Integrated Sensing & Controls for Coal Gasification – Development of Model-Based Controls for GE's Gasifier & Syngas Cooler

Topical Report for Phase III

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Table of Contents

List of Figures

1 Abstract

This report summarizes the progress for the final phase (Phase III - July 2009 – December 2010) of the 3-year DOE funded program on Integrated Sensing and Control for Coal Gasification. The original program, due to end in July 2010, was extended under a no-cost extension till December 2010.The objective of this program is to develop a comprehensive systems approach to integrated design of sensing and control systems, using advanced model-based techniques. In particular, this program is focused on the model-based sensing and control system design for the core gasification section of an IGCC plant. The program was divided into three phases. There were three main Tasks in Phase I and Phase II of the program. These Tasks were completed earlier in 2008 and 2009. The key focus of the first year of the program was on Task 1. The Task involved (i) developing a detailed first-principles transient model for the overall gasification section in Matlab/Simulink® , and (ii) developing a sensing and packaging solution and installing in the Radiant Syngas Cooler (RSC) in the TECO IGCC plant at Polk power station, Florida to obtain operation data to be used for model validation. The key focus in the second year of the program was on Tasks 2 & 3. In Task 2, initially a linear model-based analysis was performed to analyze the performance of a model-based estimation using a Kalman Filter. It performance was studied in the presence of expected errors in modeling and online sensors to figure out important sensor set to meet critical performance criteria. Thereafter, a nonlinear Extended Kalman Filter (EKF) was designed and its performance was evaluated through simulation studies for estimating key unmeasured process variables like gasifier temperature and carbon conversion, and identifying unknown/variable model parameters like gasification kinetics and RSC fouling in the presence of expected errors in modeling and online sensors. In parallel, in Task 3, a nonlinear Model Predictive Controller (MPC) was implemented, assuming ideal measurement of key process variables, and its performance was studied for optimizing the transient and steady state operation during startup as well as normal operation. The individual EKF and MPC simulation results were very promising and were presented in Topical report for Phase II in 2009. In Phase III of this program, the key focus was on combining the EKF in closed-loop with MPC to obtain the overall integrated sensing and control solution. The closed-loop performance of the integrated EKF and MPC systems was studied through simulations for startup, turndown and fuel changes in the presence of sensor (bias and noise) and modeling (unknown/varying parameters) errors. The extensive simulation performed on the integrated systems shows that the system works well even in the presence of random sensor and modeling errors. These results are summarized in this topical report.

2 Executive Summary

This section summarizes the key accomplishments of the final phase (Phase III -July 2009 – December 2010) of the three-year program. The final phase accomplishment was built on accomplishments of earlier phases of the program. This section summarizes those accomplishments as well for completeness.

2.1 Phase I and Phase II

The Phase I and Phase II of the program was divided into multiple tasks. These tasks and related accomplishments are described briefly in this section.

2.1.1 Task 1 – Modeling and Sensor Installation

The focus in Task 1 was to (i) develop a detailed transient model of the gasification section to be used for simulation studies and sensing and control system design in Task 2 and Task 3, and (ii) implement sensors in RSC in the TECO IGCC plant to obtain data for model validation.

2.1.1.1 Task 1 – Modeling for gasification section

In this subtask, a dynamic model was developed for nominal, high-pressure operation of the gasification section for both steady state as well as transient operation like turndown (i.e., throughput changes) and fuel changes (coal /coal+petcoke blends). This model was then extended to encompass the post-ignition, pressure ramp-up portion of the startup process as well, where the pressure in the syngas side as well as the steam side was raised gradually to nominal operating pressures. In parallel, another model was developed for the pre-heating phase of the startup, wherein the thermal transients in the gasifier refractory and the RSC and the corresponding thermal stresses were modeled during the pre-heating operation. This task was completed in June 2008, except for the gasifier refractory pre-heating stress model, and a detailed description of the modeling, model reduction and simulation runs was included in the previous Topical report for Phase I (June 2008). The last task of modeling the gasifier refractory pre-heating and corresponding thermal stresses was completed in 2008 Q3. In particular, a transient thermal model was implemented in Matlab/Simulink® for the temperature profile in the refractory lining during gasifier pre-heating. Also, a detailed ANSYS® model was implemented to calculate the tensile and compressive stresses in the refractory bricks due to the thermal gradients in the bricks due to heating on the inner surface. The ANSYS® stress model was coupled with the Simulink transient thermal model to obtain the overall gasifier pre-heating model. The integrated gasifier pre-heating model was simulated with baseline pre-heating temperature profiles to obtain the corresponding baseline transient tensile and compressive stress profiles in the refractory bricks, which served as the basis for subsequent MPC studies for optimized pre-heating to obtain the entitlement in terms of shortest time for completion of pre-heating.

2.1.1.2 Task 1 – Sensor Implementation in RSC at TECO Plant

In this subtask, the objective was to install sensors in the RSC in the TECO IGCC plant and obtain plant operation data that could be used for RSC model validation. Initially, three potential sensor candidates were identified: (i) radial temperature profiles at levels 7 & 10, (ii) axial temperature profile between levels 7 &10, and (iii) strain measurement in the RSC dome outside the hot syngas path. Lab tests on packaging performance for the axial temperature profile indicated high risks in packaging survivability and potential adverse impact to nominal plant operation and was thus, not pursued for implementation. Extensive lab tests were performed in 2007 and 2008 to study and improve the performance of the optical Fiber Bragg Grating (FBG) sensors under expected thermal and strain conditions. Finally, sensor packaging design and fabrication for the radial temperature sensor probes for levels 7 & 10 with integrated Type B thermocouples and optical fiber FBGs was completed in 2008 and early 2009. These radial temperature probes were installed in the RSC in the TECO IGCC plant during the plant maintenance shutdown in February/March 2009. In particular, four radial temperature probes, two at each level on opposite sides of the RSC were installed. The temperature probe on level 10 worked very well and survived for more than the thirty days that was aimed for. The temperature probe at level 7 also provided excellent temperature profile data for five days of operation after initial plant startup. However, on the fifth day of operation, the ceramic probe broke off abruptly – it was suspected that the hot gas and/or slag impinged directly onto the probe causing the abrupt breakage. Finally, a set of fiber optic FBG strain sensors were also installed in the RSC dome outside the hot syngas path to monitor strain evolution over time due to gradual fouling buildup on the heat transfer area. A key challenge for this sensor was for the optical fibers to withstand and survive a large thermal strain (~6000 $\mu\varepsilon$) due to the temperature rise at startup, and thereafter, accurately measure a very small mechanical strain (~50 $\mu\varepsilon$) due to fouling buildup over several weeks of operation. This sensor also worked very well and provided a very good measurement of the gradual fouling buildup over six weeks of plant operation, matching very well with estimated mechanical strain due to fouling. More details about this task are included in the previous Topical report for Phase II (June 2009).

2.1.2 Task 2 - Sensing System Design

The objective of this task was to design a model-based sensing/estimation system that provides online measurement/estimate of key process variables in the gasification section that are important for monitoring and control, e.g., gasifier temperature, carbon conversion, gasification efficiency, slag viscosity and syngas properties. To this end, initially, in this task, a linear model-based analysis was performed at nominal baseload operating condition to study the performance of model-based estimation in the presence of sensing and modeling errors. The linear model was derived at the nominal baseload condition from the full nonlinear model, and a Kalman filter analysis was performed to study the impact of modeling errors and sensor errors (e.g. bias and noise) on the estimation performance. Also, a sensitivity study was performed to identify key sensor biases and model parameter errors that contributed to the uncertainty in overall estimation accuracy. This analysis was then followed by a full nonlinear model-based estimation using an Extended Kalman Filter (EKF) to verify the performance of nonlinear estimator in the presence of errors in model parameters and sensor noise/bias. One key problem with the standard EKF is that it does not enforce any constraints on the estimated state or parameter variables, which are important to ensure physical validity of the model. To address this, the EKF implementation was extended to include constraints on all estimated variables to enforce them to be in expected and/or physically meaningful range. The performance of the constrained EKF was tested through extensive simulation studies in the presence of unknown errors in the model parameters, e.g. RSC fouling and gasifier kinetics, which are often not known precisely and/or change slowly over time. The EKF simulations showed that the unknown model parameters were correctly identified and updated to match simulated variations, thereby allowing accurate estimation of key process variables that were not measured but were important for monitoring and control, e.g. gasifier temperature, carbon conversion, slag viscosity and overall efficiency. More details about this task are included in the previous Topical report for Phase II (June 2009).

2.1.3 Task 3 – Control System Design

In this task, initially a nonlinear model predictive controller (MPC) was designed and implemented to optimize the steady state and transient operation during nominal plant operation (e.g. turndown and fuel changes) as well as during startup, specifically pre-heating of gasifier and RSC during startup. The MPC was implemented on the full nonlinear model of the gasification section in Matlab/Simulink® and its performance tested through extensive simulation studies. In this initial stage, the MPC implementation assumed accurate knowledge of all important state and output variables, to identify the entitlement in performance improvements achievable for nominal operation and startup.

MPC simulation studies were performed for gasifier pre-heating subject to constraints on the thermal stresses in the refractory bricks – imposing the same stress limits as obtained with the current baseline pre-heating strategy. Simulation studies showed significant reduction in total pre-heating time for the gasifier refractory, with more than 20% reduction from the baseline pre-heating time. In an alternative implementation, MPC was also tested to simultaneously reduce the startup time as well as the maximum thermal tensile stresses to identify a design tradeoff between the two. MPC simulation studies on the RSC pre-heating, subject to thermal gradient and stress constraints also showed possibility of significantly faster pre-heating– potentially completing the RSC pre-heating in less than ten hours, depending on the maximum steam flow available during pre-heating. Finally, MPC simulation studies were also performed for nominal operation including baseload operation, turndown between baseload and fifty percent load and fuel changes with up to fifty percent petcoke in coal-petcoke blend. Using a multivariable optimization and running to critical operability constraints, one optimization mode focused on minimizing the amount of oxygen used at steady-state operation at baseload or part-load – this in turn, reduces the internal electricity consumption in the air separation unit (ASU). MPC simulation studies indicated a reduction in oxygen consumption by 5-10% at baseload and half-load conditions. Similarly, MPC simulations were performed to accelerate the transient load changes (turndown) between baseload and fifty percent load conditions, allowing potentially 20% faster turndown capabilities through coordinated manipulation of multiple operating variables, while enforcing key operability constraints. These MPC studies were repeated for operation for coal-petcoke blend with up to 50% petcoke. MPC allows a smooth transition from coal to petcoke blend, maintaining desired electricity power output while simultaneously enforcing all operability constraints. MPC allowed a similar 20% improvement in ramp rates for turndown transient operations with petcoke blend. More details about this task are included in the previous Topical report for Phase II (June 2009).

