Nonlinear Model Predictive Control Experiments on a Laboratory Gas Turbine Installation

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Results on the feasibility and benefits of model based predictive control applied to a gas turbine are presented. For a laboratory gas turbine installation, the required dynamic simulation model and the real-time (nonlinear) model predictive control (MPC) implementation are discussed. Results on both model validation and control performance are presented. We applied a nonlinear MPC configuration to control the laboratory gas turbine installation and succeeded in a real-time implementation. Although the available computation time for prediction and optimization of the model limits the sample time, the advantages of MPC, i.e. constraint handling, and anticipation to future (set-point) changes are fully reached, and the control performance is good. Special attention is paid to the performance of the applied filter that compensates for inevitable mismatches between model and process measurements. In general, the opportunities of model based control of turbomachinery are promising. [DOI: 10.1115/1.1359478]

Introduction

Model predictive control is a control strategy that uses a model of the installation to predict the response over a future interval, called the prediction horizon. Future control inputs are determined through minimizing a customized criterion, *e.g.* deviation from a desired set-point, over (a part of) this future interval, the control horizon. Of the computed optimal control moves, only the values for the first sample are actually implemented and the algorithm repeats the same procedure over the next sample. The main benefit of MPC is its constraint handling capacity: unlike most other control strategies, constraints on inputs and outputs can be incorporated into the MPC optimization. Another benefit of MPC is its ability to anticipate to future events as soon as they enter the prediction horizon. Finally, MPC is an essentially multivariable control strategy, implying that control loops do not need to be decoupled, because all interactions between multiple inputs and outputs are accounted for by the model.

For gas turbine control, this implies that physical operation limits, *i.e.* compressor surge, maximum allowable expander inlet temperature or rotational speed, as well as limits on actuator actions can be included into the optimization leading to optimal control of changes in operating point even when constraints are (temporarily) reached.

In this study, we consider a small (400 kW thermal input), custom built, laboratory gas turbine setup. This installation serves for experimental validation of simulation models and to test real-time control implementations. The laboratory installation offers the opportunity to monitor and to influence the dynamic operation of a gas turbine. Industrial configurations are not available yet for these experiments. Indeed, the laboratory setup is a fair representation of a gas turbine installation. The nonlinearities, dynamics, and constraints as well as the properties of the composing components correspond to industrial systems. Relevant time scales, however, differ as the components have smaller dimensions.

The application of MPC to control this laboratory gas turbine has been introduced in Essen [1] and Vroemen [2]. Vroemen [2] introduced the standard linear MPC concept, worked out a nonlinear method based on successive linearization, and presented preliminary simulation results. Successive linearization implies that every sampling period an updated linear model is derived from an underlying nonlinear model. This linear model is used for optimization over the control horizon. This approach has been shown to be a useful and powerful extension to linear MPC.

This paper presents experimental results obtained with the nonlinear MPC implementation on the laboratory gas turbine. In subsequent sections, first the laboratory installation is briefly introduced, after which the validation of the model (parameters) is discussed, the specifics of the MPC implementation are treated, and some typical results are addressed. The paper is concluded by some recommendations for future research in model based control of turbomachinery.

The Laboratory Gas Turbine

The laboratory gas turbine has been built from an industrial turbocharger and a custom made combustion chamber. The turbocharger comprises a single stage radial compressor and a single stage axial expander. Figure 1 presents a schematic view, showing the compressor, a blow-off valve, a check-valve, a buffer tank, a throttle valve, the combustion chamber, and finally the expander. A compressed air facility is employed in the start-up procedure, but also serves to disturb to the nominal operation point to excitate the control system.

Three electrically powered valves provide opportunities to control the operation point of the gas turbine. The blow-off valve, however, is only used during startup. Due to its large capacity, it is not suited as a control input. The throttle valve influences the pressure ratio over compressor delivery and expander inlet. As no external load is connected to the shaft, the throttle valve simulates the load condition of the installation. The throttle valve, therefore, can either be used as an input to control the operation point OR as a system parameter. The fuel valve controls the power supplied to the gas turbine and is the most important control input. Due to the mechanical transmissions in the valves, the rate of change is limited to full stroke in 40 s for the fuel valve and even 120 s for the throttle valve.

