

Model Predictive Control of Once Through Steam Generator Steam Quality

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Abstract: Steam quality is a critical process variable in the once through steam generator (OTSG) operation. However, the lack of online measurement and closed loop control of steam quality limits the efficient operation of OTSGs. To resolve this problem, this paper presents a model predictive control (MPC) solution based on soft sensor measurement for OTSG steam quality. Bad status handling strategy is outlined to ensure reliable estimation and control results. Instrumentation reliability issue is also considered in the MPC design. Successful application results have demonstrated effectiveness of the developed control strategy.

Keywords: Once through steam generator, Steam quality, Model predictive control, Soft sensor.

1. INTRODUCTION

Alberta oil sands play important roles in North American and world energy market. It is estimated that over 80% of the oil sands reserves in Alberta are too deep to be extracted with the conventional mining approach (Acosta 2010). An alternative technology to retrieve these deeply buried oil sands is called SAGD (steam-assisted gravity drainage). High pressure steam is continuously injected into the underground formation to heat the bitumen and reduce its viscosity. The melted oil, together with the steam condensate, is then pumped out. The emulsion from the wells is processed in the central plant, where oil is separated from water and sold to the market. The recovered water is recycled and used to generate steam. In comparison to the mining approach, only about 15% of the surface land in the development area is disturbed (Suncor Energy 2014). SAGD operation also consumes much less water than mining. More than 90% of the process water is recycled. However, a large amount of natural gas is required to generate steam in SAGD operation. There is a strong incentive from the industry to reduce energy intensity of the steam generation process.

A common steam generation process in the SAGD operation is the once through steam generator (OTSG). It is a type of tube boiler without a boiler drum. A key variable in the OTSG operation is the steam quality. It is defined as the mass fraction in a saturated mixture that is vapour (Cengel and Boles 2002). Dry steam has a steam quality of 100%, and water has a steam quality of 0%. The boiler feed water is recycled from underground steam condensate, and has a high concentration of impurities. High steam quality will lead to deposition of solids in the boiler tubes, causing decreased heat transfer efficiency and local hot spots. If steam quality remains high for a prolonged period, it may result in tube damage or rupture. On the other hand, low steam quality means low energy efficiency, since the energy is only used to increase water temperature, but not converting water into steam. Therefore steam quality needs to be controlled within

a tight range to ensure a safe and efficient OTSG operation. The high constrain of steam quality is 80%. The desired target quality is as close to the high constrain as possible. Unfortunately there is no reliable online measurement and closed loop control of OTSG steam quality. As a result, the steam quality is usually kept much lower than the optimal to maintain a safe margin.

In this work, we propose a model predictive control (MPC) solution for OTSG steam quality control based on soft sensor measurement. The paper is organized as follows. Section 2 introduces the OTSG process and associated control problem. The steam quality soft sensor based on the work of Xie et al. (2013) is reviewed in Section 3, and the bad PV status handling strategies for a reliable soft sensor application is also presented. The MPC scheme for the steam quality control is designed in Section 4, with consideration of instrumentation reliability issue. Section 5 shows the implementation results and discusses the benefits. Concluding remarks are given in Section 6.

2. PROCESS DESCRIPTION

A simplified process flow diagram of an OTSG is shown in Fig. 1. The heating source of the OTSG is the natural gas burner. Natural gas is mixed with combustion air to burn in the burner. The hot exhaust gas travels in the opposite direction of the water flow, and the energy is then transferred into the water. Finally the exhaust gas exits the steam generator through the stack. The amount of natural gas burnt in the OTSG is determined by an energy balance calculation. The energy required is estimated by subtracting the enthalpy of the target water/steam mixture with the enthalpy of the boiler feed water. Boiler efficiency and heat loss through the stack are also considered in the calculation. The required energy is then converted into natural gas flow setpoint for FC8, called firing rate. The setpoint of the combustion air flow controller FC9 is proportional to the natural gas flow, with a bias from the stack O2 controller.