2.2 Phase III

This section summarizes the key accomplishment of the program in the final phase (2009-2010).

Design of nonlinear Extended Kalman Filter (EKF) and nonlinear Model Predictive Controller (MPC) are the key elements of the advanced model-based integrated sensing and control systems. These elements were independently designed and tested in earlier phases of the program. In phase III of the program the key focus was on integrating EKF and MPC to achieve the integrated advanced model based sensing and control solution for the gasification section of the IGCC plant.

Up to 2009 Q4, the development and testing of EKF and MPC were performed separately. While the EKF model used an early version of the reduced-order model, the MPC implementation, as it matured, was updated to use a more efficient reduced-order model. In particular the MPC implementation incurs a large model simulation expense due to repeated prediction over a long future horizon. This had motivated simplifying/eliminating certain fast transients (e.g. syngas flow and pressure relations) to enable faster model predictions and MPC simulation. In 2010 Q1, the MPC and EKF implementations were updated to a common gasification section model with the aim of integrating MPC and EKF in the overall combined sensing and control solution. The updated EKF and MPC were tested and validated individually through simulation in their existing framework (open loop simulation for EKF and “ideal plant” simulation for MPC).

In 2010 Q2, the focus was on integrating EKF in closed-loop with MPC to obtain the overall sensing and control solution. The integration necessitated re-tuning of the MPC and EKF parameters to ensure overall closed-loop system stability and performance. The integrated EKF & MPC closed-loop performance was studied through a number of simulations for steady state and transient operation, with coal and coal-petcoke blend, in the presence of sensor (bias and noise) and modeling (unknown) parameters (e.g., gasifier kinetics and RSC fouling factor) errors. In 2010 Q3, these studies were used to continue updating the EKF and MPC implementations and tuning to achieve desired closed-loop performance for tracking and optimization in the presence of sensor (bias & noise) and/or modeling (unknown model parameters) errors. The simulation results showed that the tracking performance was good both at steady state and during transients with some expected performance degradation due to sensor noise and biases. However, the simulation studies also highlighted potential issues when optimizing for minimum oxygen consumption at part load and maximum electrical power output at baseload conditions.

Based on simulation studies, further refinement of MPC and EKF were carried out in 2010 Q4, to improve performance for optimized operations. In particular, refinements were made in order to have robust solution for a) oxygen minimization at part load while still tracking the net power output setpoint and b) net electrical power output maximization at baseload condition. The simulation studies of this final solution showed a similar trend that was observed in phase II simulations with “idealized” plant and sensor measurements with, of course, certain expected minor degradation in the performance. This trend includes a reduction in oxygen consumption by 7-10% at 50% partload conditions and 1-2% increase in net electrical output at baseload load conditions with coal slurry. Similar studies for operation with coal-petcoke blend with up to 50% petcoke showed 2-6% reduction in oxygen consumption at 50% load. Similarly, the simulation studies for the transient load changes (turndown) between baseload and fifty percent load conditions showed that it was possible to have potentially 20% faster turndown capabilities through coordinated manipulation of multiple operating variables, while enforcing key operability constraints.

These results were also presented to the DoE team in the final program review in December 2010. A simulation demonstration of the gasification section model and the overall integrated sensing and control solution using EKF and MPC was also performed. In addition, software for a) simulating the gasifier section models b) unconstrained extended

Kalman filter c) model reduction algorithm used for deriving lower order model based on singular decomposition were delivered. All deliverables for this program have been met.

3 Introduction

This program is aimed at developing an integrated advanced sensing and controls solution for improved operation of IGCC plant, focusing in particular, on the core gasification section of the plant. The gasification section has a particularly harsh environment with high temperatures and pressures and presence of slag and corrosive elements. Owing to the harsh environment, limited online sensing is currently available for online monitoring and controls. Consequently, the operation of this section using a combination of simple controls and operator judgment based on limited and/or infrequent measurements is often conservative, especially for transient operations.

In this three-year program, a systematic model-based approach is developed for the design of a comprehensive sensing system combining online sensors along with online model-based estimation, and a model-based multivariable controller that optimizes the operation of the gasification section at steady state as well as through key transients like startup, turndown and fuel changes. To this end, available models for different units of the gasification section (e.g. gasifier, radiant syngas cooler (RSC)) have been combined in a common platform in Matlab/Simulink® to obtain a comprehensive dynamic model of the gasification section. Also, specific sensing technologies have been implemented in the IGCC plant at TECO Polk Power Station to obtain operation data that are used for the RSC model validation. The dynamic model of the gasification section is used in a systematic model-based analysis and design framework to design a comprehensive sensing and control system to improve the robustness and flexibility and optimize the operation of the gasification section for steady-state as well as transient operations, in particular, for startup, turndown and fuel changes.

3.1 Program Tasks

The overall three-year program consists of three main tasks:

1. Modeling, model reduction and model validation,
2. Sensing system design, and
3. Control system design.

In Task 1, available models for different units in the gasification section were combined in a common platform in Matlab/Simulink® to obtain the dynamic model for the overall gasification section, which are used for sensing and control system design in Tasks 2 and 3. Available component models for key process units were implemented in Matlab/Simulink® . Some of the existing models had only been used at steady state conditions and appropriate updates were made to allow transient simulation with these models. Furthermore, some of the models, e.g. gasifier and RSC, were of high order, i.e., they had a large number of internal states since they model spatial variation along the length of the gasifier and the RSC. Owing to the large dimension, these models are computationally expensive and not amenable to real-time transient simulations and model-based analysis and design of sensing and control systems. Thus, these high-order models were simplified through model reduction techniques to obtain lower order models while maintaining high accuracy for control. Also, in Task 1, temperature and strain sensors were implemented in the RSC in the TECO Polk Power Station IGCC plant to obtain suitable operation data that was used for validation of the RSC model. A key common challenge for all the sensors was developing suitable packaging for the harsh environment in the RSC, and appropriate mechanical design to facilitate easy installation given the limited access inside the RSC. These sensors were installed in the TECO IGCC plant in the RSC in early 2009 and plant operation data was obtained successfully.

In Task 2, the dynamic model of the gasification section from Task 1 was initially used to perform a systematic "observability" analysis. More specifically, a linear model-based Kalman filter analysis was performed to study the estimation performance for key unmeasured variables and its sensitivity to modeling and sensor errors. The sensitivity analysis allowed identifying the key sensor errors (bias and noise) and modeling errors (parametric errors) with respect to good system performance, which were then included in an online nonlinear model-based estimation algorithm using an extended Kalman filter (EKF). Simulation studies were performed in the presence of modeling errors introduced through variations in model parameters, and noise and biases in online sensors to verify the performance of the nonlinear model-based estimation system at steady-state as well as during transient operations. More details on this task are included in Topical report for Phase II (2009).

In Task 3, a model-based advanced controller was designed for the gasification section to coordinate the operation of the individual units in this section to optimize the overall section performance. In particular, a nonlinear model predictive controller (MPC) was implemented initially assuming ideal measurement for all variables needed for feedback, to optimize the performance of the gasification section at steady state and during key transients like startup, turndown (i.e. throughput changes), and fuel changes. Extensive MPC simulation studies were performed for startup, specifically gasifier and RSC pre-heating, and normal operation modes including turndown and fuel changes. These MPC simulations indicated opportunities for significant improvements in transient operation, reducing pre-heating and turndown transient times, and optimizing steady-state performance for minimized oxygen consumption. More details on this task are included in Topical report for Phase II (2009).

Finally, the design of an advanced model based sensing and control system requires integrating the comprehensive sensing solution consisting of combining online sensors along with online model-based estimation (EKF) with the model based predictive control (MPC) developed in Task 2 and Task 3. This effort was carried out in Phase III of this program and is described in Section 4.

3.2 Program Plan and Summary

Figure 1 shows the detailed program plan for each task and subtask and the key milestones. The modeling of individual gasification section components, model reduction and combination of the individual component models in Matlab/Simulink® (Tasks 1.1-1.4) to get the overall gasification section dynamic model were completed in Task 1 by June 2008. The model was extended to encompass post-ignition pressure ramp-up operation. Separately, models were implemented for pre-heating of the RSC and gasifier refractory – the latter was completed in 2008 Q3. In parallel, under Task 1.5, lab tests were performed for optical fiber FBG sensors towards implementation in the TECO Polk Power Station IGCC plant. The sensors were installed in 2009 Q1 and plant operation data was successfully obtained in 2009 Q2.

In phase II of the program, the gasification section model developed in phase I was used for analysis and design of model-based sensing and control systems under Tasks 2 and 3, respectively. More specifically, under Task 2, initially linear models were generated from the full nonlinear model at baseload operating condition and used for model-based analysis for a sensing system using a combination of online sensors and model-based estimation. Thereafter, a full nonlinear model-based estimator using a nonlinear extended Kalman filter (EKF) was implemented in Matlab/Simulink® and its online estimation performance was tested in the presence of modeling and sensor errors through steady state and transient simulations. This Task was completed in 2009 Q2.

Under Task 3, nonlinear model predictive controllers (MPC) were designed and implemented in Matlab/Simulink® to optimize the steady state and transient operation of the gasification section subject to critical operability constraints. In particular, MPC was designed for optimizing pre-heating of the gasifier and the RSC. Similarly, MPC was designed for optimized operation at nominal baseload or part-load steady state as well as for throughput changes during turndown with coal and coal-petcoke blend fuel. The performance of the MPC in achieving optimized operation for startup and nominal operation was tested through extensive simulations and this subtask was complete in July 2009.

