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NONLINEAR MODEL-BASED PREDICTOR: ITS APPLICATION TO THE CLOSED LOOP CONTROL OF THE ALSTOM GT11N2 GAS TURBINE

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ABSTRACT

The market requirements with regard to transient operation capabilities of gas turbines (GT) in utility use are becoming stringent. Besides normal frequency support features, gas turbines in local electrical grids are often required to maintain the grid frequency under various situations, including emergencies, such as, loss of national grid connection or trip of a large consumer, etc. These requirements demand high performance and stability of GT control.

On the other hand, the environmental aspects are becoming increasingly a public concern. In the past decades, remarkable progress has been made in combustion technologies of heavy-duty gas turbines. Lean premixing is a preferred technology for NOx emission reduction. Because of its flashback and extinction limits, a premix flame has usually a much narrower operation range compared to a diffusional one, adding tight constraint on GT control.

This paper demonstrates a successful implementation of a model-based predictor, a proven control technique, in the closed loop control of the ALSTOM GT11N2 gas turbine. First, an online GT model, which is integrated into the GT control algorithm, was developed. By applying appropriate assumption and simplification, this model is capable of simulating the GT process over the whole load operation range with high dynamic accuracy. Secondly, a model-based predictor for accelerating slow measured signals was implemented. It dynamically compensates the system delays in the GT process and in the measuring instruments. Thirdly, the predictor was applied to the GT core control by replacing the measured signals with the accelerated signals. The original control structure was kept unchanged.

In order to verify its performance and stability, the new control technique was validated on a real engine. Successful engine tests proved that the model-based predictor improves GT transient operation capabilities.

INTRODUCTION

The initiative innovations of control structure that became later the model-based control philosophy can be found in the works by Newton, Gould and Kaiser [1], and by Smith [2]. In the late 1950s, Newton, Gould and Kaiser pointed out that a closed loop structure can be transformed into an open one by a parallel modelling from the manipulated variable to the controlled variable. Smith invented the famous Smith predictor, a method for handling dead time in feedback control systems.

A gas turbine has a thermodynamic process that involves heat transfer, mass transfer and chemical reaction. Its governing physical laws are expressed by partial differential equations. As a controlled object, a gas turbine is a nonlinear, multiple-input and multiple-output (MIMO) dynamic system. The key challenges for its control are:

- Nonlinear dynamic behaviour,
- Delays on inputs and measurements,
- Constraints from combustion,
- Unexpected disturbances.

The traditional control techniques come to their limits when the requirements on control performance are getting more stringent while the process constraints are getting tighter. The objective of this paper is to describe a model-based predictor that addresses the above challenges.

This paper covers 3 topics, namely, “nonlinear dynamic model”, “model-based predictor” and “optimization and validation”. Each topic will be detailed in a dedicated chapter. Without a specific note, “GT11N2” hereafter refers to a GT11N2 type of gas turbine with EV combustor in gas firing.

NONLINEAR DYNAMIC MODEL

As its name suggests, a model-based predictor relies on an explicit representation of the process to be controlled. Needless to say, model accuracy determines the performance and the robustness of a model-based predictor.

Technical Background

The governing physical laws of a GT process are expressed by partial differential equations. There does not exist an analytical solution for a set of partial differential equations such as the state-equations of a gas turbine. By assuming the GT process to be a lumped parameter system, the state-equations can be simplified to ordinary ones. During start-up or warming-up phases, a gas turbine is a time-varying system, but it becomes a time-invariant system after a few hours of load operation. Its state-equations can then be formulated as below.

$$\begin{aligned} \dot{\mathbf{x}}(t) &= f(\mathbf{u}(t), \mathbf{x}(t)) \\ \mathbf{y}(t) &= g(\mathbf{u}(t), \mathbf{x}(t)) \end{aligned} \tag{1}$$

where t is time, $\mathbf{x}(t)$ and $\dot{\mathbf{x}}(t)$ are vectors of system states and state derivatives. $\mathbf{u}(t)$ is system inputs and $\mathbf{y}(t)$ system outputs. Numerical schemes, such as Gear solver, are available for solving a set of nonlinear, first-order differential equations such as Eqn. (1). Many GT models have been developed by using these numerical schemes. In principle, these models require complex numerical calculation, hence, cannot be implemented into a GT control system with limited calculation capacity. Furthermore, their identification and calibration are complicated and time consuming.