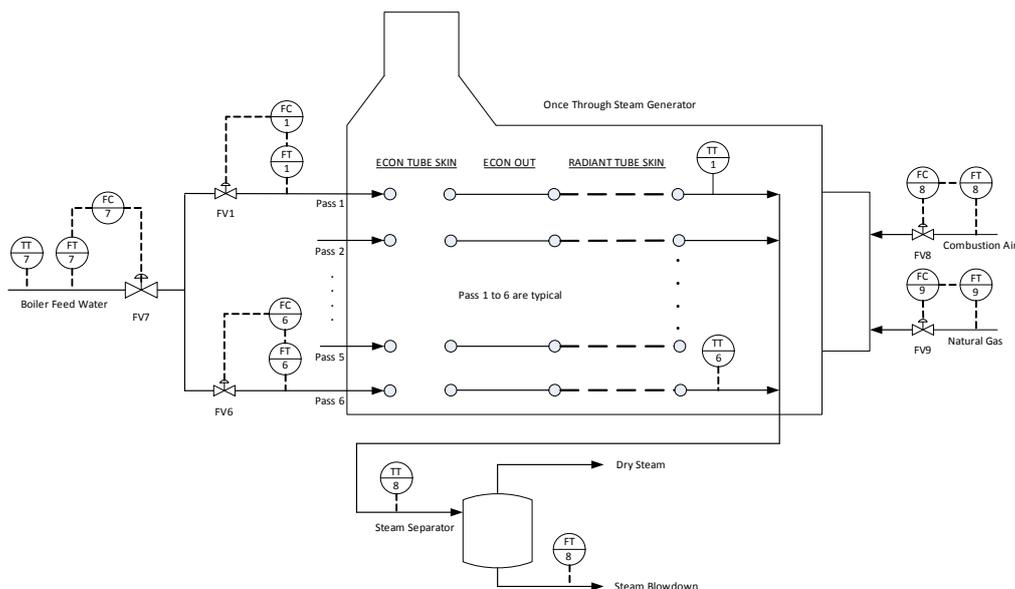


Fig. 1. Simplified OTSG process flow diagram.

The boiler feed water is fed into the steam generator by high pressure pumps. A control valve, FV7, at the inlet of the steam generator maintains the flow to a setpoint provided by the operator. The feed water is then split into six passes before being sent into the steam generator. The flow of each pass is controlled by a flow controller, FC1 to FC6. The setpoint of each pass is set by the total boiler feed water flow divided by six, so that the water is distributed evenly among the six passes. The water is heated and transformed into saturated steam/water mixture as it flows through the OTSG. Once the wet steam mixture exits the OTSG, it enters a steam separator, where the dry steam is separated and sent to the steam header, and the water is sent to the blowdown line for re-processing.

In current operation, there is no closed loop control on the steam qualities. The steam qualities may fluctuate because of external disturbance. The only intervene is the infrequent manual adjustment on the firing rate. Also due to uneven heat distribution and different tube conditions, the steam qualities of the six passes may differ. Due to these reasons, the steam quality is usually kept low to avoid violating the 80% high constrain.

3. STEAM QUALITY SOFT SENSOR

A key challenge associated with the control of OTSG steam quality is the lack of accurate online measurement. The lab sample is updated every six hours. The only available online estimation in between the lab samples is for the overall steam quality, which is calculated from mass balance of the total boiler feed water flow and the steam blowdown flow,

$$Q_{mass} = 1 - \frac{FT8}{FT7} \quad (1)$$

A problem with the mass balance calculation is the accuracy of the steam blowdown measurement. The flow transmitter FT8 is not properly sized. The actual flow is close to the low end of the calibrated range. As observed in Fig. 2, there is a

significant bias between the lab sample and the mass balance estimation.

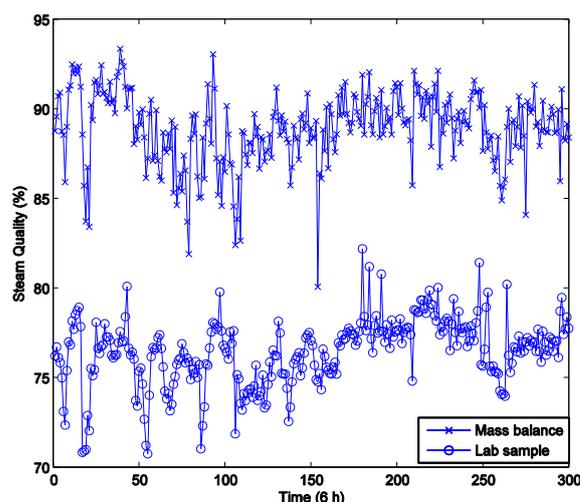


Fig. 2. Mass balance steam quality estimation and lab sample result.