The Phase III of this program was extended under a no-cost extension till December 2010. In this final phase of the program, the separate model-based sensing system using EKF designed in Task 2 and the MPC designed in Task 3 was combined to achieve the overall integrated model-based sensing and control system. The MPC and EKF design are updated and re-tuned to achieve good performance of the integrated sensing and control system. Extensive simulation studies were done to verify the performance of the integrated system in the presence of sensor error (noise and bias) and model error (parameter uncertainty). These results are documented later in this report.

These results were also presented to DoE team in a final program review in December 2010, along with simulation demonstrations of the model and developed integrated sensing and control solution. In addition, software for a) simulating the gasification section models b) unconstraint extended Kalman filter c) model reduction algorithm used for deriving lower order model based on singular decomposition were also delivered.

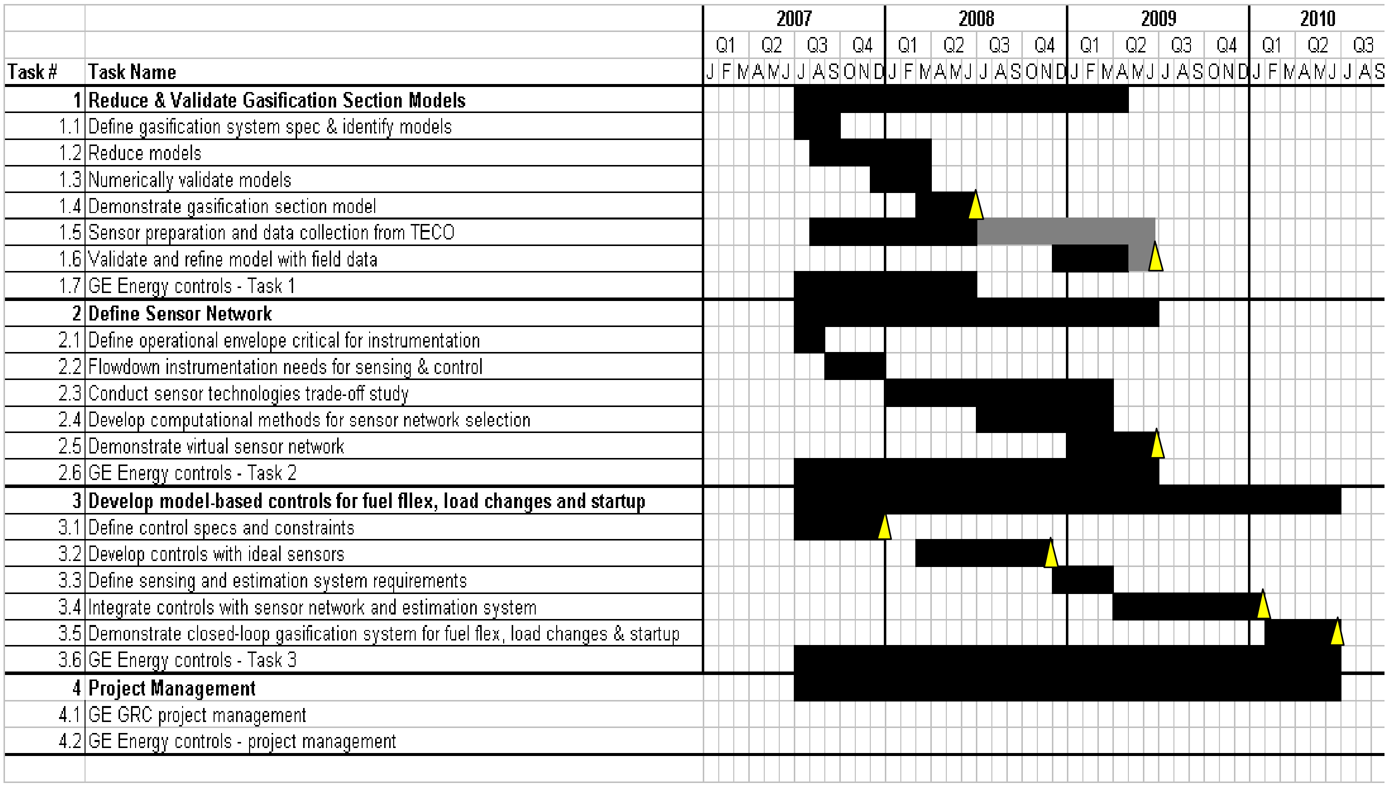

Figure 1: Program Plan and Milestones

3.2.1 Milestones & Status

The key program milestones are shown in Figure 1 by the yellow triangles. The milestones and the current status are summarized below.

- Controls requirements (Dec 2007) – completed collection of controls requirements for transient operation modes, turndown, fuel changes, and startup (pre-heating).
- Complete gasification section dynamic model in Matlab/Simulink® (Jun 2008) – All models were implemented in Matlab/Simulink® by June 2008, except the gasifier pre-heating model. The gasifier pre-heating model using a combination of Matlab/Simulink® and ANSYS® was completed in 2008 Q3.
- Advanced MPC solution with ideal sensors (Dec 2008) – Initial MPC implementation for nominal and startup operations were completed in 2008 Q4. MPC implementations were updated in 2009 Q1-Q2 as simulation studies were performed to optimize startup and nominal operation.
- Validated and updated gasification section model and sensing system design (Jun 2009) – A nonlinear EKF with constraints was implemented in Matlab/Simulink® to obtain the overall sensing system combining online sensors and model-based estimation, and its performance was tested through simulations in 2009 Q1-Q2.
- Integrated sensing and control system (Jan 2010) – This task started in Phase III. The upgrading of underlying models for EKF and MPC were completed in 2010 Q1. The integration of these two models was completed in 2010 Q2. The integration necessitated further tuning of EKF and MPC. This was completed in 2010 Q3.
- Final computer simulation demonstration of integrated model-based advanced sensing and control system (Jun 2010). The computer simulation of the final

version of the integrated advanced sensing and control system was demonstrated to DoE in December 2010.

All program milestones and deliverables have been completed.

3.2.2 Financial Plan & Status

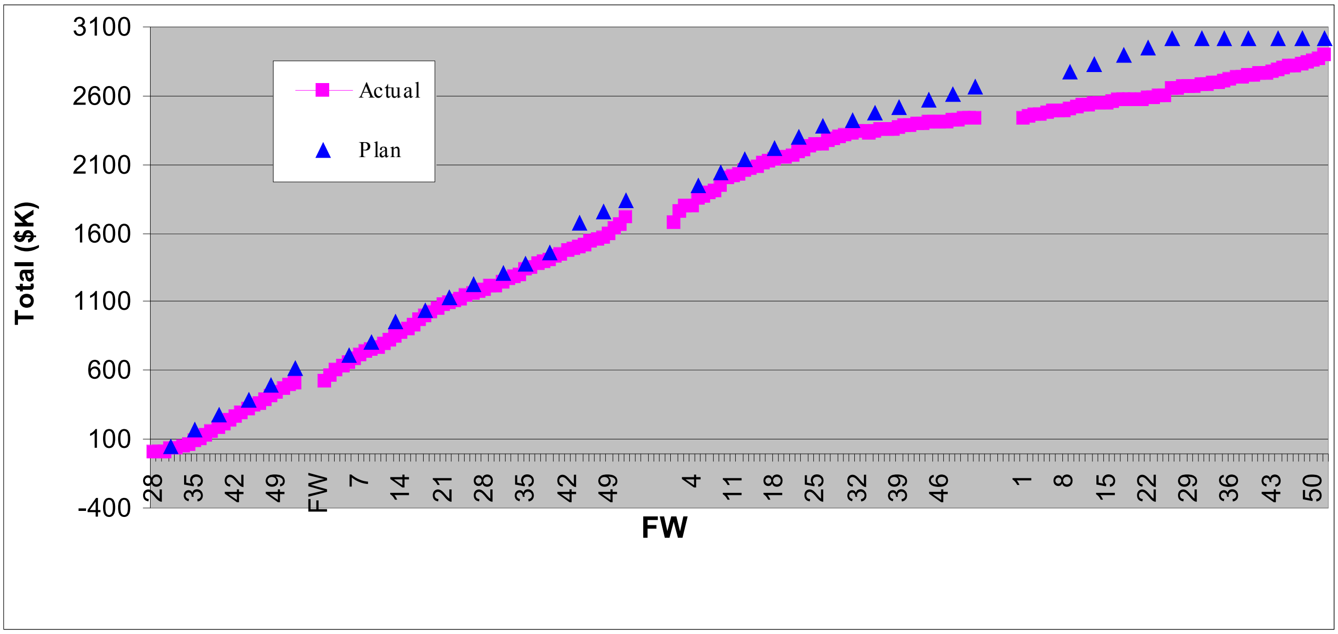

Figure 2: Planned and actual spending

Figure 2shows the planned and actual spending for the total program. The actual spending until FW 53, 2010 is $2,891K vs. a planned target of $3,016K.

4 Phase III - Design of Integrated Sensing and Control System

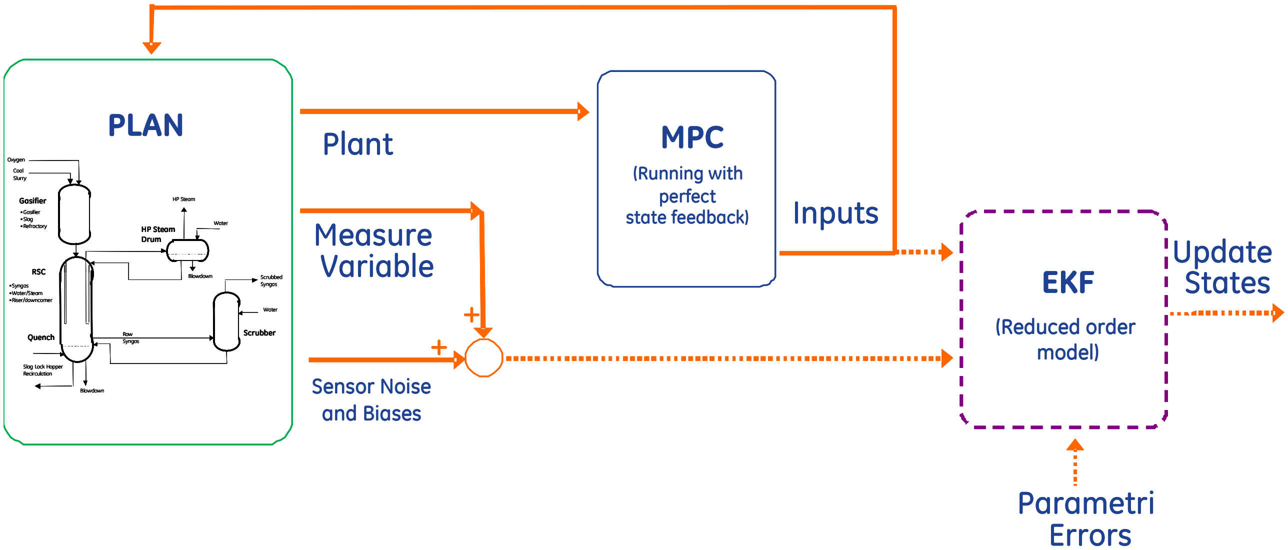

Figure 3: Schematic of previous implementation of EKF and MPC. MPC was running with perfect state feedback from plant while EKF was running in open loop.