Linear or static models are developed by further simplifying the state-equations to be linear or to be static. The assumption of linearity is valid when a gas turbine is running close to a predefined operation point. The model error increases when the gas turbine drifts away from this point. Needless to say, static models cannot simulate GT dynamic behaviour.

Model Assumptions

The dynamics of a GT thermal block depends mainly on volumes and metal masses along its thermal process. During transient phases, volumes store or discharge fuel, air or flue gas, and metal masses absorb or release heat. From our experiences, we know that,

- The effect of metal masses on GT dynamics is of secondary order compared to that of volumes,
- Volumes along the GT process can be artificially moved to the beginning or to the end of the process without bringing much distortion to the dynamic behaviour,
- A GT process without volumes and metal masses can be considered as static,
- The dynamics of actuators (compressor variable inlet guide vane (VIGV), fuel control valve (CV) with fuel distribution system (FDS), etc.), and measuring instruments (power, temperature and pressure measurements, etc.) can be assumed to be linear.

With these assumptions, a new GT model was developed. It consists of two types of sub-models: “nonlinear but static (NBS)” or “linear but dynamic (LBD)”. For a NBS sub-model, Eqn. (1) can be further simplified.

$$\mathbf{y}(t) = g(\mathbf{u}(t)) \tag{2}$$

For a LBD sub-model, Eqn. (1) becomes linear differential equations.

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{A} \cdot \mathbf{u}(t) + \mathbf{B} \cdot \mathbf{x}(t) \\ \mathbf{y}(t) &= \mathbf{C} \cdot \mathbf{u}(t) + \mathbf{D} \cdot \mathbf{x}(t)) \end{aligned} \tag{3}$$

where **A**, **B**, **C** and **D** are coefficient matrices.

As a result, the numerical calculation of solving Eqn. (1) can be dramatically reduced to that of solving Eqn. (2) and Eqn. (3). Instead of assuming the whole process to be static or linear, the approach proposed here is to divide a GT process into subprocesses and assume some of them to be linear and some of them to be static. As a whole, a model developed with this approach can still simulate the non-linear and dynamic behaviour of a gas turbine.

GT11N2 Model

A GT11N2 model was developed with a structure as shown in Fig. 1. It consists of 9 sub-models, the rectangular ones are NBS sub-models and the elliptical ones are LBD sub-models. All LBD sub-models are single-input and single-output (SISO) systems. In the figure, TAT stands for the temperature after turbine and pk2 for the pressure at compressor outlet.

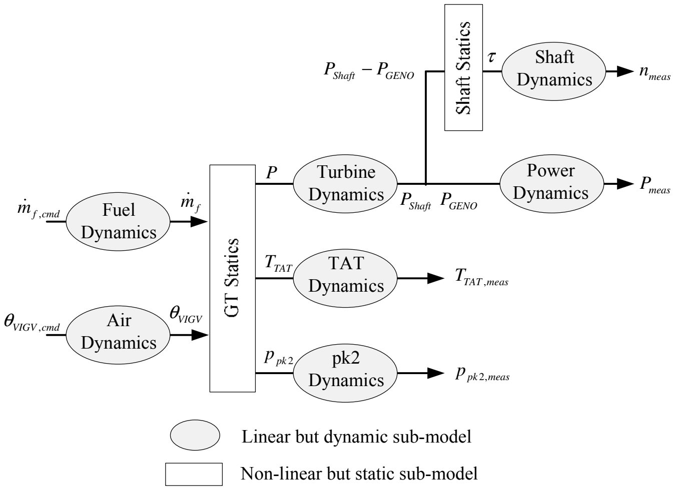

FIGURE 1. GT11N2 MODEL CONSISTING OF TWO TYPES OF SUB-MODELS

As a typical NBS sub-model, “GT Statics” has 2 inputs, namely, fuel mass flow ($\dot{m}_f$) and VIGV position (θ_{VIGV}), and 3 outputs, namely, GT power (P), TAT (T_{TAT}) and pk2 (p_{pk2}). GT power is calculated as follows.

