HYDROGEN BLENDING AND PARTIAL LOAD CONTROL MODELING: UPDATED DESIGNS AND SIMULATIONS

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Abstract. As discussed in Harper et al. [1], EPRI has been investigating potential issues in real gas turbine hydrogen blending and flexible load control. Earlier research and operations have shown that gas turbines operating under variable partial load may experience more operational issues. This is partly due to the demands placed on the control system by a gas turbine operating at highly variable efficiencies and load. Demonstrations of hydrogen blending have been conducted on many gas turbines [2-6]. However, these demonstrations have generally not been completed under "real world" flexible loading operations of a gas turbine. It is highly likely that if hydrogen is utilized in large capacities in gas turbines in the future, it will be under variable and highly flexible loading operations due to the costs of hydrogen and the prevalence of Variable Renewable Energy (VRE, Solar, Wind) in that potential future scenario. As detailed in Harper et al. [1], without hydrogen, gas turbine peaker operation can be highly variable with many starts and load changes in short periods of time. The initial study found that traditional load control techniques may lead to operational issues in meeting grid demands and gas turbine operational requirements for robust operation when hydrogen blending is added. This work expands on the previous study of Harper et. al [1] by examining additional scenarios. The gas turbine model and control system have been updated to reflect the timescales of state changes (pressure, temperature, and power) more accurately with changes in boundary conditions (fuel/air flow). This is combined with an evaluation of an updated Model Predictive Control (MPC) architecture designed to control the blending rate, load, and combustion firing temperature accurately. These system design changes are detailed along with simulation results.

1 Nomenclature

AGC	Automatic Generation Control
CPR	Compressor Pressure Ratio
DCS	Distributed Control System
DLN	Dry Low NOx
FMI	Function Mock-Up Interface
FSR	Fuel Stroke Reference
GT	Gas Turbine
H_2	Hydrogen
IGV	Inlet Guide Vanes
LHV	Lower Heating Value
GUI	Graphical User Interface
MIMO	Multiple Input Multiple Output
MPC	Model Predictive Control
NG	Natural Gas
NOx	Nitrous Oxide
PID	Proportional Integral Differential
N	Number of data points
VRE	Variable Renewable Energy
$y_{SP}(t)$	Process variable setpoint at the current instant
$\bar{y}_{SP}$	Process variable setpoint average
$y_{MPC}(t)$	Process variable at the current using MPC

2 Introduction

Hydrogen is an active area of research for reducing carbon emissions in gas turbine combustors [7,8]. In that vein, development of gas turbines, fuel systems and controls which can blend hydrogen with natural gas up to fully fuelled with natural gas are being developed. EPRI has been engaged in providing understanding of these developments on the gas turbine BOP [10].

Much of the development has focused on the design of the gas turbine combustor which has many operational concerns and design changes that may be required to operate with these blends [9]. Fuel systems have operating with hydrogen fuel in refineries for decades but fuel delivery systems with hydrogen and natural gas separate streams in multi-circuit dry low NOx combustion systems in operation today require some additional changes to the fuel delivery system [10]. Gas turbines operational profiles have changed from providing only firm baseload power to dispatchable variable load power. This operation brings challenges in operability, life, emissions profiles, heat rate and profitability of the assets.

Fig. 1 is a plot of real data from the gas turbine utilized as the performance and operational basis for this updated analysis. The figure shows a typical operational profile for the asset, starting 5 times in one 24-hour

period while also controlling to a variable load demand on Automatic Generation Control (AGC) while at load.