Figure 3 shows the architecture used in Phase II, wherein the MPC with ideal sensors, i.e. perfect knowledge of all state and output variables from the plant, and the EKF-based sensing system using a combination of online sensors and model-based estimation were developed and tested in parallel. In Phase III of the program, the separate designs for MPC with ideal sensors and the EKF-based sensing system were coupled to obtain the overall integrated sensing and control system, as shown in Figure 4.

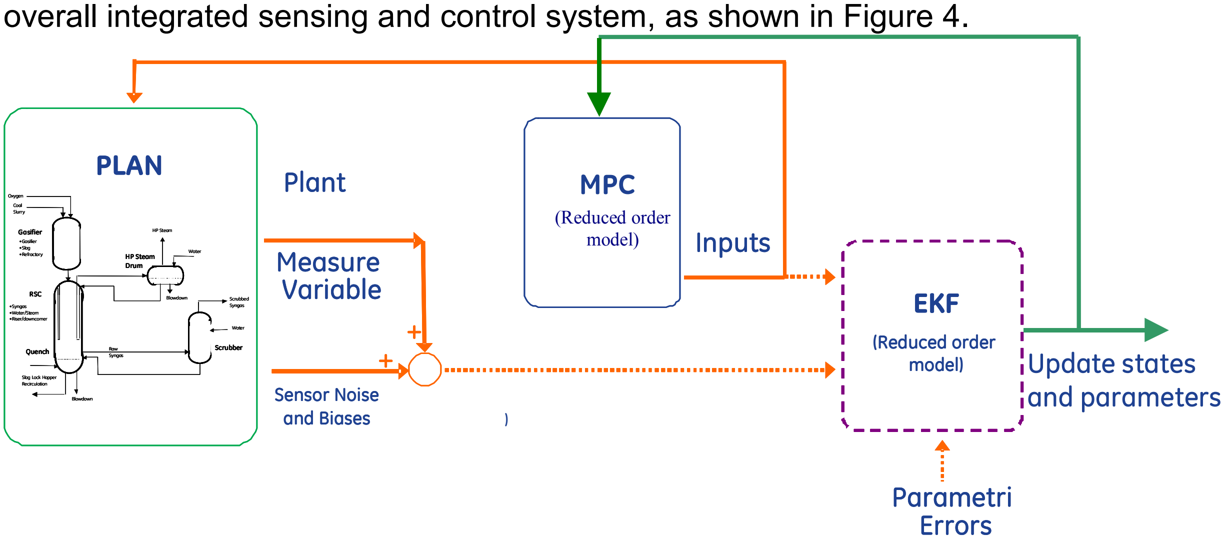

Figure 4: Schematic of Integrated EKF and MPC. The EKF updates the states and parameters for reduced order model used in MPC that no longer uses the perfect state and parameter information from the plant.

In a phased approach to this task, first the separate implementations of MPC and EKF were unified in a combined implementation, using the latest reduced-order model common to both and a common linear model generation routine to achieve high computational efficiency. Thereafter, the integrated control and sensing system was retuned for stability and performance robustness to random combinations of sensor noise, bias and modeling error. The final retuned system was studied using Monte-Carlo simulations for both coal slurry feed and coal-petcoke blend. For all these simulations, the system is initially simulated in open loop with only the EKF enabled (without engaging MPC controller) for about 60 minutes. This time is required for initial transients in estimated states and parameters to settle down. Thereafter the MPC controller is engaged to study the performance of the integrated EKF-MPC system for steady state and transient operation. The simulation results for coal slurry feed based on a number of Monte-Carlo simulations with random combinations of sensor noise and bias and modeling error (RSC fouling and gasifier kinetics) are presented next.

Simulations studies conducted with the integrated control and sensing system using coal slurry feed show good tracking performance during steady state as well as transient operations. Figure 5 and Figure 6 show one such result. Figure 5 shows various phases of each simulation and the performance improvement in each phase. The simulation is initiated (point ‘A’) at base load condition with only the EKF enabled. The simulation runs for almost 60 minutes without any external control input (open loop). After that the MPC is engaged at point ‘B’. The MPC quickly tracks the Net Electrical output and scrubber syngas pressure to the respective reference set points. At a steady state point ‘C’ the MPC engages in net electrical output maximization mode while respecting all the operational constraints (e.g., maximum slurry feed, ASU limit etc). At a later steady state operation point ‘D’ the MPC suspends the Net Electrical output maximization mode in preparation for the Net Electrical output turndown. Operation phase ‘E’ to ‘F’ represents 25% faster ramp tracking in net MW as well as scrubber syngas pressure compared to the nominal operation to 50% part load. Since, it is normally not desirable for the IGCC plant to turn down all the way to zero load due to startup complexities, the end of this turn down transient may represent the parking of the plant during the low demand period. During this period, one objective would be to minimize the oxygen consumption while maintaining certain minimum load (net electrical output as well as scrubber syngas pressure). The point ‘G’ represents the starting point of such a phase. At point ‘G’ the MPC engages the minimization of the oxygen consumption mode while maintaining 50% load. Phase ‘I’-‘J’ of the simulation represents the ramp up transient tracking of Net Electrical output from 50% load to base load condition at 20% faster rate compared to the nominal rate. Once at the base load, the MPC again engages the maximization of Net Electrical output mode at a steady state operation point ‘K’. As mentioned, all through this simulation the scrubber pressure is also tracked to a given reference trajectory as shown in the bottom graph of Figure 5.

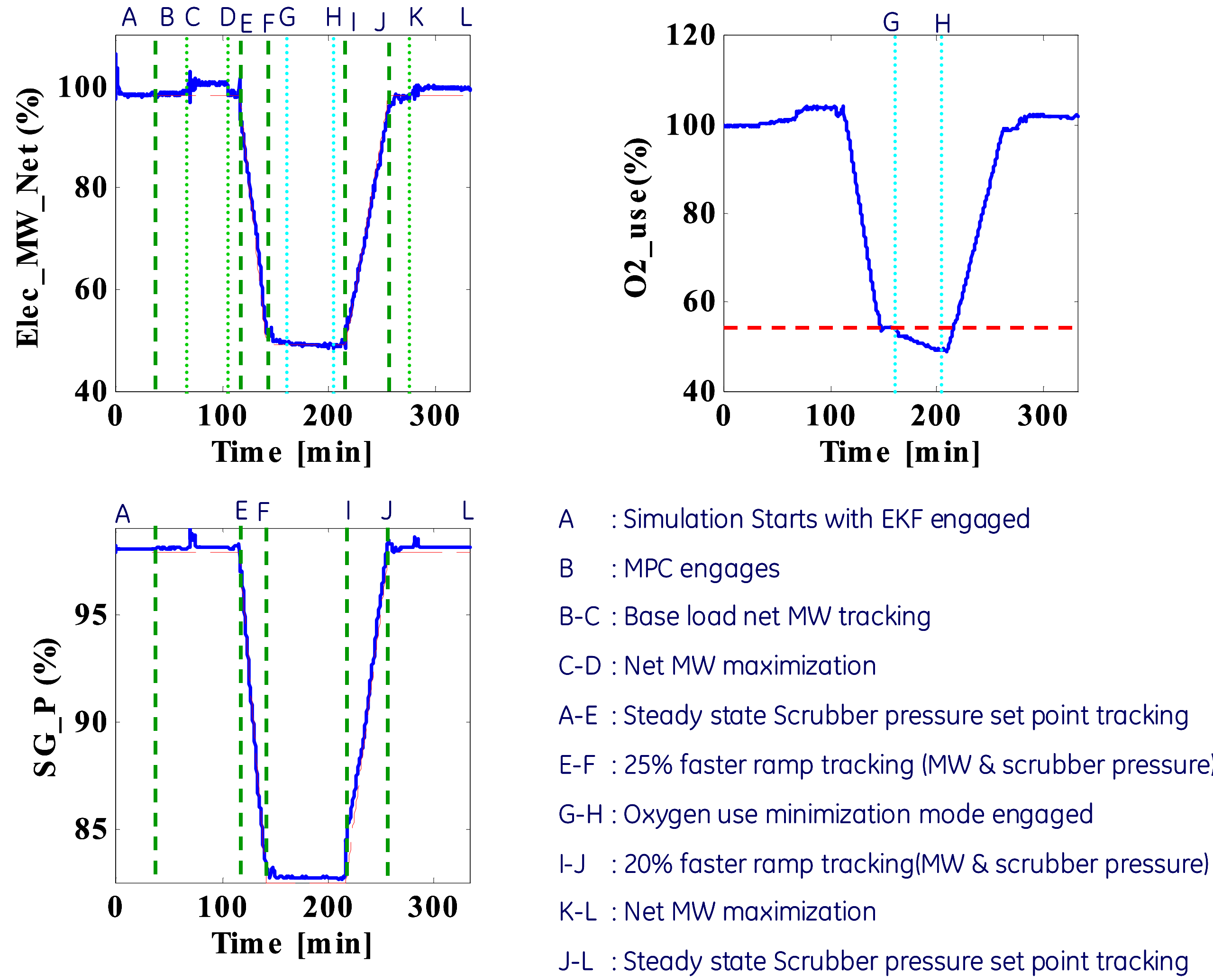

Figure 5: Integrated sensing and control system closed loop response to coal throughput changes from 100% -50%-100% with sensor and parameters error. The MW output and scrubber pressure (blue) track the reference profile (red) with 25% (ramp down) to 20% (ramp up) faster ramp rate compared to nominal.