$$P = f_p(\dot{m}_f, \theta_{VIGV}) \cdot \eta_P(\frac{T_{amb}}{T_{amb,ref}}, \frac{h_{LHV}}{h_{LHV,ref}}...) \tag{4}$$

where f_p is a function to calculate GT power under a reference condition. η_p is a correction function for condition changes. T_{amb} is the ambient temperature and h_{LHV} is the fuel low heating value. $T_{amb,ref}$ and $h_{LHV,ref}$ are the values of the reference condition.

TAT and pk2 are calculated by similar equations.

$$T_{TAT} = f_{TAT}(\dot{m}_f, \theta_{VIGV}) \cdot \eta_{TAT}(\frac{T_{amb}}{T_{amb,ref}}, \frac{h_{LHV}}{h_{LHV,ref}}...) \tag{5}$$

$$p_{pk2} = f_{pk2}(\dot{m}_f, \theta_{VIGV}) \cdot \eta_{pk2}(\frac{T_{amb}}{T_{amb,ref}}, \frac{h_{LHV}}{h_{LHV,ref}}...) \tag{6}$$

where f_{TAT} and f_{pk2} are functions to calculate TAT and pk2 under the reference condition. η_{TAT} and η_{pk2} are correction functions.

As a typical LBD sub-model, “TAT Dynamics” is an SISO system, the real TAT in the process (T_{TAT}) as its input and the measured TAT ($T_{TAT,meas}$) as its output. It can be approximated by a second order delay with a pure time delay.

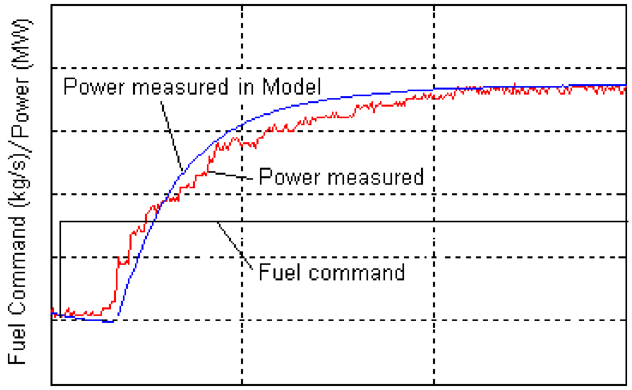

FIGURE 2. MODEL CALIBRATION RESULT WITH REGARD TO MEASURED POWER DURING A FUEL STEP RESPONSE TEST

$$L(T_{TAT,meas}) = \frac{1}{(t_{CT} \cdot s+1)(t_{TAT} \cdot s+1)} e^{-l_{TAT} \cdot s} \cdot L(T_{TAT}) \tag{7}$$

where $L()$ represents Laplace transform. l_{TAT} is TAT transport delay in the combustor and in the turbine. t_{CT} and t_{TAT} are time constants, t_{TAT} depends on TAT measurement dynamics and t_{CT} on metal masses in the combustor and the turbine.

Model Identification and Calibration

Eqn. (4), (5) and (6) of NBS sub-models can be approximated by polynomial expressions. The coefficients of the polynomials can be identified by engine design data and field operation data under steady state conditions.

The transfer functions of LBD sub-systems are calibrated by engine transient data, especially field data of step response tests. Fig. 2 shows the model calibration result with regard to the measured power during a fuel step test. The black line is the fuel step, the red curve is the measured power from field and the blue one the power simulated by the model. The two power curves show a good match.

The model calibration result of measured pk2 is shown in Fig. 3. The red curve is the measured pk2 from field and the blue one the simulated one by the model. Despite an initial offset at the beginning, the model shows good dynamic accuracy for measured pk2. It will be explained later that an initial offset as in Fig. 3 does not bring additional error to the model-based predictor introduced in the next chapter. Therefore, no effort was made to remove the offset to force a match to the actual field date.