In addition to the bias problem, the blowdown flow transmitter also has slow drift overtime. Fig. 3 shows the difference between the lab sample and the mass balance estimation over five months. It can be seen that the bias between the two is not constant.

As for the pass quality, there is no online measurement available. The lab sample is only updated every six hours. Within the lab sampling interval, there is no indication on how the pass flow qualities change.

Facing the above challenges, steam quality soft sensors based on the work of Xie et al. (2013) have been configured in the distributed control system (DCS) to provide real time estimations of the overall steam quality and the individual

pass qualities. A hybrid modelling methodology is used to develop the soft sensor models. Process information and knowledge are included to select the soft sensor inputs and to set up the model structure. Then the data driven approach is applied to identify the model parameters.

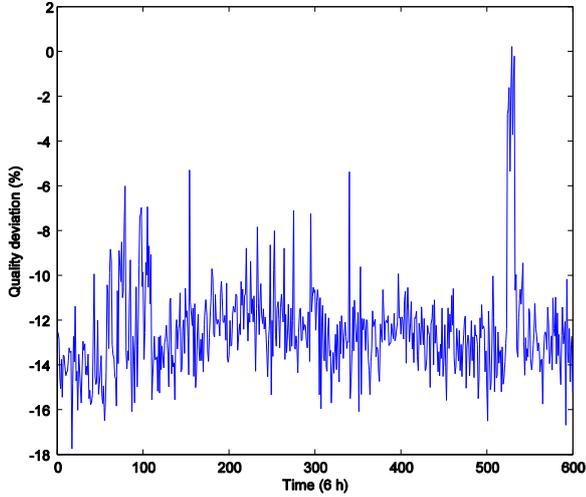


Fig. 3. Bias between mass balance calculation and lab sample.

The overall steam quality soft sensor predictor $\hat{Q}(t)$ is constructed as

$$\hat{Q}(t) = k \cdot Q_{mass}(t) + \beta(t) \quad (2)$$

$$\beta(t) = \alpha \cdot [\bar{Q}(t-1) - k \cdot Q_{mass}(t-1)] + (1-\alpha) \cdot \beta(t-1), \quad (3)$$

where $Q_{mass}(t)$ is the mass balance quality estimation at lab sampling update time t , as shown in Eqn. 1; $\bar{Q}(t-1)$ is the previous lab sample updated at sampling time $t-1$; k is the scaling parameter to overcome the proportional error of the mass balance estimation; α is the forgetting factor.

The individual pass quality model is built on the basis of heat balance of the pass flow. The soft sensor predictor $\hat{Q}_i(t)$ for the i -th pass is constructed as

$$\hat{Q}_i(t) = X_i(t) + \beta(t) \quad (4)$$

$$X_i(t) = k_1 u_1(t) + k_2 u_2(t) + k_3 u_3(t) \quad (5)$$

$$\beta(t) = \alpha \cdot [Q_i(t-1) - X_i(t-1)] + (1-\alpha) \cdot \beta(t-1), \quad (6)$$

where $u_1(t) = \frac{FT7(t)}{FTi(t)} Q_{mass}(t)$, $u_2(t) = \frac{FT7(t)}{FTi(t)} [TT8(t) - TT7(t)]$, $u_3(t) = [TTi(t) - TT7(t)]$, $Q_i(t-1)$ is the previous lab sample for pass i ; k_1 , k_2 , and k_3 are the model parameters to be identified; α is the forgetting factor parameter.

The details of the soft sensor model structure and parameter identification are available in Xie et al. (2013), and will not be repeated here.

Fig. 4 and 5 show the performance of the overall steam quality and pass 1 steam quality soft sensors. Table 1 summarizes mean error and standard deviation of error for all

soft sensors. We can see that all the soft sensors have good estimation accuracy.