Figure 6 shows more details on the overall plant response with the integrated sensing and control system to change in coal throughput from base load to 50% part load and then back to base load in the manner as described earlier (Figure 5), in the presence of sensor (one random combination of sensor bias) and modeling error (RSC fouling and Gasifier kinetics). For this simulation, the plant RSC is 30% fouled and the gasifier kinetics is 70% of the nominal value. The EKF is initialized to nominal values of these parameters (RSC fouling=0 and Gasifier kinetics scale factor =1). The simulation response shows that despite the presence of sensor noise and parameter error the integrated sensing and control system has a good Net Electrical output set point tracking performance for both, at the steady state as well as the transient operation. This is similar to what was observed with “ideal” plant and sensor earlier and reported in 2009 Topical report. Further the integrated system is able to maximize the Net Electrical output for this combination of sensor noise and bias and model parameter error by more than 2% at the base load and cut down the oxygen consumption at partload by about 10%. Figure 6 also shows that the EKF estimates of gasifier kinetics scale factor (Eta_{sf}) and the RSC fouling factor ($Fouling_{sf}$) at base load condition are quite good. However, at part-load conditions due to limited “observability” of the parameters in the system, the parameter estimation is less accurate. More specifically, since EKF estimates all the states, parameters and biases such that combinations of all these result in minimum variance estimate to match the sensor measurements, the individual parameters are not guaranteed to track the actual parameters. However, the overall closed-loop response shows that even in the presence of sensor and modeling errors and despite the limited “observability” of the parameters in the system, the integrated sensing and control system is able to track the load and syngas pressure references well: tracking 20-25% faster turndown ramp rates. In the figure the blue graph in Elec_MW_Net and SG_P represent the actual response whereas the reference trajectories are shown as red graph.

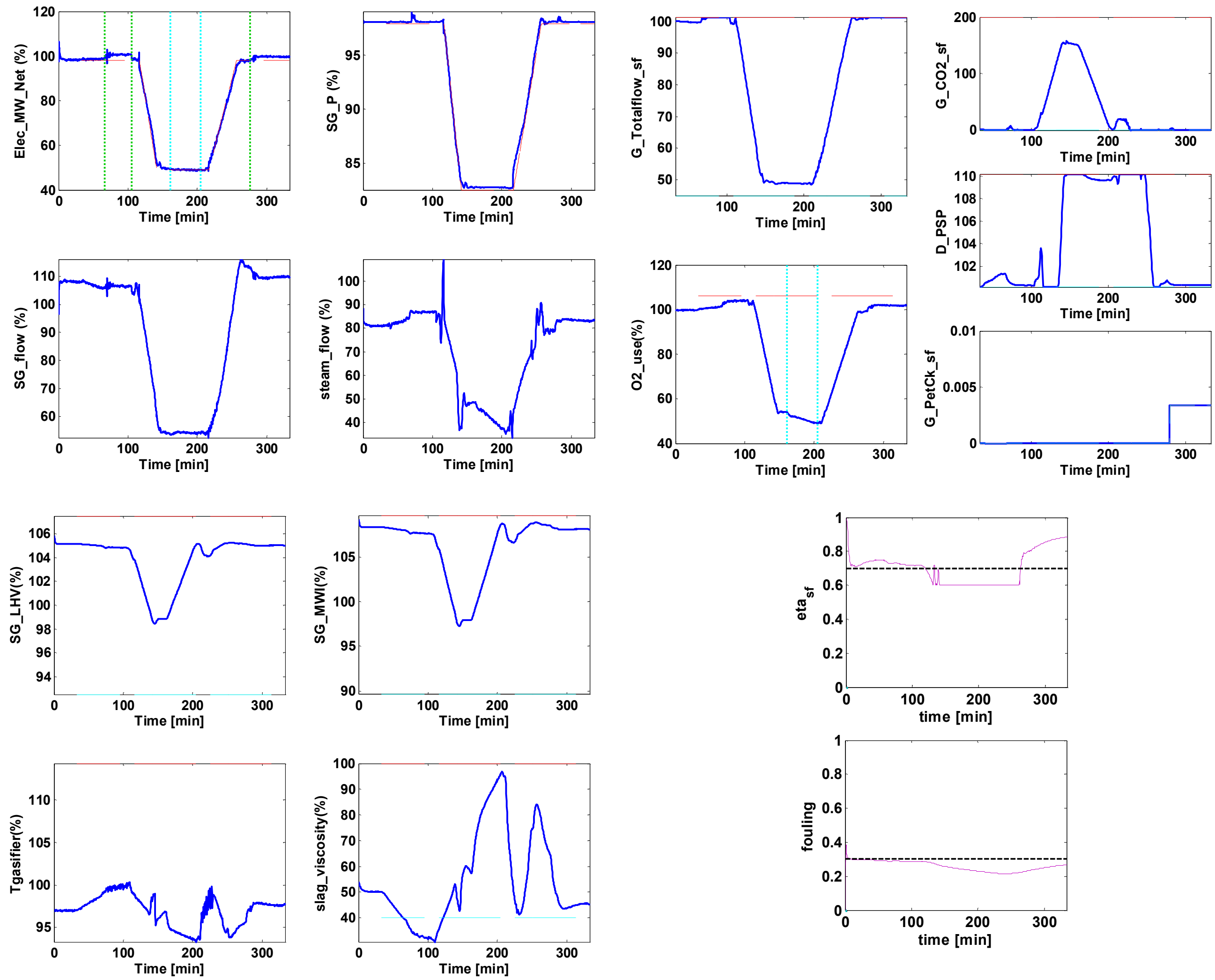

Figure 6: Integrated sensing and control system closed loop response to coal throughput changes from 100% -50%-100% with one combination of random sensor biases and parameters error.

As mentioned earlier, the designed integrated sensing and control close loop system was studied using Monte-Carlo simulations using random combinations of the sensor biases for each run. These results are presented in Figure 7and Figure 8. For all these simulations the plant RSC is 30% fouled and gasifier dynamics is 70% of the nominal value whereas, the estimator is initialized with nominal gasifier kinetics (eta_{sf}=1) and no fouling in the RSC (fouling=0). Histograms of the maximum sustained net electrical power output gain at base load condition and maximum sustained saving in oxygen consumption at 50% part load observed in Monte-Carlo simulation are presented in Figure 7. The simulation shows that the gain in net electrical power output could be as much as 2-2.5%, however, this gain is uneven and depends upon the sensor noise and bias combination. This is due to non-perfect observability in the system. Due to non-perfect observability some performance constraint parameters like carbon conversion, slag viscosity and Wobbe index cannot be estimated very accurately. This results in more conservative optimized performance due to constraints posed on these signals. The Monte Carlo simulation also shows that 7-10% sustained saving in oxygen consumption over the nominal consumption for 50% load can be achieved by judicious manipulation of control inputs. For consistency purpose, the saving in oxygen consumption is normalized with respect to the net electrical power output to account for any slight changes in electrical power output during the optimization of oxygen consumption phase. This gain is similar to what was observed with “perfect” sensors as reported in 2009 Topical report for Phase II.

Finally, Figure 8 shows the time traces and histograms of gasifier kinetics parameter (eta_{sf}) and RSC fouling for the same Monte-Carlo simulations. As mentioned earlier, each simulation starts in open loop with model-based estimator (EKF) engaged for an hour before the controller (MPC) is activated. This is required for the estimates of “unknown” parameters in model (used both for EKF and MPC) and sensor biases to settle to its steady state values as seen in subplots in Figure 8. Without this open loop operation, it has been observed in multiple simulations that the interaction between the estimator and the controller may lead to closed loop system instability. The time traces of the parameters also show that these parameters are estimated more accurately at the base load steady state condition as compared with the part load steady state condition or during the transient operations, due to poor observability at part load conditions. Since the parameters observability is better as the base load condition, starting the simulation at these conditions also helps in more accurate estimation of these parameters. Starting at baseload condition, once the estimation has converged close to the “correct” value, it does not change significantly again on account of poor observability. The histograms at the bottom of Figure 8 correspond to the average value of corresponding parameters for each Monte-Carlo simulation. The figures show that the average estimated parameter values over each simulation are close to actual values.

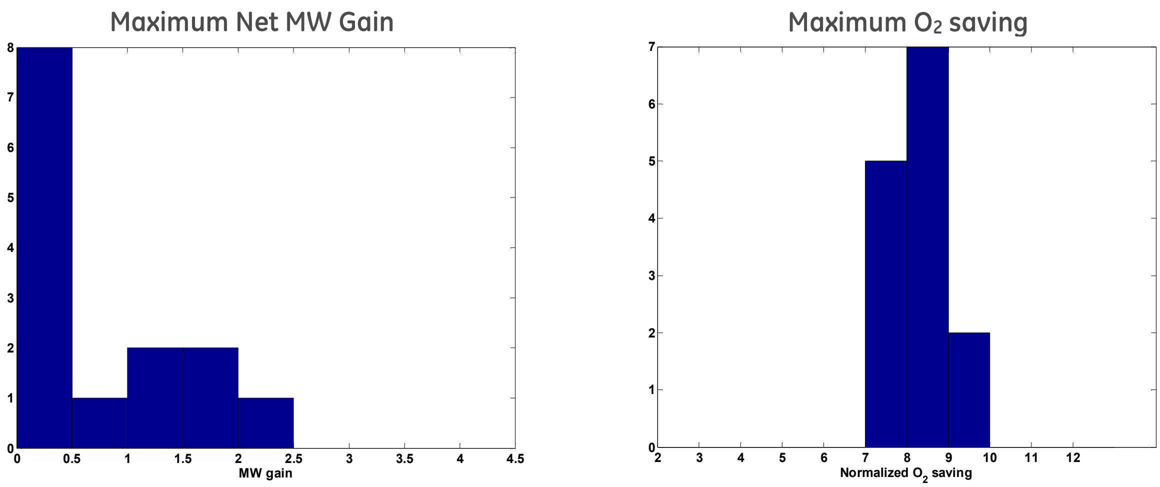

Figure 7: Monte Carlo simulation results for Net Electrical output gain at the base load condition and oxygen saving at 50% part load condition for various random combination of sensor error (bias) and model parameter error (gasifier kinetics and RSC fouling) using the integrated sensing and control system for coal throughput changes from 100%-50%-100%.