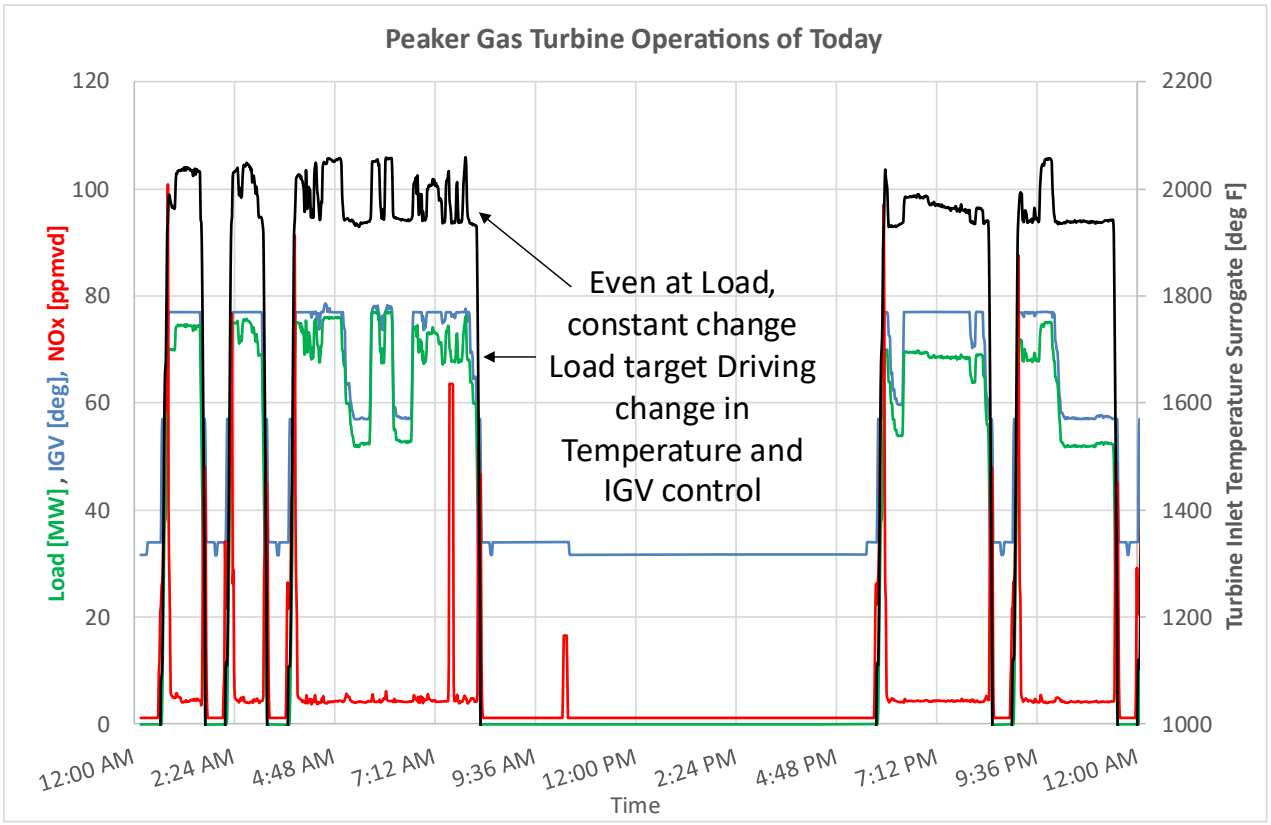


Fig. 1. Simple Cycle gas turbine operational profile example

Operational control, ensuring acceptable system performance (heat rate, load), condition (combustion / exhaust temperatures), emissions is a greater challenge under these more variable conditions. As new fuels such as hydrogen emerge and are blended with traditional natural gas fuels, this challenge is likely to increase. Fig. 2 shows data taken from a hydrogen demonstration for a gas turbine operated in partload with blends of hydrogen. The variable emissions and firing temperatures even under stable load and hydrogen blending conditions exhibit this challenge.

Given this, the authors have undertaken a study to focus on understanding potential gas turbine control under these scenarios through modelling the fuel delivery, the gas turbine and the gas turbine controller. First by modelling traditional control architectures, then by more modern controls to evaluate the potential pitfalls and efficacy of new control techniques. This study update includes fidelity, design, and methodology changes from the previous study.

Model Predictive Controls can be hindered in real applications due to their computational requirements. This is specifically due to the model utilized in the control. Higher fidelity models require more computational power. This may be a limiting factor in the adoption of MPC controls. The author's linear MPC, however, is not significantly more computationally intensive than the PID, but as more fidelity and model accuracy are required this could impact system performance and adoption of improved system control models.

3 Model Design Updates

As in [1] the gas turbine and fuel delivery systems were modelled in the Modelica systems programming language utilizing the Modelon Impact programming environment. Based on gas turbine hydrogen blending demonstrations [2,4,5], an updated fuel delivery system was modelled to add additional realism to the model. In addition, the GT model performance was updated based on a real frame gas turbine performance. As well the gas turbine model and gas turbine instrumentation models were updated to more accurately model the timescales and flow dynamics of the fuel delivery and gas turbine system. As the system was updated to more accurately reflect operational timescales more realistic operating conditions could be used to evaluate control techniques. As such, real gas turbine operations, using the same performance as modelled were used as inputs.