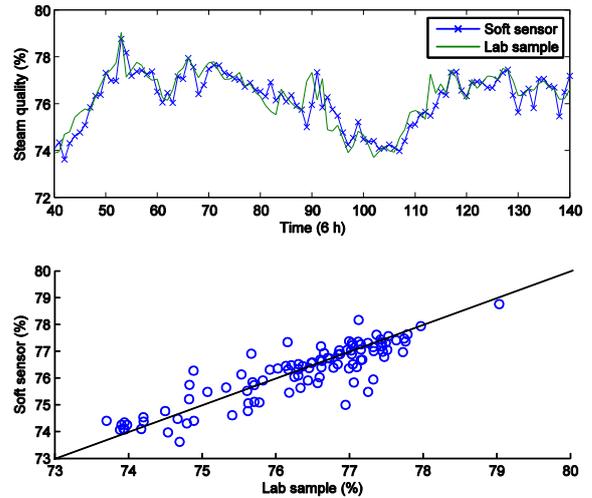


Fig. 4. Overall soft sensor performance. Upper plot: time series trend of the soft sensor and lab sample. Lower plot: Scatter plot of the soft sensor.

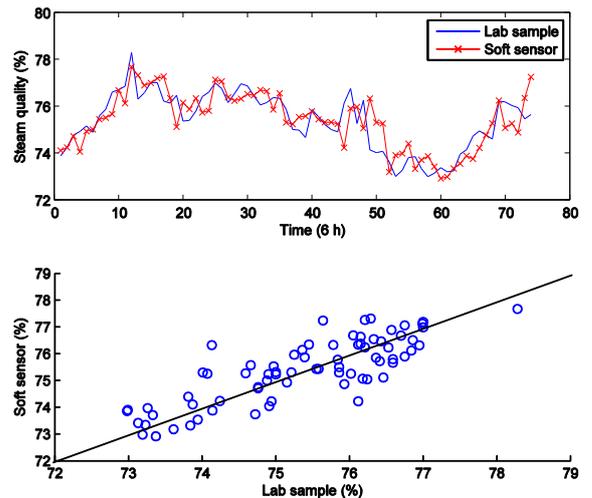


Fig. 5. Pass 1 soft sensor performance. Upper plot: time series trend of the soft sensor and lab sample. Lower plot: Scatter plot of the soft sensor.

Accuracy of the soft sensors heavily depends on process variable measurements and lab samples. If any of the inputs are not reliable, the corresponding soft sensor estimation results will also be questionable. In the following scenarios, a bad status will be marked for the soft sensor that uses the abnormal inputs:

1. Process variable measurements show bad status.

The models of the soft sensors are built based on the measurements of total boiler water flow, boiler water temperature, pass flows, pass steam outlet temperatures, total steam temperature, and steam blowdown flow. The accuracy of the soft sensor

Table 1. Soft sensor performance

	Pass 1	Pass 2	Pass 3	Pass 4	Pass 5	Pass 6	Overall
Mean error	0.022%	0.021%	0.19%	0.15%	0.17%	0.074%	-0.058%
Standard deviation of error	0.70%	0.99%	1.18%	1.09%	1.17%	1.14%	0.57%

outputs completely depends on the reliability of the aforementioned measurements. When an instrument has a bad status, it indicates that the process variable measurement is not reflecting the real process condition. Hence the soft sensor that has the bad measurement as an input cannot be trusted either.

2. Process variable is out of normal range.

The soft sensors have a limited range due to the data from which the model is built. If the process variables, including the lab samples, are beyond the envelope of the identification data set, the accuracy of the soft sensors cannot be guaranteed.

3. Lab sample fails to update.

Lab samples play important roles in the soft sensor updating scheme. It enables the soft sensor with adaptive ability to deal with time varying behaviour of the process (Mu et al. 2006). In the OTSG process, samples are taken by the field operators, and the testing results are sent into DCS via an OPC connection. Occasionally a sample can be missed. The OPC connection may also fail due to communication system issues. If the lab sample is absent for an extended period of time, the soft sensor output may drift away. Currently the lab result is updated every six hours. In consideration of shift changes or some other high priority operation issues, a time limit of 10 hours is set for the maximum lab update interval. If the sampling interval times out, the corresponding soft sensors will be mark as bad.