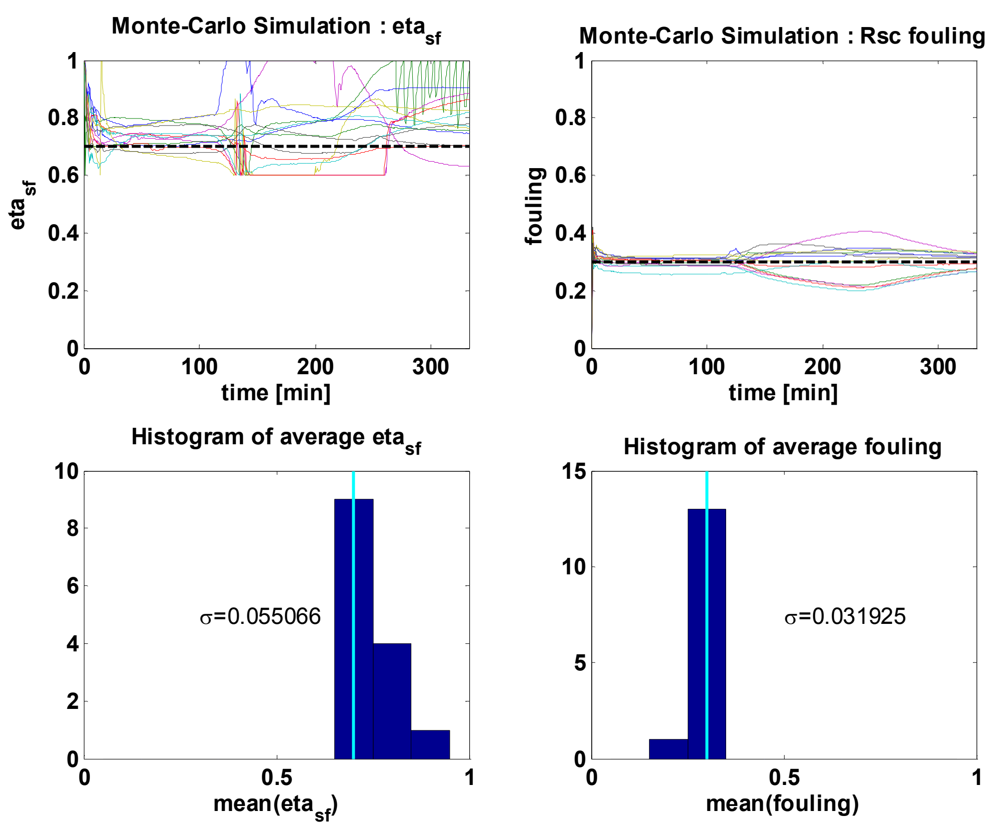

Figure 8: Monte Carlo simulation results for gasifier kinetics and RSC fouling for various random combination of sensor bias and model parameters error for the integrated sensing and control system closed loop system to coal throughput changes from 100%-50%-100%.

Similar simulation studies were also carried out for coal-petcoke fuel blend. These results are presented next. Figure 9 shows various phases of simulation with coal-petcoke fuel blend. The simulation is initiated (point ‘A’) at base load condition with EKF engaged. The simulation runs for almost 60 minutes without any external control input (open loop). After that the MPC is engaged at point ‘B’. The MPC quickly tracks the Net Electrical output and scrubber syngas pressure to the respective reference set points. Operation phase ‘C’ to ‘D’ represents 25% faster ramp tracking in net MW as well as scrubber syngas pressure compared to the nominal operation to 50% part load. Again, since it is normally not desirable for the IGCC plant to turn down all the way to zero load due to startup complexities, the end of this turn down transient may represent the parking of the plant during the low demand period. During this period one objective would be to minimize the oxygen consumption while maintaining certain minimum load. The point ‘E’ represents starting of such a phase. At point ‘E’ the MPC engages the minimization of the oxygen consumption mode while maintaining 50% load. At point ‘F’ the MPC disengages the oxygen minimization mode in preparation for transient operation. Phase ‘G’-‘H’ of the simulation represents the ramp up transient tracking of Net Electrical output from 50% load to base load condition at 20% faster rate compared to the nominal rate. Once at base load, the MPC again engages tracking of Net Electrical output as well as scrubber syngas pressure mode and maintains the steady state operation. As mentioned, all through this simulation, the scrubber pressure is also tracked to a given reference trajectory as shown in the bottom graph of Figure 9.

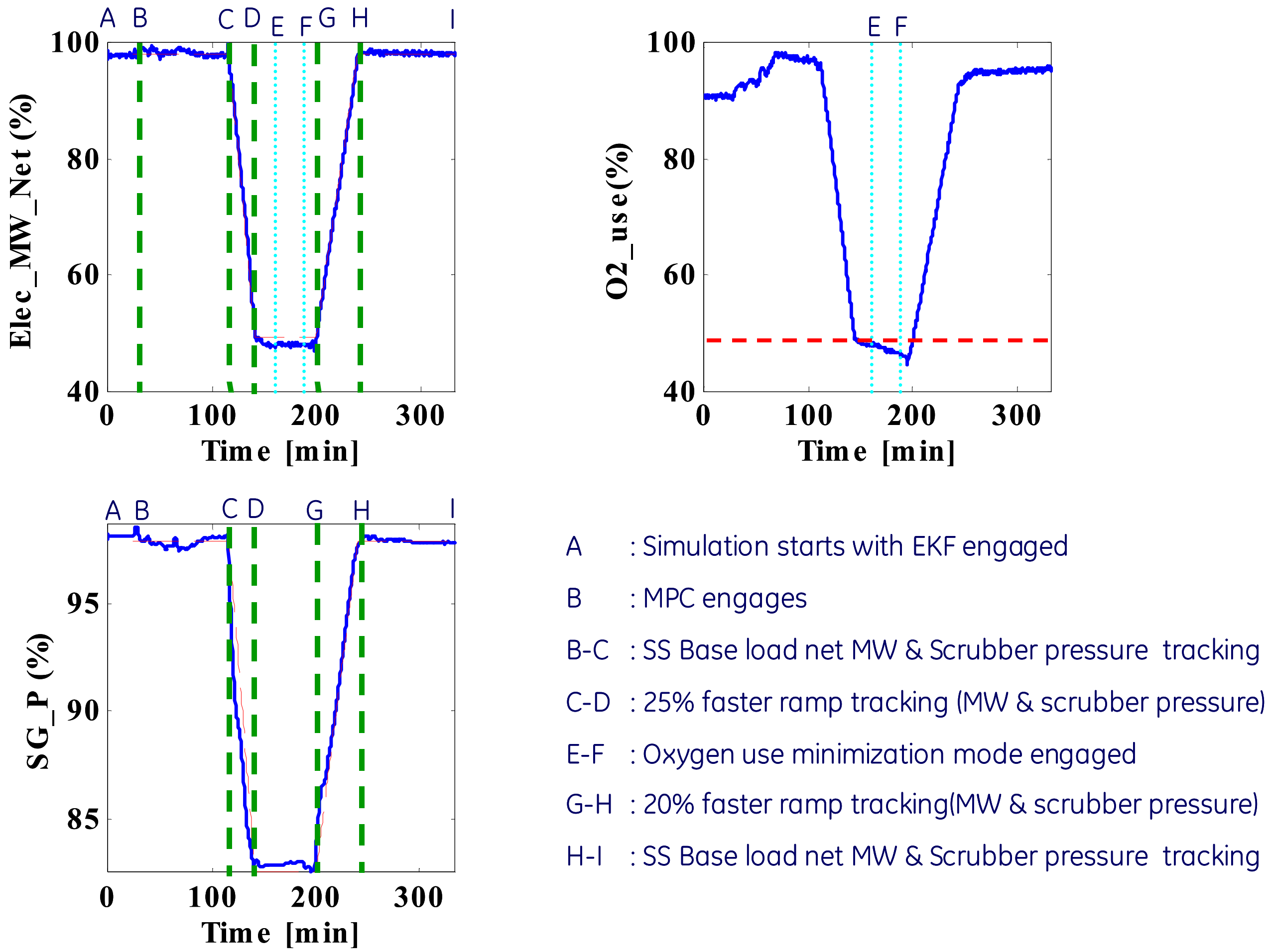

Figure 9: Integrated sensing and control system closed loop response to coal-petcoke blend throughput changes from 100%-50%-100% with sensor and parameters error. The MW output (blue) track the MW reference (red) with 25% (ramp down)-20% (ramp up) faster ramp rate compared to nominal.

Figure 10 shows more details on the overall plant response to the integrated sensing and control system to changes in coal-petcoke blend throughput from base load to 50% part load and then back to base load in the manner as described earlier (Figure 9), in the presence of one random combination of sensor error (bias) and modeling error (RSC fouling and gasifier kinetics). Similar to the coal case, for this study the plant RSC is 30% fouled and the gasifier kinetics is 70% of the nominal value. The EKF is initialized to nominal values of these parameters (RSC fouling=0 and gasifier kinetics scale factor =1). The simulation response shows that despite the presence of sensor noise and parameter error the integrated sensing and control system has a good steady state as well as the transient operation tracking performance for both, the Net Electrical output as well as scrubber syngas pressure. This is similar to what was observed with “ideal” plant and sensor earlier and reported in 2009 Topical report for Phase II. Further the integrated system is able to cut down the oxygen consumption by about 6% at partload. This is again similar to what was observed with “ideal” plant and sensors and reported in 2009 Topical report. Figure 10 also shows the EKF estimates of gasifier kinetics scale factor (Eta_{sf}) and the RSC fouling factor ($Fouling_{sf}$) over the duration of the simulation. The figure shows that plant parameters namely gasifier kinetics scale factor and RSC fouling factor estimates are slightly less accurate: at base load condition, the EKF estimates slightly faster gasifier kinetics whereas at the partload condition it estimates slightly slower kinetics. Further, at baseload condition the RSC fouling is accurately estimated close to the actual value of 30%, while the estimation deteriorates at part load condition. This is due to limited “observability” of the parameters in the system, especially for small throughput at partload operation. Similar to coal case, since EKF estimates all the states, parameters and biases such that combinations of all these result in minimum variance estimate to match the sensor measurements, the individual parameters are not guaranteed to track the actual parameters. Nevertheless, the overall closed-loop response shows that even in the presence of sensor and modeling errors and despite the limited “observability” of the parameters in the system, the integrated sensing and control system is able to track the load and syngas pressure references well: tracking 20-25% faster turndown ramp rates. In the figure the blue graph in Elec_MW_Net and SG_P represent the actual response whereas the reference trajectories are shown as red graph.

