank level and the heating and cooling exchangers.

Fig. 8 and 9 illustrate the controller comparison of the benchmark MPC controller, the split dynamics controller and the controller with QP optimisation included. The high reduction in tank level trips and the lack of improvement on the overall cost/benefit of the system; may be due to the way the controller is modelled. For example, priority settings and actuator move weights were tuned to make sure the primary aim of the controller is satisfied. Therefore the optimiser aims to limit the level of tank trips before optimising for CHP energy savings and biogas production to improve the overall cost benefit. For this reason the optimised controller has worked towards achieving its aim. Further work may be required to improve the controller settings to improve the overall cost/benefit of the system.

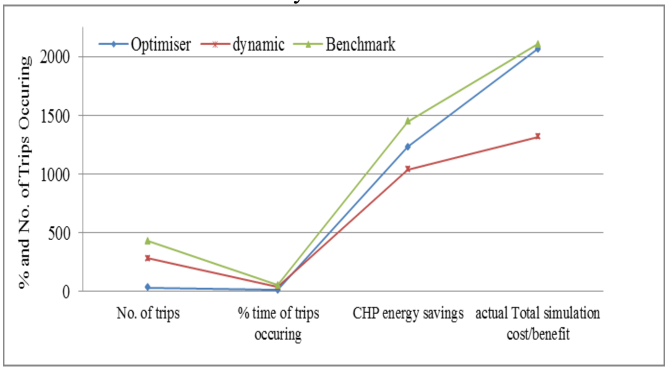


Fig.8. Controller evaluation comparison

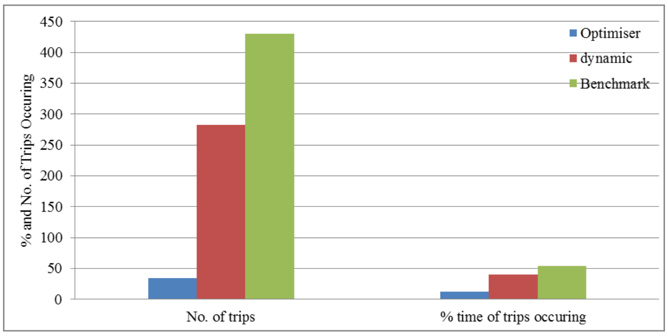


Fig.9. Controller evaluation comparison

4. CONCLUSIONS

The simulation results illustrate that the multi objective control problem of AD can be controlled with respect to scheduling and inventory. This is a positive result and has illustrated the variables that are most difficult to control. The simulation also highlights the problems associated with the system dynamics. The large variability in the system means variables such as temperature settings take considerably long time to heat or cool down with the boiler/cooler settings whilst the cooling effect on increased feed is more instantaneous. The inventory simulation achieved the aims of the study by providing (1) Reduction or complete elimination of level trips - Over 85% reduction in level trips is achieved through application of the flat structure controller, with further reduction with the optimiser and split dynamics system, (2) Optimisation of biogas production - increase production at least 12% for the flat structure and (3) Defining optimum settings for best operation - through cost/benefit analysis, optimum settings for temperature, feed flow and feed to CHP units are achieved. As the aims of control are satisfied by the control system designed, thus the process is controllable in the simulation environment and further study is required to test the controller on industrial scale.

Acknowledgments

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