4. MPC CONTROLLER DESIGN

The main purpose of OTSG steam quality control is to achieve a common target for each individual pass quality while maintaining the total boiler feed water flow at a setpoint given by the operator. MPC is a good fit for this type of multi-variable control application.

The first step to design a MPC controller is to choose the controlled variables (CVs). A very natural selection for the CVs will include the six pass qualities. However, it is observed that the pass steam outlet temperature measurements have drifting problem. Fig. 6 shows an example of how the pass temperatures change over 3 days' period.

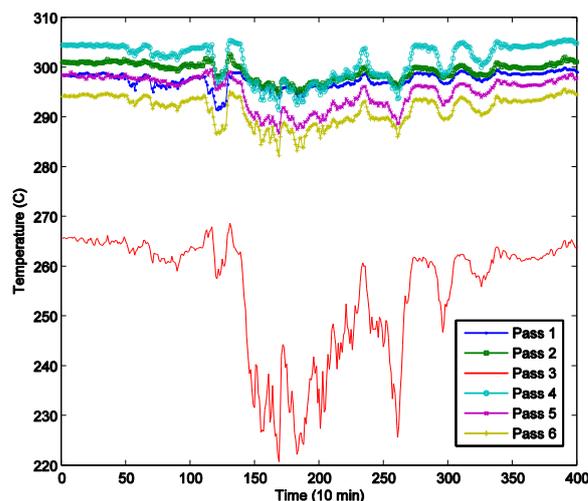


Fig. 6. Pass temperature drifting.

The steam pressure, however, remained the same during the three days. Due to the saturated nature of the steam/water mixture, the steam temperature should not change if the pressure remains constant. The common steam outlet temperature also remained the same during the period, which supports the conclusion that the pass temperature transmitters have a drifting problem.

The pass temperature is a key input to the pass quality soft sensor model. Drifting temperature will result in drifting pass steam quality estimations. Fig. 7 shows pass 4 steam quality soft sensor output during the same period. As seen in the figure, when the temperature drifts, the steam quality soft sensor output can have a 2% change, but such change is not observed in the lab samples. The pass soft sensor result is seriously affected by the temperature drifting issue.

By carefully examining the temperature trend in Fig. 6, one can notice that the temperature drifting on all the passes occurs at the same time, and the magnitudes of the drifting are also similar. If only the differences between the pass qualities and the pass quality average are to be controlled, much of the impact caused by pass temperature drifting can be removed. Again pass 4 is used as an illustrative example in Fig. 8. The change of pass 4 quality deviation due to the temperature change is less than 0.5%, which is much smaller than the change of the absolute value.

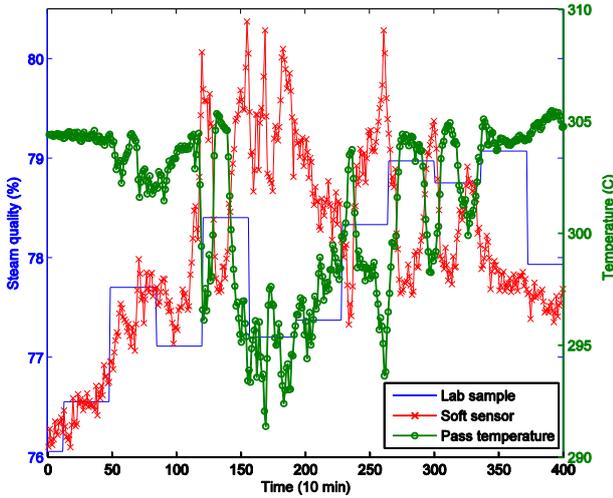


Fig. 7. Impact of temperature drifting on pass 4 steam quality estimation.