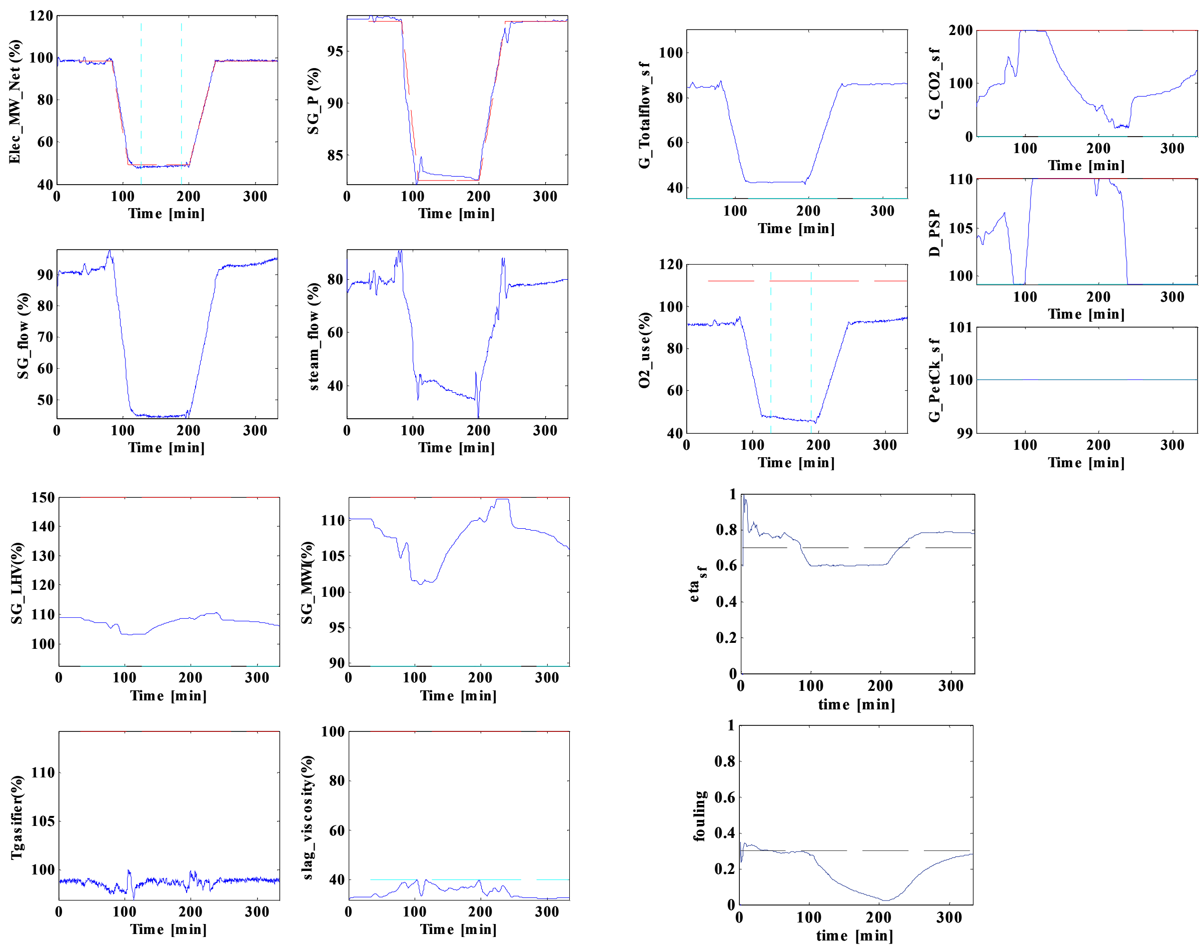

Figure 10: Integrated sensing and control system closed loop response to coal-petcoke blend throughput changes from 100%-50%-100% with one combination of random sensor bias and parameter errors.

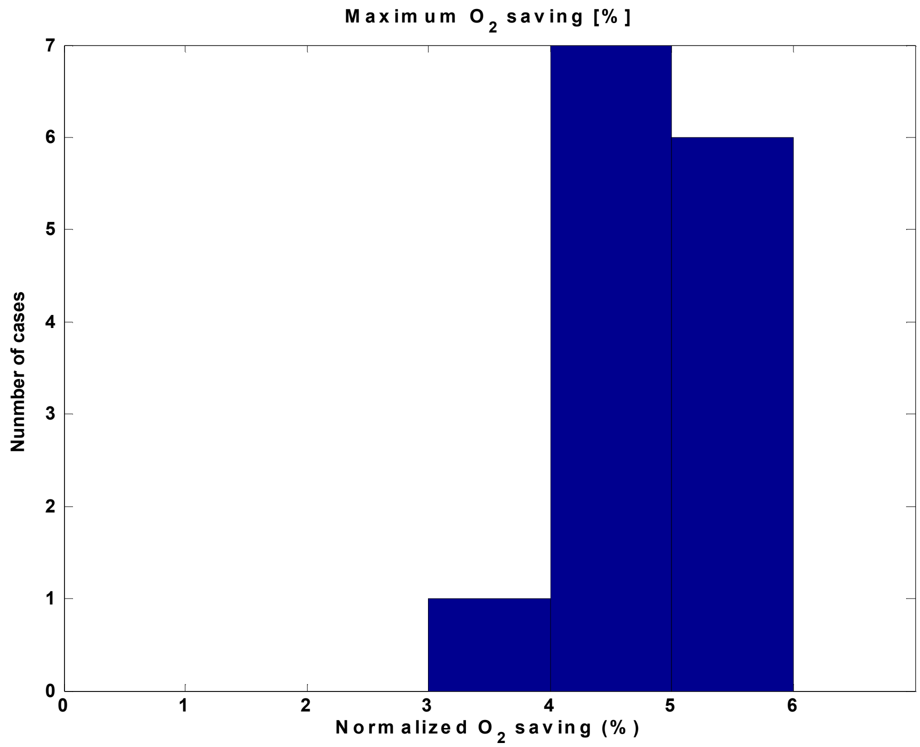

Figure 11: Monte Carlo simulation results for normalized oxygen saving at 50% part load condition with various random combination of sensors error (noise and bias) and model parameters error (gasifier kinetics and RSC fouling) for the integrated sensing and control system to coal-petcoke blend throughput changes from 100%-50%-100%.

As mentioned earlier, similar to coal fuel, the designed integrated sensing and control close loop system was studied using Monte-Carlo simulations using random combinations of sensor biases for each run. These results are presented in Figure 11 and Figure 12. For all these simulations, the plant RSC is 30% fouled and gasifier kinetics is 70% of the nominal value whereas the estimator is initialized with nominal gasifier kinetics (eta_{sf}=1) and no RSC fouling (fouling=0). Histogram of the maximum sustained saving in oxygen consumption at 50% part load observed in Monte-Carlo simulation is presented in Figure 11. The Monte Carlo simulation shows that 3-6% sustained saving in oxygen consumption over the nominal consumption for 50% load can be achieved by judicious manipulation of control inputs for most cases of sensor bias combination. For some combination of sensors bias, this gain may be quite small. This is due to non-perfect observability in the system. Due to non-perfect observability some performance constraint parameters like carbon conversion, slag viscosity and Wobbe index cannot be estimated very accurately. This results in more conservative optimized performance due to constraints posed on these variables. For consistency purpose, the saving in oxygen consumption is normalized with respect to the net electrical power output to account for any slight changes in electrical power output during the optimization of oxygen consumption phase. This gain is similar to what was observed with “perfect” sensors as reported in 2009 Topical report.