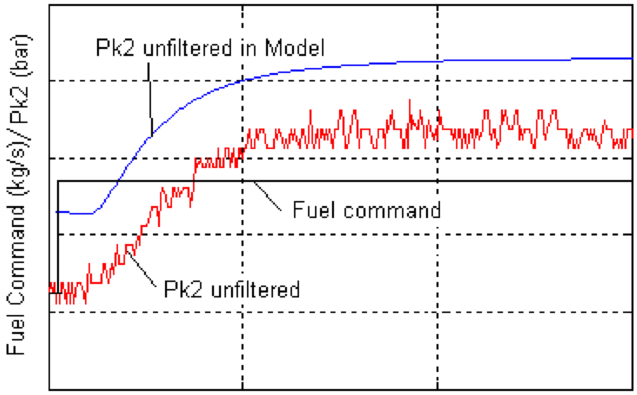

FIGURE 3. MODEL CALIBRATION RESULT OF MEASURED PK2 DURING A FUEL STEP RESPONSE TEST

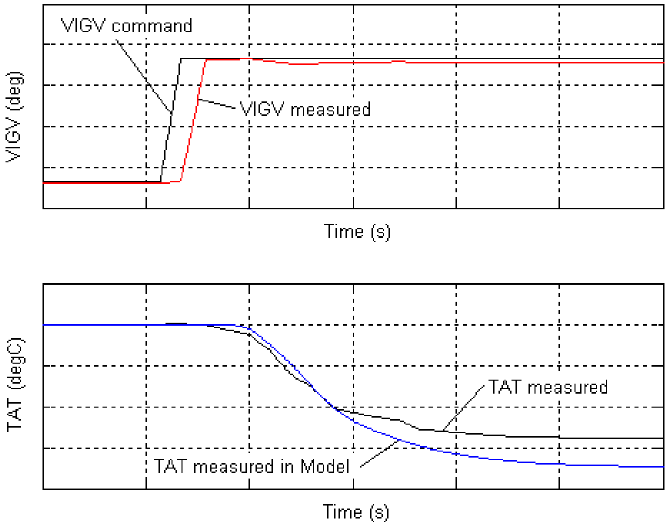

FIGURE 4. MODEL CALIBRATION RESULT OF MEASURED TAT DURING A VIGV STEP RESPONSE TEST

The calibration result of measured TAT during a VIGV step response test is shown in Fig. 4. During the test, the VIGV was changed stepwise as shown in the upper sub-plot. The black curve in the bottom sub-plot is the measured TAT from field and the blue one the simulated one by the model. The model shows an acceptable dynamic characteristic with regard to TAT dynamics. Further improvement of the "GT Statics" is needed in order to reduce the persisting static error.

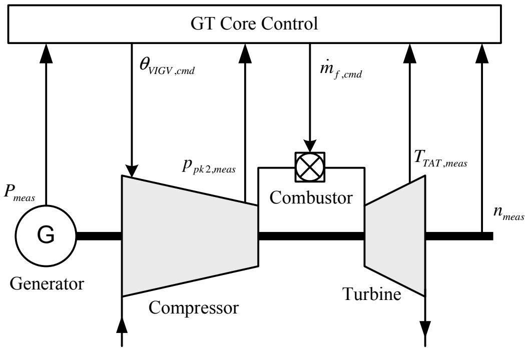

FIGURE 5. TYPICAL CORE CONTROL OF A GAS TURBINIE WITH ONE COMBUSTOR

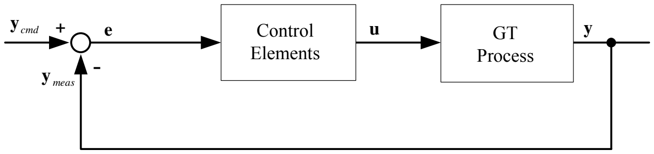

FIGURE 6. BLOCK DIAGRAM OF A TYPICAL GT CLOSED LOOP CONTROL

MODEL-BASED PREDICTOR

The model proposed in last chapter requires limited numerical calculation, therefore, can be implemented into GT control algorithm for on-line simulation. In this chapter, a model-based predictor for improving GT control dynamic performance will be described.