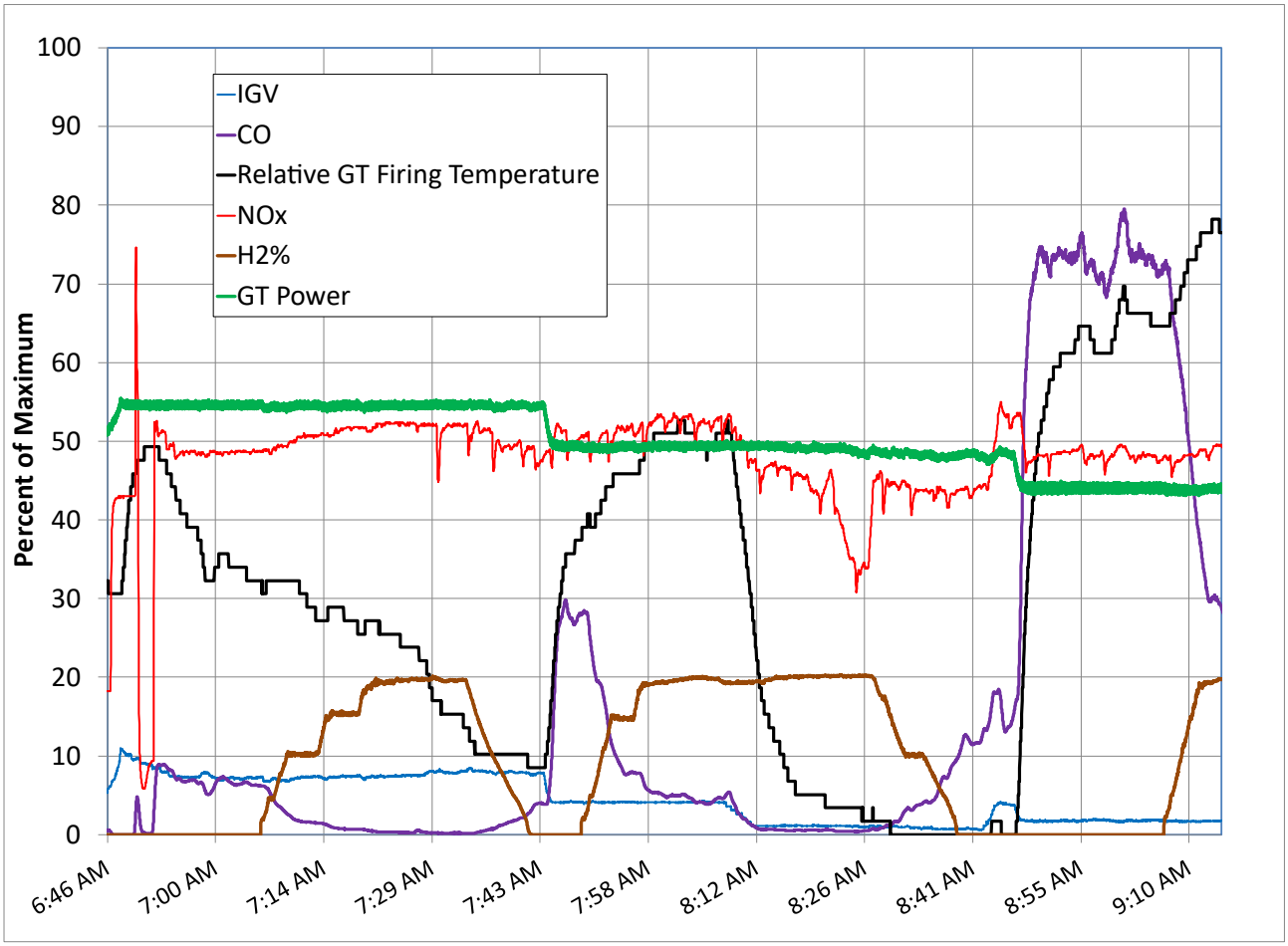


Fig. 2. Gas Turbine Hydrogen Demonstration Partload Operation

3.1 New GT Model

The new gas turbine model was built on a heavy-duty frame gas turbine. The baseload performance of the gas turbine is shown in Table 1. The gas turbine model compressor and turbine efficiency and flow maps were adjusted to match the performance of the turbine discussed in [1].

Table 1. Gas Turbine Performance Summary

Design Turbine Inlet Temperature (K)	1420
Baseload Power (MW)	78
Baseload Heat Rate (BTU/KW-hr)	10,000
Compressor Pressure Ratio	13
Compressor exit temperature (K)	633

The original model used by the authors included compressor and turbine components modelled through flow and efficiency maps but no components in the gas turbine included volumes which impact the effect of a change in control (e.g. fuel flow change) to a change in operation. The authors added volume to the gas turbine model to account for this. The fuel delivery system was updated with full dynamic piping system models to account for flow dynamics and time components in system changes. In the original model, the gas turbine was modelled with compressor and turbine maps for those sections only. Including these dynamic components adds the realistic effect of flow dynamics when operational conditions are changed. Measurement delays were added to the firing temperature and hydrogen blend measurements to account for the lag in condition change relative to its measurement in the gas turbine controller. For example, a firing temperature delay of 3s and a hydrogen blend delay of 10s were evaluated.

3.2 Fuel Delivery System

In the original study the fuel delivery system included the hydrogen and natural gas fuel gas supply, a hydrogen flow/blend control valve, natural gas shutoff valve and a blended gas total fuel control valve. This system is shown in Fig. 3. This figure includes the fuel delivery information as well as the measurements used to control the fuel delivery and gas turbine operations (fuel and air control). More detail on this system is available in [1].