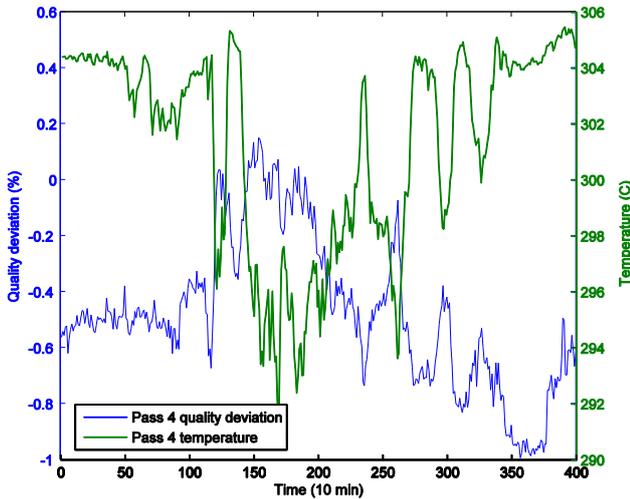


Fig. 8. Impact of temperature drifting on pass 4 steam quality deviation.

Recall that the objective of OTSG steam quality control is to maintain the individual pass qualities to a common setpoint, i.e., zero deviation of all pass qualities from the setpoint. Thus the control objective can be re-formatted as: control all pass quality deviations to zero, and control the overall steam quality to the setpoint.

The quality deviation of pass i is calculated as

$$\Delta\hat{Q}_i = \hat{Q}_i - \frac{\sum_{j=1}^6 \hat{Q}_j}{6}. \quad (7)$$

Out of the six pass quality deviations, only five of them are independent variables due to the degree of freedom. That is, for instance, if $\Delta\hat{Q}_1, \Delta\hat{Q}_2, \dots, \Delta\hat{Q}_5$ are controlled to zero, the other pass quality deviation $\Delta\hat{Q}_6$ will also be zero. Hence only five pass quality deviations have to be controlled. The pass flow setpoints of the six passes, $FC1, FC2, \dots, FC6$ are adopted as the manipulated variables (MVs) to control the pass quality deviations.

Note that the pass quality deviations do not reflect the absolute value of the steam qualities, so the overall steam quality soft sensor output $\hat{Q}(t)$ has to be included as a CV. The firing rate trim, which is a multiplier coefficient applied to the enthalpy based firing rate calculation output, is selected as the MV for $\hat{Q}(t)$. The trimmed firing rate is then applied to the natural gas and combustion air flow controllers.

In current operation, the total boiler feed water flow is determined by the control room operators or the plant master controller. The local steam quality MPC controller does not have the privilege to change the total feed water flow. Therefore the summation of all the pass flow setpoints must be equal to the desired total flow setpoint. The summation of pass flow setpoints $\sum_{i=1}^6 FCi$ is included in the controller as a CV.

In summary, there are in total seven CVs, and seven MVs. Table 2 provides a list of all the variables.

Table 2. CV and MV list of the MPC

Controlled variables	Manipulated variables
5 Pass quality deviations $\Delta\hat{Q}_1$ to $\Delta\hat{Q}_5$	6 Pass flow setpoints $FC1$ to $FC6$
Overall steam quality $\hat{Q}(t)$	Firing rate trim coefficient
Total pass flow setpoint $\sum_{i=1}^6 FCi$	

As discussed in Section 3, the status of soft sensor outputs may turn bad. We designed the following bad status handling strategy for the MPC controller:

1. A pass quality soft sensor goes bad.

The corresponding pass quality deviation will be removed from the CV list. The flow control for that pass will be switched to local control mode. The flow setpoint will be the total feed flow divided by six, and become a disturbance variable in the MPC controller. The pass quality will also be dropped from the pass deviation calculation for the other passes. For instance, if pass 1 quality has a bad status, the pass deviation for the other passes will be calculated as

$$\Delta\hat{Q}_i = \hat{Q}_i - \frac{\sum_{j=2}^6 \hat{Q}_j}{5}, \quad (8)$$

where $i = 2, 3, \dots, 5$.

2. Three or more pass quality soft sensors go bad.

All pass quality deviations will be dropped from the MPC controller, and all pass flow controls will be switched to local mode, since the remaining quality deviations are unlikely to reflect the real process condition.

3. Overall steam quality goes bad.

An option is to only switch the firing rate to local control. However, after discussion with other stakeholders, it is decided that switching off the whole MPC controller is the preferred solution, as a safety precaution.