Contributed by the International Gas Turbine Institute (IGTI) of THE AMERICAN SOCIETY OF MECHANICAL ENGINEERS for publication in the JOURNAL OF ENGINEERING FOR GAS TURBINES AND POWER. Paper presented at the International Gas Turbine and Aeroengine Congress and Exhibition, Munich, Germany, May 8–11, 2000; Paper 00-GT-040. Manuscript received by IGTI Feb. 2000; final revision received by ASME Headquarters Jan. 2001. Associate Editor: M. Magnolet.

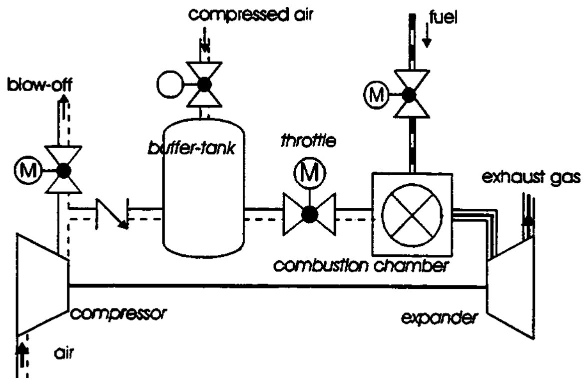

Fig. 1 Schematic view of the gas turbine installation

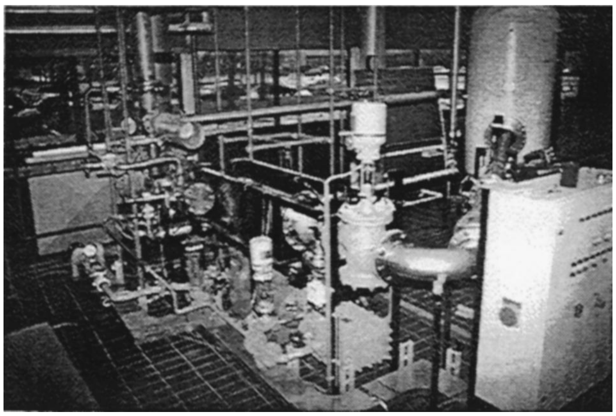

Fig. 2 Photograph of the gas turbine installation

A LabVIEW based data-acquisition system has been realized. This system provides opportunities to measure, monitor and store the available measurement signals, including pressures, temperatures, valve positions, rotational speed, and mass flow through a built-in orifice. The LabVIEW program is also able to implement new valve positions during automatic control.

Figure 2 presents a photograph of the installation showing the large buffer-tank (height over 2 meters) on the back and the combustion chamber and the throttle valve, above the fuel supply line, in front. For detailed information, the reader is referred to Essen [2].

Dynamic Simulation Model

A physical simulation model has been developed. This model is preliminarily introduced in Vroemen [3] and described in detail in Essen [1]. The model has a one-dimensional, generic, modular, component-wise structure. Components are compressor, expander, control valves, combustion chamber, flow-restrictions, and piping. The physical basis and the modular approach ensure the applicability of the model for a large class of compressor/expander systems.

Components are modeled by their characteristics, *i.e.* a set of (nonlinear) steady algebraic equations determining the mass flow through the component as a function of pressure, temperature, rotational speed, etc. In this way the performance characteristics are used as static momentum balances. The dynamic behavior of the components is modeled by volumes, positioned in between two components. Inside each volume the conservation equations *for mass*, *momentum*, and *energy* are solved, *i.e.* two coupled ordinary differential equations in pressure and temperature.

The model configuration for the laboratory gas turbine in Fig. 3 shows three volumes representing the effective volumes of the

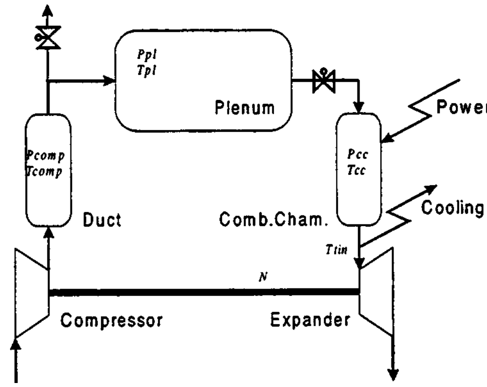

Fig. 3 Model configuration with coupling volumes between successive components

compressor duct, the buffer-tank plus piping (plenum), and the combustion chamber. The describing equations for each volume are