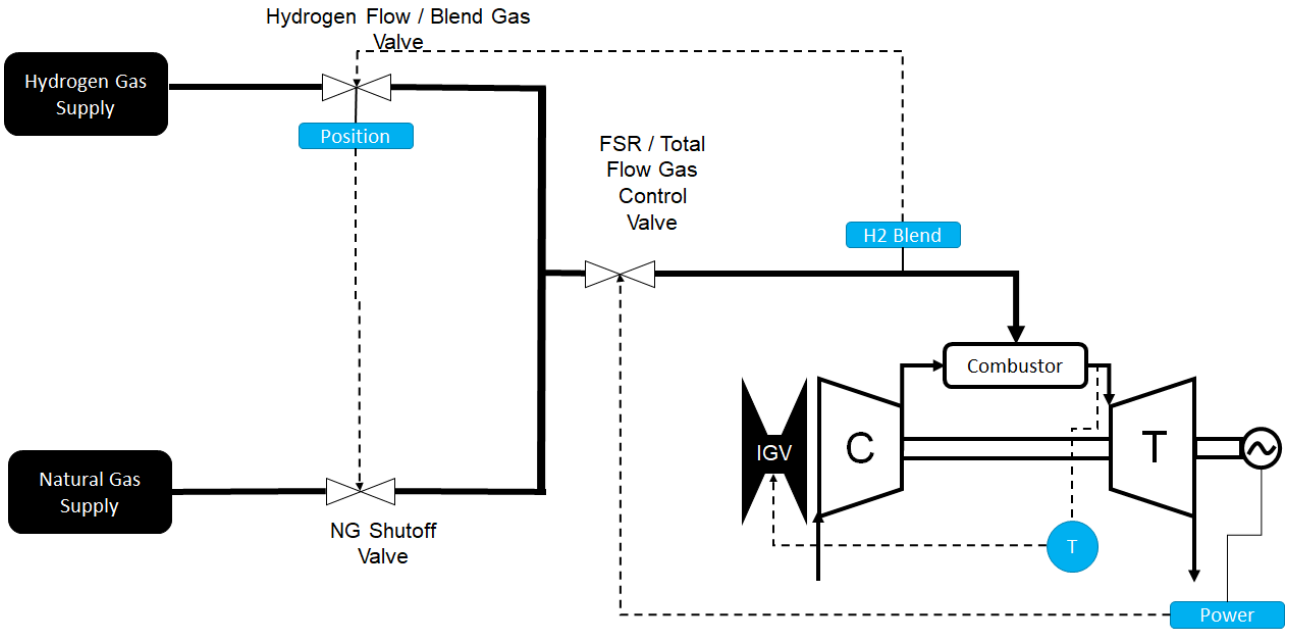


Fig. 3. Original study gas turbine fuel delivery and gas turbine system I/O for monitoring

Variable pressure conditions were utilized for the fuel delivery system in the original analysis, however, based on hydrogen system designs utilized by several OEMs pressure control valves were added to the fuel delivery system. As well piping systems with realistic volumes were added to model the flow dynamics of the fuel delivery system. A representation of the updated model is shown in Fig. 4.

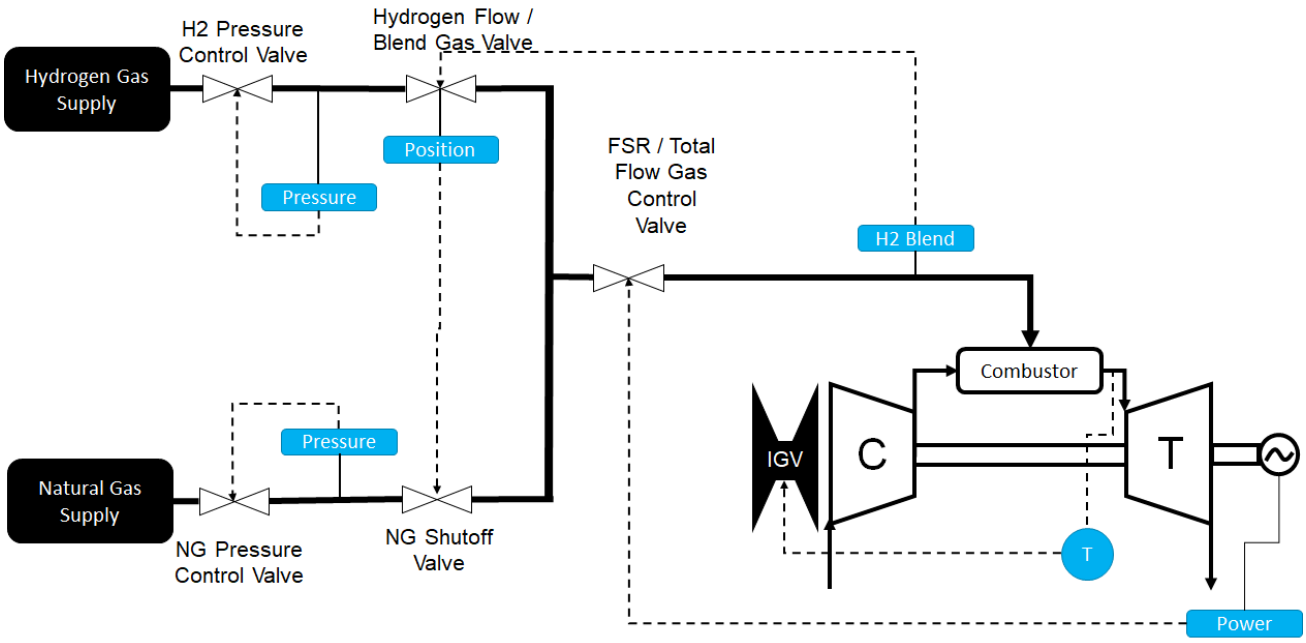


Fig. 4. Updated gas turbine fuel delivery and gas turbine system I/O for monitoring

3.3 Partload and Baseload Control

In the original analysis total fuel was controlled to target the load demand of the gas turbine while the Inlet Guide Vanes (IGVs) were controlled to target the design turbine inlet temperature of the gas turbine. In typical single speed frame gas turbines this is representative of partload control and where IGVs are at their maximum, the turbine is understood to be at a baseload condition and control changes to total fuel being controlled to target the turbine inlet temperature (or some related temperature such as exhaust temperature). This control update is included in the updated model with logic flow as shown in Fig. 5.