5. CONTROL PERFORMANCE AND BENEFIT ANALYSIS

The steam quality controller is configured in DCS with built-in MPC function blocks.

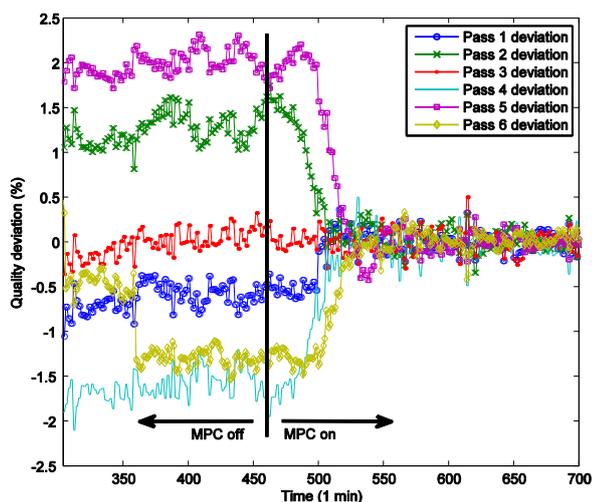


Fig. 9. Pass quality deviation control performance.

Fig. 9 shows the pass quality deviation control performance. Pass 1 to 5 pass deviations used in the controller as CVs are all controlled to zero. Pass 6 quality deviation is also displayed in the figure. It goes to zero as the other pass quality deviations are controlled to zero, which endorses the degree of freedom analysis in Section 4. With MPC on, the average gap between the highest pass quality and the lowest pass quality is reduced from 3.08% to 0.78%.

Fig. 10 shows the comparison of the overall steam quality performance. As seen in the figure, the overall steam quality variation is significantly reduced. The standard deviation of steam quality decreased from 1.35% to 0.25%.

With the proposed MPC control, all the pass qualities can be controlled tightly to the target setpoint, and thus higher steam quality can be achieved without violating the high constrain. In Fig. 10, the average steam quality has risen from 75.58% to 77.64%, an increase of 2.06%. Assume that the boiler feed water runs at 175C and 11300 kPa, and the saturated steam/water mixture runs at 313C and 10300 kpa. The energy required to generate 1kg of steam can be calculated as (Green and Perry 2007).

$$E = \frac{[(1419-747)+(2720-1419) \cdot Q\%]}{Q\%}, \quad (9)$$

where Q is the steam quality. By increasing the steam quality from 75.58% to 77.64%, the energy to produce 1kg of steam has declined from 2191 kJ/kg to 2166 kJ/kg, a 1% reduction in energy consumption. Looking at Fig. 10, there is sufficient

safety margin to control the steam quality even closer to the 80% constrain, and therefore save more energy.

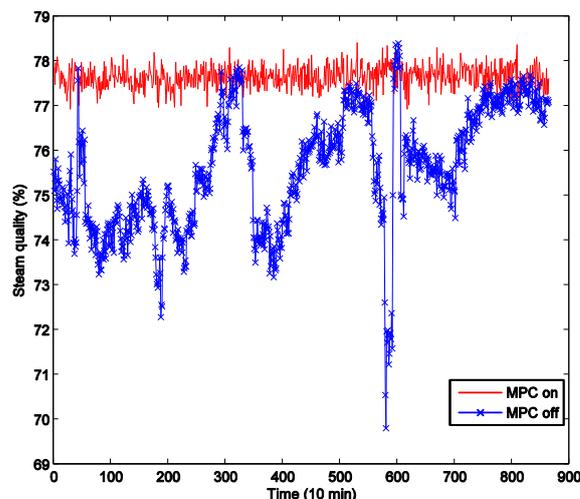


Fig. 10. Overall steam quality control performance.

6. CONCLUSIONS

This paper employs soft sensor and MPC technologies to implement OTSG steam quality control. The MPC scheme is designed to minimize the impact of unreliable instrumentations. The application result demonstrates the effectiveness of the proposed measurement and control strategy. By controlling steam qualities tightly, the energy intensity of SAGD operation can be reduced, leading to lower operating cost and less greenhouse gas emissions.

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