$$\frac{dT}{dt}=\frac{RT}{pV}\left[\gamma\left(\dot{m}_{\text{in}}\frac{C_{p,\text{in}}T_{\text{in}}}{C_p}-\dot{m}_{\text{out}}T+\frac{Q}{C_p}\right)-T(\dot{m}_{\text{in}}-\dot{m}_{\text{out}})\right]$$

$$\frac{dp}{dt}=\frac{\gamma R}{V}\left(\dot{m}_{\text{in}}\frac{C_{p,\text{in}}T_{\text{in}}}{C_p}-\dot{m}_{\text{out}}T+\frac{Q}{C_p}\right)$$

In which the term Q represents the added combustion power or the extracted expander cooling power, respectively. A power balance on the rotational speed of the gas turbine shaft gives the seventh state equation.

System simulation based the performance maps of the components extended by dynamic coupling equations is widely accepted in the literature and presented, among others, by Schobeiri [4] and Garrard [5] with regard to aero engines and Botros [6,7] with regard to compressor stations and piping. Apart from the characteristics, only little detailed (geometric) system information is required.

For control purposes, fast simulation is required and the model configuration is kept as simple as possible. Therefore, piping and buffer tank have been lumped into a single plenum volume. Due to its relative large size (>2 m^3), the cut-off frequency (determined by the residence time of the largest volume) of the model is estimated at 0.2 Hz. When transients at a faster time scale need to be controlled, the model may fail. In that case, the plenum should be split into multiple volumes in series, combined with an instationary momentum balance, Essen [1], allowing compressible flow at the expense of a considerably larger simulation time. As the required time scale for controlling the operation point (approximately 20 s) corresponds to this limit, our model of the laboratory gas turbine is suitable for application in a model based controller.

Parameter Validation

Due to the physical nature of the model, a large number of parameters is involved. Two types of parameters are distinguished. The first type influences the stationary operating points of the installation. These parameters include pressure drop factors and efficiencies. *Pressure drop factors* determine the mass flow through components (often hidden in the component characteristics). *Efficiencies* include the (polytropic) efficiencies of compressor and expander, and the combustion efficiency. These steady state parameters have been validated by extensive experiments in a systematic procedure based on a mass and power balance.

During the validation of the steady-state parameters we had to modify the compressor performance map (available from the original manufacturer) to have the map agree with the experimental results. Reasons for this mismatch are not fully understood but may be in the interaction between components and in the methods by which the maps of separate components are determined.

Due to the lumped influence of the expander cooling system, the neglected temperature dependency of the heat capacity, and the inherent dynamic character of the combustion process, it appeared difficult to determine the efficiencies of expansion and combustion. In the present model, the combustion efficiency is a static function of the fuel-air ratio. This leads, however, to significant (dynamic) model mismatches in the expander inlet temperature when suddenly more fuel is injected.

The second type of parameters influences the transient operation of the installation. These parameters include the size of the effective volumes, the inertia of the gas turbine shaft, and the move rates of control valves. The transient behavior did not introduce any problems; all the inertia parameters were easy to select from straightforward (physical) start values.

With validated parameters, the performance of the model is good. Both steady state and transient simulations agree well with experimental results.

Nonlinear MPC Implementation

For the gas turbine setup the emphasis is on real-time implementation of MPC and we defined rather straightforward control objectives as set-point and trajectory control, combined with constraints on inputs and outputs. For our MPC configuration we use Primacs, a package for real-time model based control that is being developed by TNO-TPD (Delft, The Netherlands). Although Primacs was originally designed for linear MPC, the modular structure allowed us to implement the *successive linearisation* approach. The connection to the LabVIEW environment has been established by DDE over an Ethernet connection. We succeeded in a real-time implementation of MPC on the laboratory installation. The sample interval was limited to 1.2 s on a ordinary Pentium 200 PC.