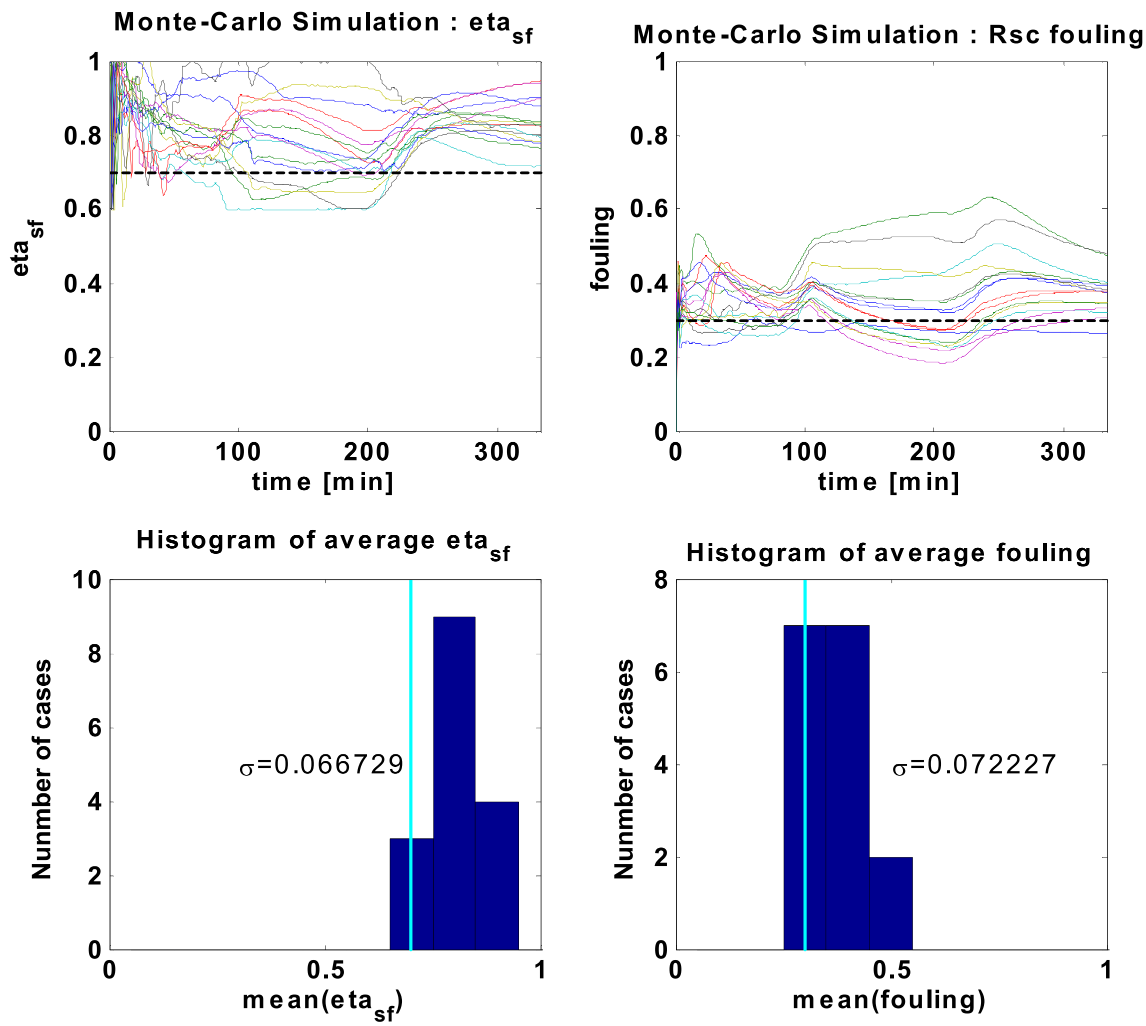

Figure 12: Monte Carlo simulation results for gasifier kinetics and RSC fouling for various random combination of sensor noise and model parameters error for the Integrated sensing and control system closed loop system to coal-petcoke blend throughput changes from 100%-50%-100%.

Finally, Figure 12 shows the time traces and histograms of gasifier kinetics parameter (eta_{sf}) and RSC fouling for the same Monte-Carlo simulations. As mentioned earlier, each simulation starts in open loop with model-based estimator (EKF) engaged for an hour before the controller (MPC) is activated. This is required for the estimates of "unknown" parameters in model (used both for EKF and MPC) and sensor biases to settle to its steady state values as seen in subplots in Figure 12. Similar to coal fuel cases, without this open loop operation, it has been observed in multiple simulations that the interaction between the estimator and the controller may lead to closed loop system instability. The time traces of the parameters also show that these parameters are estimated more accurately at the base load steady state condition as compared with the part load steady state condition or during the transient operations, due to poor observability at part load conditions. Since the parameters observability is better as the base load condition, starting the simulation at these conditions also helps in more accurate estimation of these parameters. Starting at baseload condition, once the estimation has converged to the "correct" value, it does not change significantly again on account of poor observability. The histograms at the bottom of Figure 12 correspond to the average value of corresponding parameters for each Monte-Carlo simulation. The figures show that unlike the coal case, in coal-petcoke cases, the average parameter values over each simulation are not very accurate. The performance of the EKF parameter estimation could possibly be improved by further retuning of the EKF. Despite this, as shown in Figure 10, the Integrated sensing and control system has good steady state as well transient tracking performance and is able to optimize the operational cost within the operational constraints.

5 Conclusions

An IGCC plant is a large chemical plant that is traditionally designed to operate mainly at steady-state conditions, coupled to a power generation plant, which is intended to operate in a robust and flexible manner. It is highly desired to achieve high degree of reliability and increasingly flexible operation in terms of turndown or load-following capability and fuel changes while achieving optimum overall plant efficiency. This in turn, implies a need for increasing automation for coordinated and optimized operation of the various sections of the plant to meet fluctuating power generation objectives. One of the main hurdles in increasing automated operation of the plant is limited sensing of the critical parameters available in the real time, e.g., slag viscosity and carbon conversion due to harsh sensing environment with in the gasifier section. This situation can be improved by using soft sensors to complement the hardware sensor available in the plant. This program is focused on developing advanced integrated sensing and control systems to achieve the objectives of higher reliability and flexible operation with optimized efficiency. In particular, this program focuses on the gasification section, which is the core section of the plant, yet most limited in terms of automated operation, due in large part to a very harsh environment and corresponding limitations on online sensing. Motivated by this, the aim is to develop a systematic model-based approach for analysis and design of sensing and control systems, using physics-based models in online sensing and control.

In Phase I of this three-year program a dynamic model of the gasification section was developed and implemented in Matlab/Simulink® for normal operation. The model was validated using TECO Polk Power Station IGCC plant in Phase II of the program. Apart from this, the key focus in Phase II of the program was to perform (i) a linear model-based analysis for sensing system design, (ii) design and implement a nonlinear model-based constrained EKF to obtain a comprehensive sensing system integrating online sensors with model-based estimation, and (iii) implement an MPC for optimized operation of the gasification section during startup pre-heating as well as nominal operation with coal and coal-petcoke blend fuels. The initial MPC implementation assumed "ideal" sensors (no noise and bias) and "ideal" plant (no parameter uncertainty). Extensive simulation studies were performed to evaluate the performance of the model based constrained EKF and the MPC independently. Using linear model-based analysis key sensor biases and model parameters were identified. These were included in an online nonlinear model-based estimation using a constrained EKF. The simulation studies showed that the EKF could successfully identify the unknown model parameters and provide an accurate estimate of key process variables that were not measured, but were important for process monitoring and operation. Similarly, extensive simulation studies were done to evaluate the MPC performance for nominal operation at part-load and baseload conditions and for turndown between part-load and baseload conditions. In one optimization mode at steady-state conditions, MPC yielded potential reduction of oxygen consumption by up to 10%. In another optimization mode for transient operation during turndown, MPC simulations yielded faster ramp-up and ramp-down capabilities by 20% faster than baseline nominal capability corresponding to the ASU rate limits. The MPC implementation can be configured for optimization of different objectives depending on the operation mode. These optimization objectives include carbon conversion, efficiency, oxygen consumption and power output at steady state, and turndown ramp rates during load transients. This capability provides for an enhanced robustness and flexibility in the gasification section operation. Similarly, MPC simulations were used to study the operation with coal-petcoke blends, and optimization for nominal operation at part-load and baseload conditions and turndown, yielding similar improvements as with coal fuel.

In Phase II of the program, a sensing system integrating available online sensors and real-time model-based estimation, and an MPC were designed and tested separately through extensive simulation studies. The main focus of Phase III of the program was to integrate the designed sensing and control systems to obtain the overall integrated sensing and control system and test out its performance. In this effort, first the underlying physics-based models were updated to a common version, and then the EKF and MPC were coupled and re-tuned extensively for good closed-loop performance of the integrated sensing and control solution. The physical model has many “unknown” parameters, e.g., gasifier kinetics, RSC fouling etc. The EKF provides estimates of these parameters as well as of outputs important for efficient and safe operation like the gasifier temperature, carbon conversion, slag viscosity etc. in the presence of random sensors noise and bias. This integrated solution was tested through Monte-Carlo simulations with random combinations of sensor biases in the presence of model parameter errors. The simulation was designed to test performance of the integrated sensing and control system for Net electrical output and syngas pressure setpoint tracking as well as minimizing the oxygen use at the part load condition, with coal as well as coal-petcoke fuel blend while respecting all the operating constraints like ASU rate and minimum carbon conversion etc in the presence of random and unknown sensors noise and bias and unknown plant parameters, e.g., gasifier kinetics and RSC fouling factor. For the coal slurry operation the MPC additionally maximizes net electrical output at the base load condition.

The simulation studies show that the steady state as well as the transient tracking performance of integrated system is good despite the presence of sensor and modeling errors. Further, the integrated system provides the capabilities to the turn down 20% (ramp up) or 25% (ramp down) faster than the nominal operation while maintaining all the operational constraints. The integrated system also enables the optimization of various objective functions depending upon the current operation mode, thus providing operational flexibility. More specifically, for example, in the current setting, the MPC maximizes the net electric power output at base load condition whereas it minimizes the oxygen usage at the part load condition. Again in the framework of current studies, the Monte Carlo simulation studies show that the system net electrical output could be increased by about 2% of the nominal value at the base load condition with coal slurry. Further, the oxygen consumption could be reduced by 7-10% at part load condition for coal slurry. With coal-petcoke blend fuel, the oxygen saving was a bit less at around 3-6% - this is in part due to the more constrained operation with petcoke owing to the higher carbon content. The EKF also estimated the unknown model parameters like gasifier kinetics and RSC fouling. The estimates were good at baseload conditions, and deteriorated a bit during transients or at partload conditions. This is due to the fact that the parameters are more observable due to the higher sensitivity at baseload operation with higher throughput. The parameter observability is reduced at partload operation. Due to limited observability it is not always possible to estimate the unknown model parameters and compensate for sensor noise and bias accurately. Nevertheless, the integrated sensing and control system using EKF and MPC works very well for steady state and transient tracking as well as optimization.

The simulation studies have shown promising results for the EKF and MPC implementations individually as well as for the final integrated EKF & MPC solution. These results can be used as the basis for pursuing a future implementation of the developed sensing and controls solution in an IGCC plant, in a staged manner. One option could be to implement the EKF first using available online sensors in the gasification section and mature its performance in plant application – validating both the underlying model and the model-based estimation solution. Thereafter, MPC can be implemented and integrated with EKF to achieve the advanced sensing and control solution, first using in an “advisory” mode to aid operators and then in an automated closed-loop mode as the technology is matured in plant application. In a separate direction, the developed advanced sensing and control solution for the gasification section could be expanded or integrated with sensing and controls for the other sections towards an overall plant control system for optimizing the overall plant operation.