GT Core Control

The core control or the closed loop control (CLC) of a gas turbine enables a GT to deliver required power by controlling the fuel and air mass flows. All process variables have to be controlled within acceptable operation limits. Fig. 5 shows a typical GT core control. GT power at generator terminal (P_{meas}), pk2 ($p_{pk2,meas}$), TAT ($T_{TAT,meas}$) and GT shaft speed (n_{meas}) are measured variables. The fuel mass flow command ($\dot{m}_{f,cmd}$) and VIGV position command ($\theta_{VIGV,cmd}$) are generated by the core control.

Fig. 6 shows a typical closed loop control for GT process. The control elements generate manipulated variables **u** based on the error **e**, which is the difference between the desired values $\mathbf{y}_{cmd}$ and the measured values $\mathbf{y}_{meas}$. **u**, **e**, $\mathbf{y}_{cmd}$ and $\mathbf{y}_{meas}$ are all vectors.

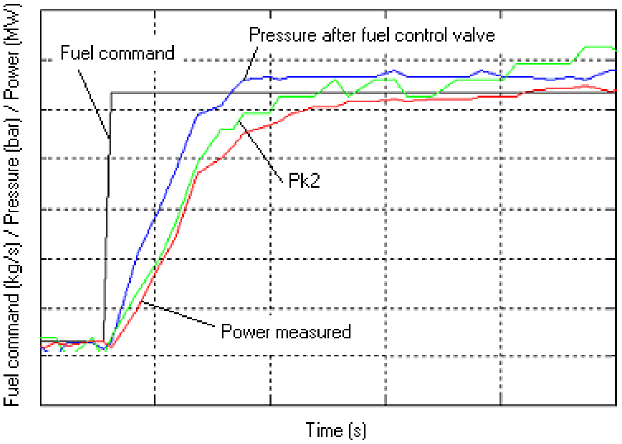

FIGURE 7. DYNAMICS OF PK2 AND MEASURED POWER IDENTIFIED DURING A FUEL STEP RESPONSE TEST

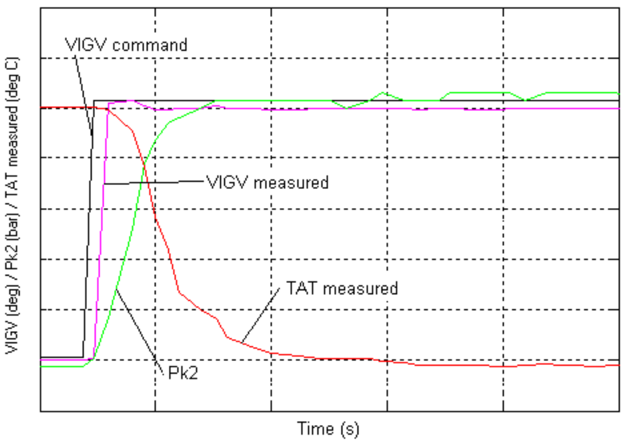

FIGURE 8. DYNAMICS OF PK2 AND MEASURED TAT IDENTIFIED DURING A VIGV STEP RESPONSE TEST

GT Process Dynamics

As mentioned above, the dynamics of a GT thermal block is mainly determined by volumes along the process, for example, volumes in the compressor, combustor and the turbine. Besides the thermal block, the fuel distribution system holds a large volume and has a big a impact on the GT dynamics. In addition, the measuring instruments bring additional delays. Step response tests are used to identify the GT process dynamics.

Fig. 7 shows a typical result of a fuel step response test and Fig. 8 that of a VIGV step test. As shown in these diagrams, the measured power, pk2 and TAT are delayed from the fuel and VIGV commands. These delays restrict the performance of GT control.