Because of inevitable model mismatches and measurement noise or errors, a *filter* is required to correct the prediction of the internal model towards the actual process measurements. In our implementation we tested a first order integrating (output disturbance) filter. In this filter, a number of extra states (d) track the offset between process measurements and model predictions. The filter equations are given by

$$\begin{bmatrix} x(k+1) \\ d(k+1) \end{bmatrix} = \begin{bmatrix} A & 0 \\ 0 & I \end{bmatrix} \begin{bmatrix} x(k) \\ d(k) \end{bmatrix} + \begin{bmatrix} 0 \\ K_f \end{bmatrix} [y_m(k) - y_p(k)] + \begin{bmatrix} B \\ 0 \end{bmatrix} u(k)$$

$$y_m(k+1) = [C \quad I] \begin{bmatrix} x(k+1) \\ d(k+1) \end{bmatrix} + Du(k)$$

in which y_p is a process measurement and y_m is the corresponding model prediction. Note that only the outputs and not the states are updated. A basic extension to this scheme to avoid linearization errors in the filter correction is a one-sample-ahead nonlinear prediction for y_m.

This first order filter performs well as long as all controlled outputs can be measured (or accurately reconstructed by other measurements). Otherwise, the filter cannot correct the model predictions accurately and the controller performances degrades. In our configuration, a problem arises with the reconstruction of the mass flow through the compressor. As it is impossible to measure it directly it should be reconstructed from the compressor characteristic. This reconstruction, however, is not only very bad conditioned by almost flat curves in the compressor map near the surge line, but it may also be corrupted by deviations between measured and modeled *states* (rotational speed, pressure ratio). Although we did not attempt this, an augmented Kalman filter, that updates the model *states* instead of the *outputs*, could possibly improve this problem. It is, however, not easy to implement in a nonlinear setting [1] and requires sufficient measured outputs to feedback.

Results

In this section some typical experimental results are presented and discussed with emphasis on constraint handling and robust performance. Constraint handling appears to be a realistic advantage of MPC for control of turbomachinery. Most ''conventional'' controllers cannot deal with constraints at all, especially not when constraints (like surge and expander temperature) are not on *controlled* outputs. For the laboratory installation, surge and expander temperature constraints are reached frequently. Also (move) constraints on the actuator inputs strongly influence the controlled operation. Figure 4 displays the operating area of the gas turbine installation in the compressor characteristic, indicating the constraints.

Note that the ''surge-ratio'' constraint is a safety margin to the real surge line defined by the ratio of actual compressor mass flow and the corresponding mass flow at the surge line for the same pressure ratio.

Sine Responses. This result illustrates the capabilities of the MPC controller to track a periodic reference trajectory. A sinusoidal trajectory for the rotational speed (period 75 s, amplitude 80 rev/s, mean 438 rev/s) is specified while the throttle valve serves as a (known) load-disturbance on the installation (sine with half frequency: period 150 s, amplitude 0.3, mean 0.7). The fuel valve is now the only input. In Fig. 5*a* both sine functions are presented. Figure 5*b* shows the tracking result over a time interval of one full period of the disturbance in a steady state response, that is, after the switch-on phenomena vanished.

Indeed, Fig. 5*b* shows that the controller is able to follow the trajectory on the rotational speed, except for the two rising flanks. There, the temperature constraint is reached, as can be seen in Fig. 6*a*, which displays the expander temperature over the same time interval. Moreover, a difference can be seen between the first

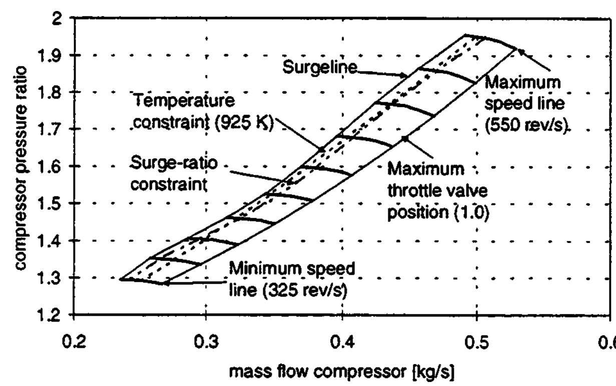

Fig. 4 Simulated operation area, limited by constraints, projected onto the compressor map