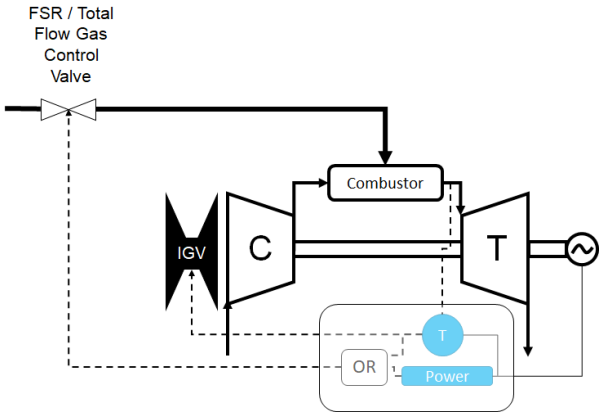


Fig. 5. Updated baseload and partload control logic flow

4 MPC UPDATES

In the previous study results [1], the authors discussed the use of the Functional Mock-Up (FMU) package to utilize the Modelica language based cyber-physical model with the MPC controller developed in MATLAB Simulink. While the authors were able to utilize the FMU for this simulation, working in different environments was challenging and the authors decided to investigate the development of an MPC based in Modelica language for this part of the study. MATLAB based MPC controller is composed of two components, which is an MPC controller and a Kalman filter observer that calculates the mathematical states for the MPC controller. The codes of both components were developed in MATLAB Simulink languages but converted to Modelica language in this work. This conversion was necessary to enable a seamless integration of the MPC with the gas turbine model. Having the MPC and GT models in the same computational environment provided a fairer comparison than running the MPC as an FMU package in the GT model. The authors do acknowledge prior study in MPC development in Modelica language [12] but the code of outdated and difficult to run in the current version of Modelica language.

The MPC concept was summarized in previous publication [1], but in general terms it is an advanced control strategy developed in the last decade that recently became used to improve performance of power cycles. Differently from traditional PIDs that are simply based on an error minimization approach between the process variable and the setpoint, an MPC is based on an optimal control concept. Optimal control is characterized by an objective function shown by Eq. 1, which is used to minimize the deviation between the process variable and its setpoint, but also to minimize and calibrate the command of the manipulated variable. Eq. 1 was the main objective functions used in the code of the MPC controller developed in this work.

$$J = \frac{1}{2} \cdot [Q \cdot (y - r)^2 + R \cdot u^2] \quad (1)$$

The first term (y - r) in Eq.1 represents the error between the process variable y and its setpoint r whereas the second term u^2 represents the minimization of the manipulated variable. Q and R represents the tuning parameters that can provide an optimal tracking of the reference setpoint, with a minimization on the use of the manipulated variables.

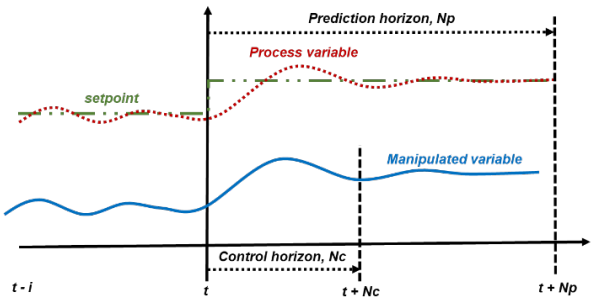


Fig. 6. MPC general concept

As shown in Fig. 6, the general concept of the MPC is to design a sequence of optimal control actions within a time moving optimization window, that is defined as predicted horizon Np and by the control horizon Nc. In this time window optimization problem, only the first-time step control signal of the manipulated variable is applied to the physical system actuator; however, the optimization problem is recomputed at each time step and a new prediction in the time window is performed based on the collection of new measurements. This concept is named receding horizon represents the methodology implemented in the code of this MPC controller, which was previously described [1].

5 MPC MODEL DEVELOPMENT

The MPC was developed from similar logic developed by EPRI to control for steam temperature control in Combined Cycle Gas Turbines (CCGT). The MPC controller is tuned with a linear model based on the system operation tuning described in the MPC and PID Tuning and Training section. As mentioned in Section 4, the EPRI MPC Controller includes the Controller and Kalman filter observer component models. The Kalman filter observer provides an estimate of the monitored system state utilizing both measurement (i.e., process variable) and predictions (i.e., manipulated variable change) from the mathematical model of the system. This estimate can help to reduce noise inherent in a real system and provide the computational states to the MPC controller for the state feedback control action. The estimate is updated in the Kalman when the new measurement and control valve command is provided to it.

In real control applications, the computational states of the physical system are not usually entirely measurable; in particular, with an MPC when an empirical state-space model is derived from experimental measurements and used to tune the MPC. Thus, an estimation of the computational states (that are represented by the state-vector) is usually performed

using the manipulated variables and the process variables of the physical plant, to have a better quantification of the system response during real-time operation. At each time step, the manipulated variables and the process variables measured from the physical plant are fed into a computational device (i.e., observer) that provides a real-time estimation of the state-vector. This estimation is calculated one step ahead because the MPC needs the state-vector at the current time step to compute the control action. Eq. 2 shows the mathematical formulation implemented in the observer, where A and B represents the state-space matrices of the plant (i.e., empirical model that captures the time response between the manipulated and process variable that must be controlled in the plant) and H is a matrix that cancels the error between the estimated process variable (i.e., $\underline{\hat{y}}$) and the measured one ($\underline{y}$). $\Delta\underline{u}$ is the incremental manipulated variable change at the current instant and $\underline{\hat{x}}_{t|t-1}$the state-vector estimation at the current instant based on an ahead calculation at the previous time step (t-1).

$$\underline{\hat{x}}_{t+1|t} = A \cdot \underline{\hat{x}}_{t|t-1} + B \cdot \Delta\underline{u}_t + H \cdot (\underline{y}_t - \underline{\hat{y}}_{t|t-1}) \quad (2)$$

In general terms, the first term of Eq. 2 ($A \cdot \underline{\hat{x}}_{t|t-1} + B \cdot \Delta\underline{u}_t$) is seen as a "prediction" because it is a calculation based on the incremental manipulated variable change at the current instant and on an estimation of the state-vector at the current time step, which was performed at the previous time step. On the other hand, the last term $H \cdot (\underline{y}_t - \underline{\hat{y}}_{t|t-1})$ is seen as "innovation" because it is an error minimization between the measurement of the process variable at the current time step and the estimation of the process variable performed at the previous time step.