Model-Based Predictor

In order to compensate the delays caused by the GT process and by the measuring instruments, a model- based predictor, which dynamically accelerate the slow measured signals, was implemented. The predictor is expressed as follows.

$$y_{accel} = y_{meas} + (y^{model} - y^{model}_{meas}) \tag{8}$$

where y_{meas} is a measured signal, y^{model} the real process variable in the model, and y^{model}_{meas} the measured signal in the model. y_{accel} is then the accelerated signal. If the transfer function from the process variable to the measured signal is known, then the predictor can be simplified.

$$y_{accel} = y_{meas} + (1 - G(s)) \cdot y^{model} \tag{9}$$

where $G(s)$ is the transfer function. The essence of this predictor is to dynamically correct the measured signal in a way that its delay can be eliminated by a delay compensator $y^{model} - y^{model}_{meas}$ or $(1 - G(s)) \cdot y^{model}$.

When a GT is running at a steady state, $y^{model} - y^{model}_{meas}$ and $(1 - G(s)) \cdot y^{model}$ become zero, hence, $y_{accel} = y_{meas}$. It is obvious that an initial offset in the model as shown in Fig. 3 will be ignored by the delay compensator. When a GT is in a transient state, then $y^{model} - y^{model}_{meas}$ and $(1 - G(s)) \cdot y^{model}$ will show up and dynamically compensate the delay.

A model-based control can be realized by replacing the measured signals with the accelerated signals as shown in Fig. 9. The delay compensator $\mathbf{y}^{model} - \mathbf{y}^{model}_{meas}$ is added onto the measured signal $\mathbf{y}_{meas}$ for acceleration purpose. Since there are usually more than one signal that need to be accelerated, $\mathbf{y}^{model} - \mathbf{y}^{model}_{meas}$ and $\mathbf{y}_{meas}$ are vectors. One important advantage of this new control is that the original control scheme does not need to be changed. It will be demonstrated later that the new model-based control improves GT dynamic performance, especially, when the process dynamics is slow.

OPTIMIZATION AND VALIDATION

With its high operational flexibility and rugged design, the ALSTOM GT11N2 gas turbine is suited to a variety of applications, ranging from simple-cycle operation, through industrial co-generation applications, to combined-cycle power generation [3]. A few years ago, ALSTOM built a power plant consisting of 5 GT11N2s in the Middle East. The plant supplies electricity and steam to an oil refinery and the surplus electricity is sold to the national grid. A reliable electricity and steam supply is

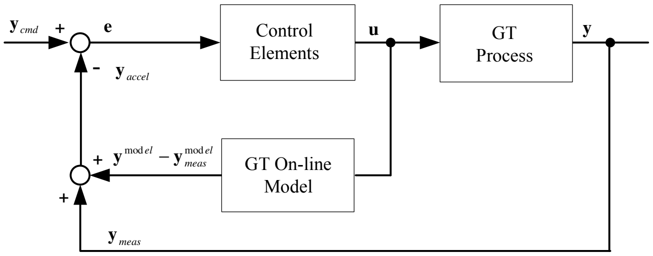

FIGURE 9. BLOCK DIAGRAM OF A GT CLOSED LOOP CONTROL WITH A MODEL-BASED PREDICTOR

critical for the refinery operation, hence, the customer specified demanding requirements with regard to partial load rejection and island mode operation.

Application to GT11N2

In order to fulfil customer's requirements, the GT11N2 core control was redesigned using the model-based predictor. Measured signals, such as, GT power, TAT and pk2 were replaced with accelerated signals. Because the accelerated signals have better dynamic response, the GT closed loop control could be tuned tighter. For example, the PI integration times of the load and VIGV controllers were reduced to one third of their original settings. The combustor control concept was also adjusted in order to ensure a stable combustion during transients.

The redesigned GT11N2 core control was optimized and validated on one customer engine. Two test campaigns were conducted: the first one was to collect data for identification and optimization, and the second one to evaluate the control performance.