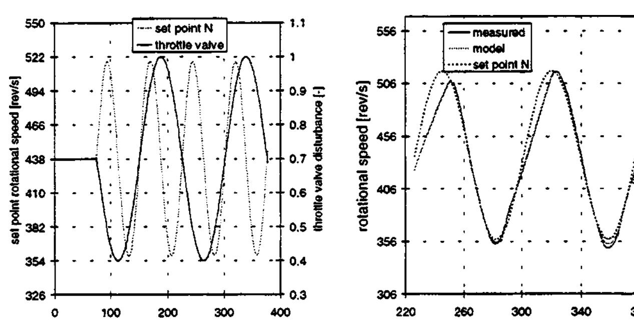

Fig. 5 (*a*) Sinusoidal trajectories for the rotational speed and throttle valve disturbance. (*b*) Measured and predicted responses of rotational speed.

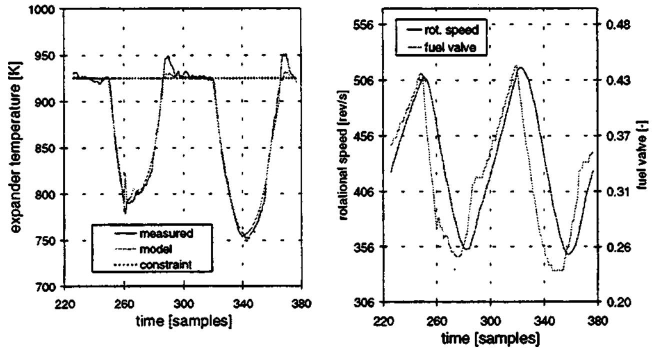

Fig. 6 (*a*) Expander temperature during sine response experiment. (*b*) Comparison between control output (rotational speed) and input (fuel valve).

rising and the second rising flank. This difference is caused by the opposite influence of the throttle valve (*i.e.*, gas turbine load) disturbance in these two situations.

Figure 6*a* shows that the controller indeed manages to keep the temperature within the constraint. Clearly, however, a temporary constraint violation of the measured expander inlet temperature can be seen. As the controller is able to keep the (filtered) model value within the constraint, this appears to be a filter problem. The controller is simply not aware of the violation because the filter is not fast enough to compensate the mismatch of the expander temperature. Indicated solutions are in a higher filter gain for this output, a faster MPC sampling time, and, of course, in an improved modeling of the (dynamic) combustion efficiency.

Figure 6*b* compares the actual rotational speed with the fuel valve input. This illustrates the anticipative behavior of the controller. Already 12 samples (one prediction horizon) before a change in sign of the derivative of the rotational speed, the fuel valve changes direction. Anticipation will be discussed in a separate subsection.

Surge or Temperature Constraint. Close to the surge line, depending on the rotational speed level, the simulated operating area in Fig. 4 is either restricted by the surge-ratio constraint or the temperature constraint. This has been verified in two experiments, at two different constant rotational speeds. It is examined whether the controller ''stops'' at the surge constraint or at the temperature constraint when the mass flow through the expander is forced to decrease. The experiments involve a constant set-point on the rotational speed and a decreasing set-point on the mass flow. As controlled inputs, both the fuel and the throttle valve are used. The desired operating points are located across the surge line. The corresponding constraints are indicated in Figs. 7*a* and *b*, showing that at the high rotational speed (438 rev/s), the controller stops at the surge ratio constraint of 0.97, while at the low rotational speed (350 rev/s), the controller stops at the temperature constraint of 925 K. These experimental results compare to the expected results from the simulation and show that the MPC controller is able to maintain constraints on outputs that are not controlled.

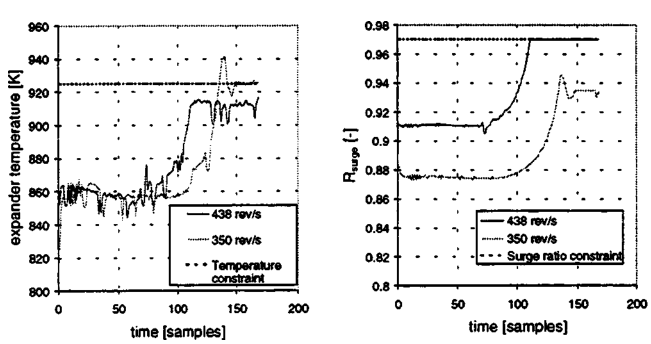

Fig. 7 (*a*) and (*b*) Expander inlet temperature and surge ratio parameter for two experiments with constant rotational speed and decreasing mass flow