The MPC controller includes three inputs, the Kalman filter observer estimated system state, the MPC controlled dependent parameter setpoint of the process variable, and the prior step independent controlled parameter value (the manipulated variable). The MPC outputs both the manipulated variable, utilized by the system for control, and the change in the manipulated variable from the previous solution step. The MPC also includes any required manipulated variable constraints.

In the development of the MPC control the authors evaluated different structures and techniques. It was found that the use of Modelica language algorithms as opposed to equations worked best for the development of the MPC components. As the controller requires the redefinition and iteration of parameters and the algorithm functions include causality while the equation functions do not and algorithm functions do not require an equal number of unknowns and equations in the calculation, the use of algorithms was found to be most appropriate for development of these controller models.

6 MPC and PID Tuning and Training

To ensure the PID performance was the best possible PID control loops were tuned based on the simulation results. The MPC was also similarly trained on a data set originating from the model. PID tuning was completed via Modelon Impact provided sources, public sources such as [12].

6.1 Training Data

The model was exercised to train specifically the MPC model. The hydrogen flow control, the FSR, and the IGV valves were each adjusted to determine their independent impact on Turbine Inlet Temperature, Power and Hydrogen Blending. Note that the pressure control valves for all simulations utilize PID control and were set to specific fuel pressures based on engine condition. For this training data the pressure setpoints were 29 bars.

7 Scenarios

Based on the original system model design the control testing was done on very short interval load change conditions and with varying hydrogen supply pressure conditions as shown in Fig. 7.

For this updated study, the operation from Figure 1 was utilized for the simulation. As this turbine was not operating with a hydrogen blend, a blend target was chosen in addition to the operational data.

8 Simulation Configuration

At this point in the MPC model development the hydrogen flow control valve MPC controller was developed in Modelica and available for simulation. For the PID control results all valve controls are utilized tuned PID controls. In the MPC results, only the hydrogen flow/blend control valve uses the author developed MPC controller. The MPC controls for the other valves are currently in development and expected to show similar improvements in operation relative to the PID controls.

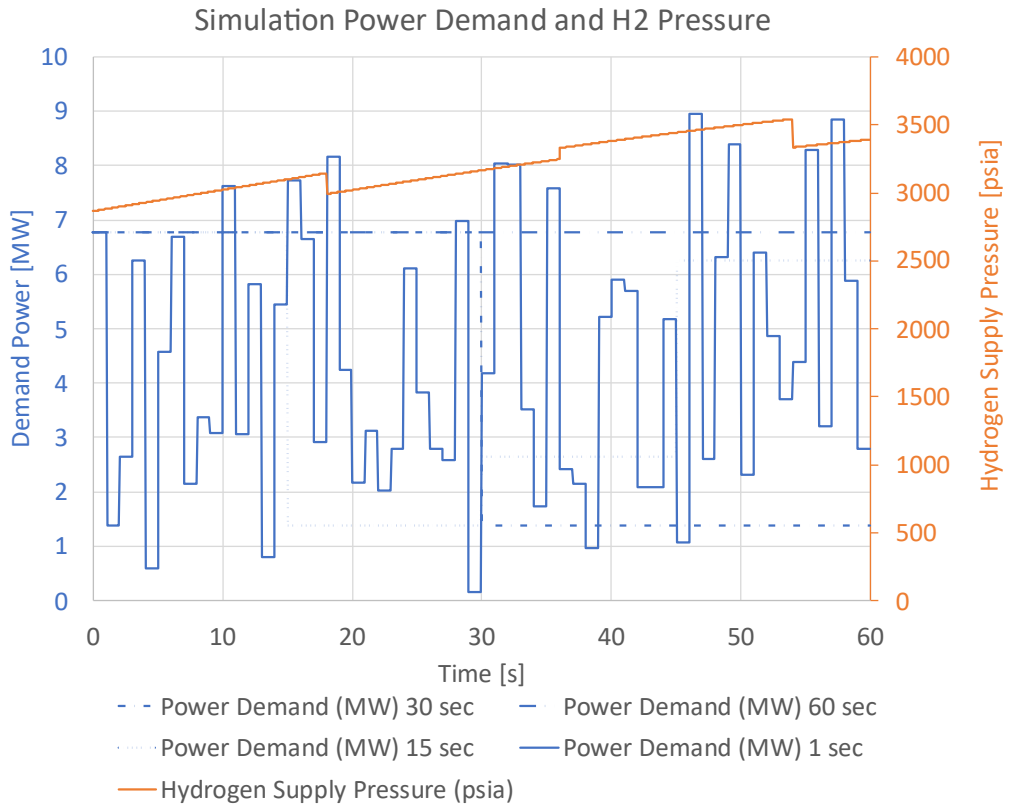


Fig. 7. Original simulation Power Demand Scenarios and Hydrogen input pressure conditions

9 RESULTS

As discussed above the real gas turbine operational data from Fig. 1 was used as the setpoints for gas turbine power and turbine inlet temperature. These conditions were used in the model as variable setpoints for the PID and MPC controlled simulations. The hydrogen blend for this simulation was set to 50% by volume. 50% by volume was chosen as a blend was shown in the previous study [1] to be the most challenging to control accurately for the hydrogen blend and for the largest negative impact to the accuracy of control of power and turbine inlet temperature.