Power Step Response Tests

The objective of power step response tests was to check if the new model-based control delivers better dynamic performance. Tests were repeated at different loads and with different step sizes, so that the new design can be validated over the whole load range. During the tests, NOx emission, combustion pulsation and flame density were carefully watched to ensure sufficient margins from combustion rich and lean limits. Fig. 10 shows the dynamic performance of the new GT11N2 core control. As shown in the 2nd sub-plot, the fuel mass flow was increased quickly and smoothly. The overshoots of TAT and TIT (turbine inlet temperature) were very small.

In the 1st, 4th and 5th sub-plots, the accelerated GT power, TAT and TIT are plotted in blue dotted lines. It is obvious that the accelerated signals have better dynamic response than the measured signals.

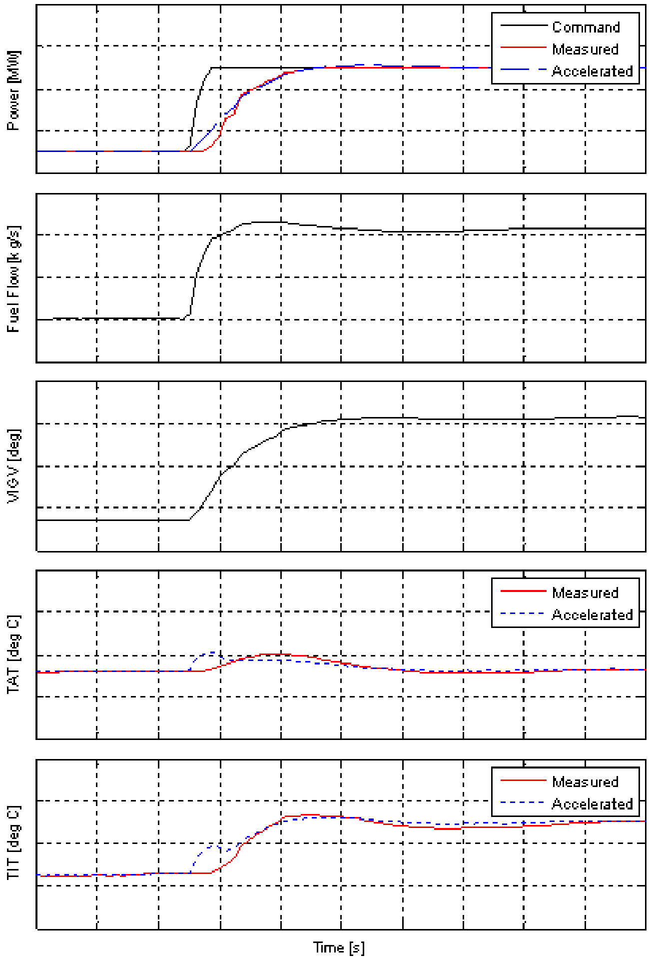

FIGURE 10. DYNAMIC PERFORMANCE OF THE REDESIGNED GT11N2 CORE CONTROL DURING A POWER STEP RESPONSE TEST

Partial Load Rejection Tests

Partial load rejection tests were carried to optimize the closed loop control and to validate the new island operation control. During the tests, the local electrical grid was disconnected from the national grid and some big consumers were cut off. The tests were repeated with different load sizes. Fig. 11 shows the test result of a 25% partial load rejection.

As shown in the topmost sub-plot, the measured power at generator terminal dropped in one step. GT process variables in other sub-plots were all controlled in a fast and smooth manner. The speed overshoot in the bottommost sub-plot is below the limit that was agreed with the customer.