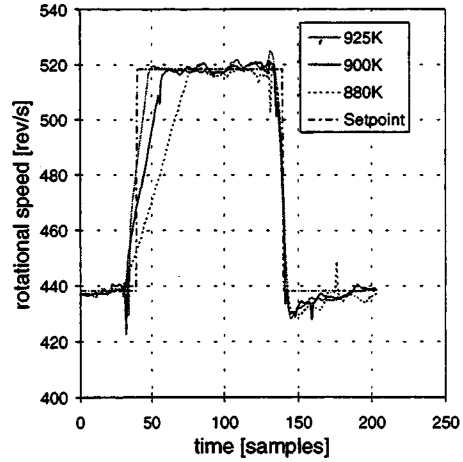

Fig. 8 Rotational speed for different settings of the temperature constraint

Temperature Constraint Level. Results on the influence of the level of the temperature constraint on the controlled variable rotational speed are presented in Fig. 8. For three different values of the temperature constraint (880, 900, and 925 K), the same steps are put on the set-points of the rotational speed and the expander mass flow (not shown). Lowering the maximum allowable expander temperature results in a slower system response. Obviously, the allowed increase of the fuel flow per sample has to be reduced. As expected, the temperature constraint does not influence the response to a lower set-point. In fact, these responses are approximately equal. Figure 9 indicates that the controller manages to keep the constraints, although they are temporarily violated as discussed before.

Disturbances. A rigorous way to apply a disturbance to the system is the injection of compressed air into the buffer tank by (manually) opening the valve (Fig. 1). In the experiment presented in Fig. 10, the system response for constant rotational speed and expander pressure is examined. The controller cannot anticipate to this unmodeled disturbance and all deviations should be compen-

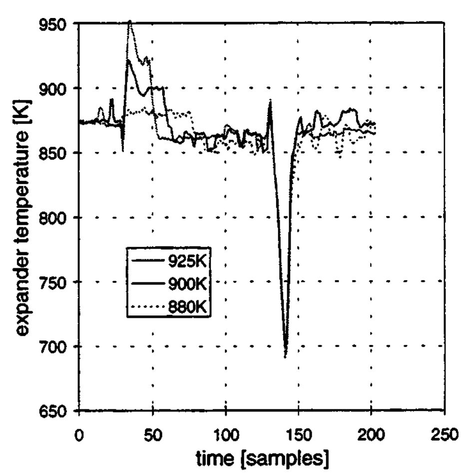

Fig. 9 Expander inlet temperature

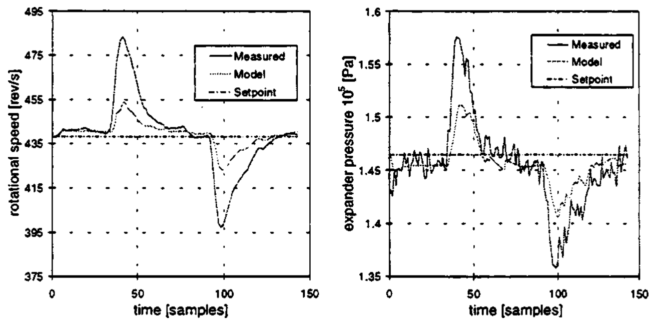

Fig. 10 (*a*) and (*b*) Predicted and measured rotational speed and expander pressure during compressed air disturbance

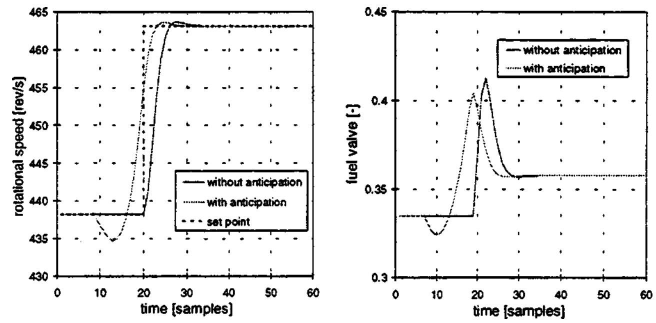

Fig. 12 (*a*) and (*b*) Simulated response of rotational speed with and without anticipation

sated by the filter. At sample 35 the compressed air valve is opened, while at sample 90 the valve is closed again. The injected mass flow of compressed air is approximately 0.05 kg/s (or 12 percent of the expander mass flow). Although large filter corrections must be applied, the controller manages to reach the original set-points of both speed and pressure again. The system is therefore robust for large disturbances and the filter performs well at this time scale.