The following figures show the hydrogen blend, power, and turbine inlet temperature control accuracy relative to the target (the actual GT data).

Fig. 8. 24 Hour PID and MPC simulation results

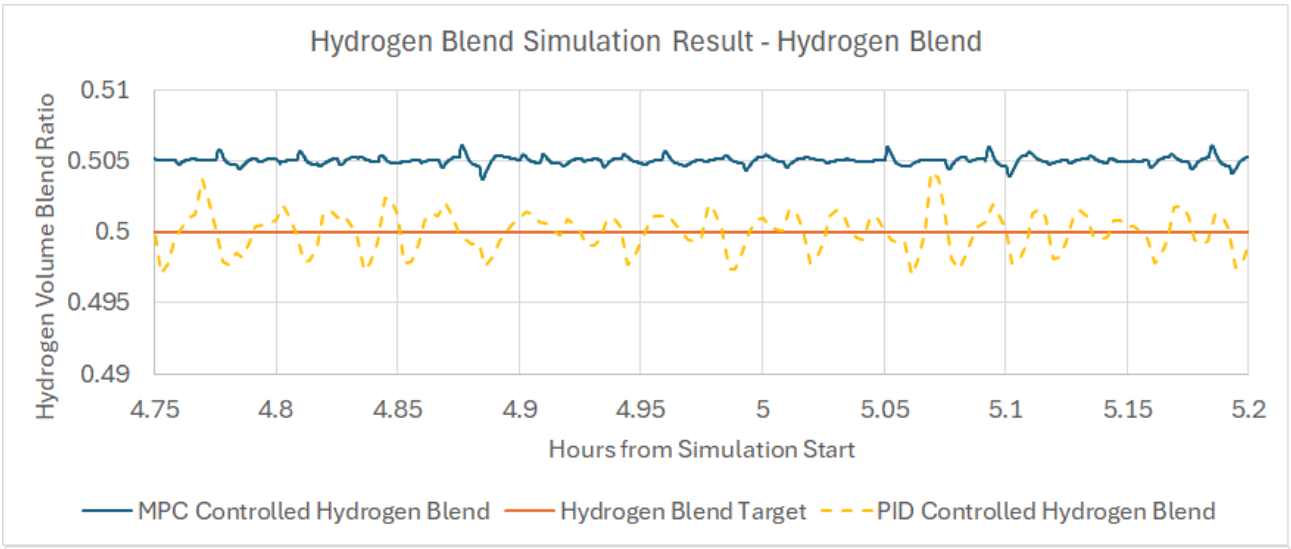
shows results from the full 24-hour operation. From this data it's clear that both the PID and the MPC simulations have reasonable accuracy, but difficult to distinguish between them. The spikes in hydrogen blend control stick out relative to the 50% blend target. Thise occur during unit shutdown where it is likely not representative of realistic operation (blends may be limited during startup/shutdown and the PID and MPC controls were challenged to control at very low loads).

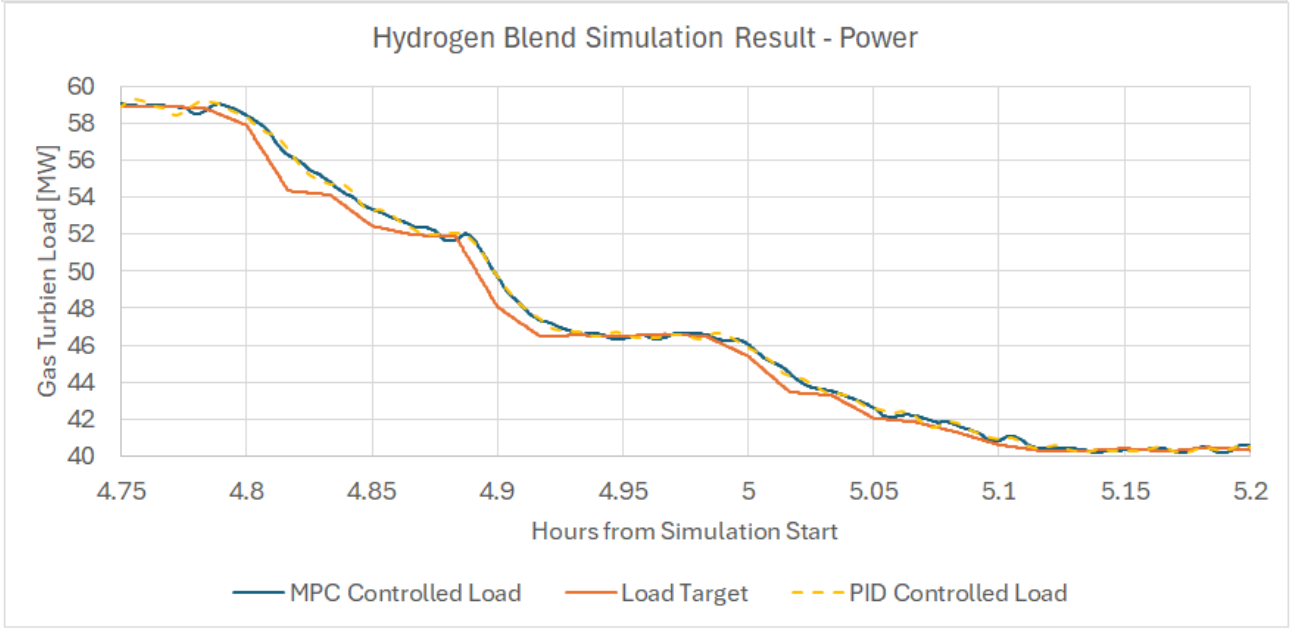
Fig. 9 is a smaller time window of ½ hour of simulation time during a load change of the gas turbine. The hydrogen blend results are instructive. The MPC results exhibit a small, 0.005%, offset from the hydrogen blend target. This is a result currently under investigation by the authors. The PID controls are centred at 0.5%. It is also clear that the MPC controls exhibit a smaller variation in hydrogen blend, about half the amplitude of the variation in the PID control. There are small variations in load and turbine inlet temperature control but not significant difference. The authors intend to look at the accuracy of the temperature and load controls more closely upon completion of the MPC controllers for these valves.