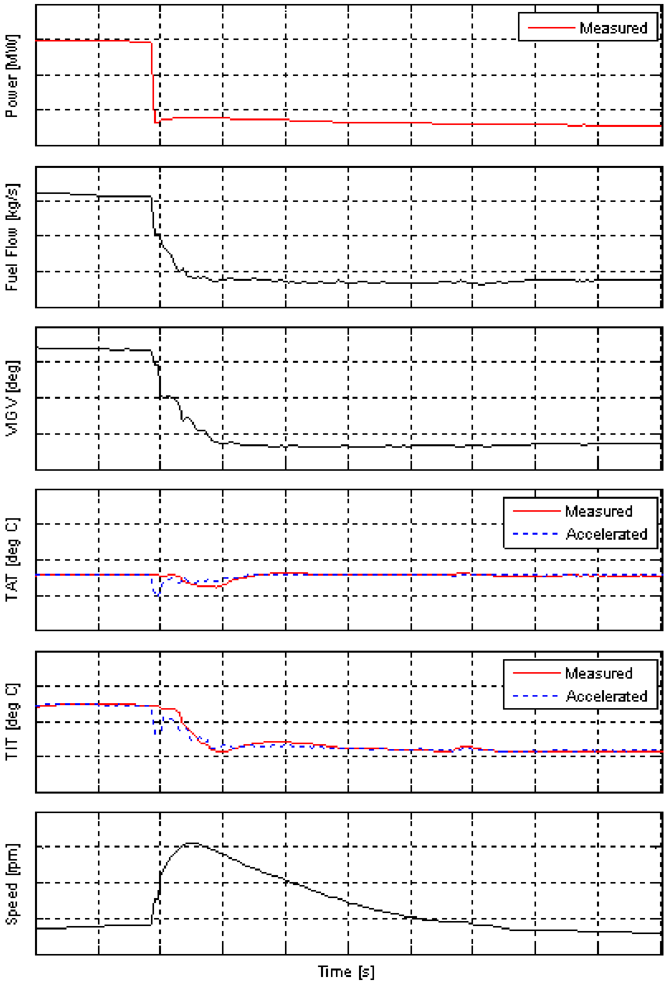

FIGURE 11. DYNAMIC PERFORMANCE OF THE REDESIGNED GT11N2 CORE CONTROL DURING A PARTIAL LOAD REJECTION

Conclusions

The validation tests were successful. The customer's requirements with regard to partial load rejection and island mode operation were fulfilled.

- It is proven that the proposed model-based predictor improves the dynamic performance of GT control. The redesigned GT11N2 closed loop control is capable of changing 20% of the rated base load in 10 seconds.
- With improved transient operation capabilities, the GT11N2 is capable of performing a partial load rejection of 20% of its rated base load and the grid frequency can be maintained within acceptable limits.

NOMENCLATURE

Abbreviations and Acronyms

CLC	Closed Loop Control
CV	Control Valve
EV	Environmental
FDS	Fuel Distribution System
GT	Gas Turbine
LBD	Linear But Dynamic
MIMO	Multiple-Input and Multiple-Output
NBS	Non-linear But Static
NOx	Mono-Nitrogen Oxides
pk2	Pressure at Compressor Outlet
SISO	Single-Input and Single-Output
TAT	Temperature After Turbine
TIT	Turbine Inlet Temperature
VIGV	Variable Inlet Guide Vane

Symbols

h_{LHV}	Fuel low heating value (MJ/kg)
l_{TAT}	Transport delay in measured TAT (s)
$\dot{m}_f$	Fuel mass flow (kg/s)
n	Shaft speed (rpm)
p_{pk2}	Pressure after compressor outlet (bar)
P	Power (MW)
P_{Shaft}	Power at shaft (MW)
P_{GENO}	Power at generator terminal (MW)
t	Time (s)
T_{amb}	Ambient temperature (°C)
t_{TAT}	Time constant of TAT delay, depends on TAT instrument dynamics(s)
t_{CT}	Time constant of TAT delay, depends on metal masses in combustor and turbine (s)
T_{TAT}	Temperature after turbine (°C)
$\mathbf{u}(t)$	Vector of system inputs
$\mathbf{x}(t)$	Vector of system states
$\dot{\mathbf{x}}(t)$	Vector of system state derivatives
$\mathbf{y}(t)$	Vector of system outputs
θ_{VIGV}	VIGV position (°)
τ	Shaft torque (MN · m)

Subscripts and Superscripts

$accel$	Accelerated
cmd	Command
$meas$	Measured
$model$	Value or variable calculated in model
ref	Value or variable at reference condition

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