Fig. 8. 24 Hour PID and MPC simulation results

The authors acknowledge that the improvement in control of Hydrogen Blending with MPC relative to the PID appears is small. However, the hydrogen blend delay may vary up to 1 minute. In future work, that type of time delay will be added and may show a larger improvement in the MPC control performance versus the PID. The authors have not yet implemented a full

MPC model as PID controls are still utilized in the Load and IGV control for the model.





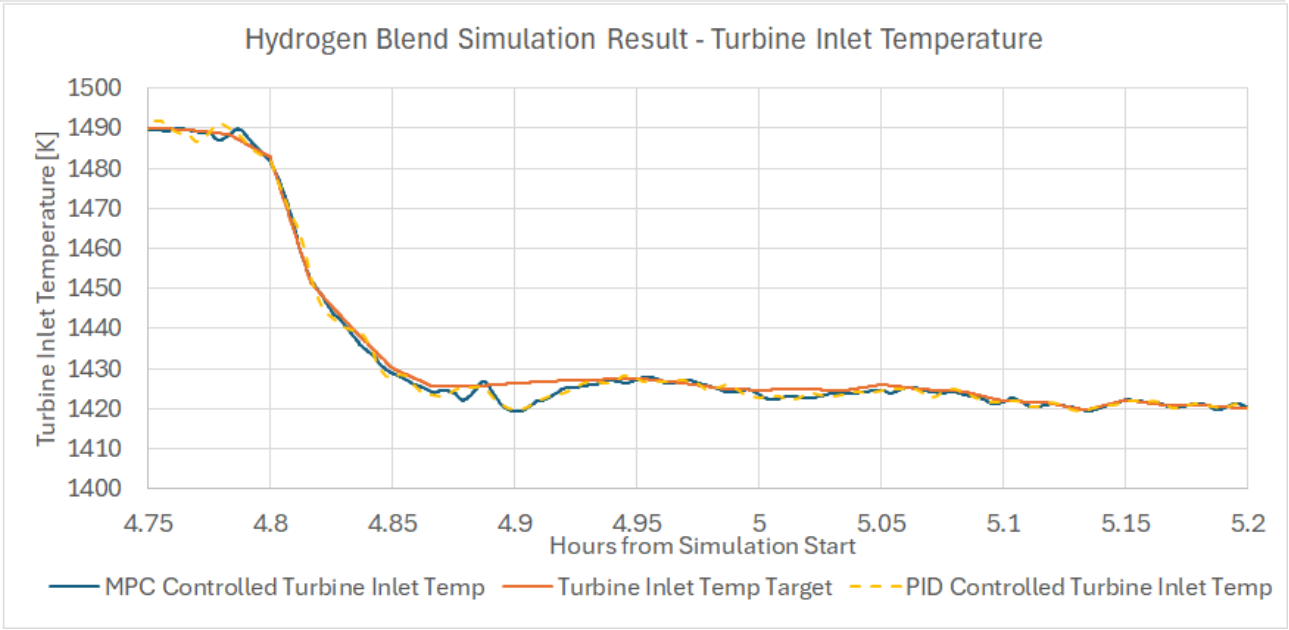


Fig. 9. ½ hour PID and MPC simulation results

10 CONCLUSIONS AND NEXT STEPS

The intention of this multi-phase study has been to evaluate the potential controls challenges with variable load control of gas turbines in a blended gas environment and compare traditional control methods to a model predictive control system. The authors have developed an MPC controller in the Modelica language which, while previously developed, was not currently available for use in present day Modelica model environments. Accuracy of the MPC control showed improvement relative to the PID. The improvement in results matches that seen in gas turbine steam temperature control accuracy with MPC previously developed by EPRI. Using the MPC approach in real gas turbine control system can be also considered a feasible approach because several OEMs has the MPC algorithm available in their software package as a function block. Operators can tune the MPC function block with just a few steps. Originally, one of the barriers of using the MPC in industrial control system was the computational effort, but improvements in the MPC algorithms and in the computational power of industrial digital control systems (DCS) made the MPC a feasible approach. For example, the code used in this work can run relatively fast (i.e., 80-100 ms sample rate) because there is a fixed number of iterations to find an optimal solution. In addition, if there is not a significant difference in two following iterations on the variable that must be optimized, the number of iterations is stopped.

The authors will be continuing this work by adding additional MPC controllers (for temperature and load) and adding additional simulation scenarios (such as variable hydrogen blends). Also, in future work, the authors will add a larger time delay in the hydrogen blend line to evaluate a higher benefit of the MPC controller versus the PIDs.

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