Transient Response. In the simulation shown in Fig. 11, the transient behavior during a set-point change is indicated in the (compressor) characteristic. A new set-point has been specified at a lower rotational speed, while the fuel valve is the only input. It can be seen that the surge constraint is nearly reached by the compressor mass flow. Note the difference between compressor and expander mass flows due to depressurizing the buffer tank. For a gas turbine like the laboratory installation, there is a potential danger of surge during fast ''downwards'' transients. A typical example is emergency shutdown. A model based controller is able to anticipate to this problem.

Anticipation. Anticipation is the ability of the controller to react before an actual set-point change is commanded. In this subsection we present some results on anticipative behavior of model predictive control. In Fig. 12*a*, the simulation results of a system response to a set-point change in rotational speed with and without anticipation are compared. The fuel valve, Fig. 12*b*, is the only input and no constraints on the output nor on the temperature are applied. Without anticipation, the controller starts responding as soon as the set-point change is activated. Remarkable is the ''inverse controller response'' that the system displays in the case

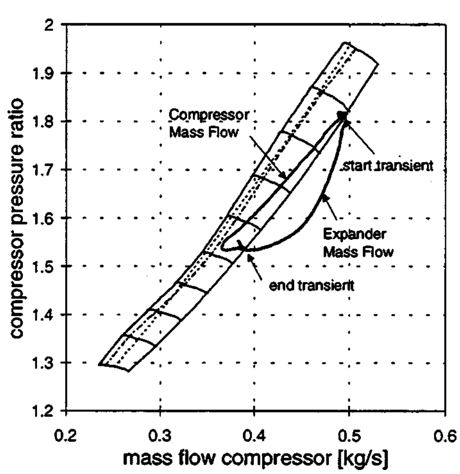

Fig. 11 Simulated transient response displayed in the compressor map

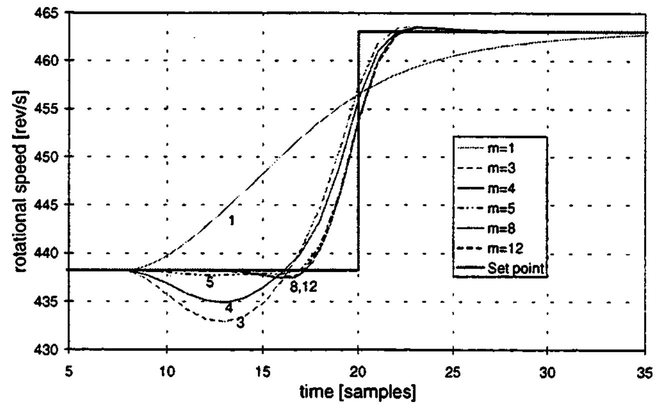

Fig. 13 Response of rotational speed for different settings of the control horizon (*m* samples) for a prediction horizon of 12 samples

with anticipation. First the fuel valve is closed and the rotational speed lowers, then the fuel valve opens again and the rotational speed rises to its new set-point value. The inverse response does not seem to be the optimal response to the set-point change. It appears, for instance, already better when the ''negative'' control moves (in the first few samples) are suppressed.

This phenomenon of anticipative behavior appears to be strongly related to the relative size of the control horizon with respect to the prediction horizon. The prediction horizon is the number of samples for which the future system is predicted, while the control horizon is the number of samples for which new future inputs are computed (in general the degrees of freedom). Suboptimal solutions are an inherent consequence of differences between these two horizons and cause an ''inverse'' response. These suboptimizations can be improved by increasing the control horizon relative to the prediction horizon. The influence of the size (m) of the control horizon relative to the prediction horizon (12 samples) on the simulated performance is investigated and shown in Fig. 13.

Conclusions

We applied a nonlinear MPC configuration to gas turbine control. We succeeded in a real-time implementation, due to hardware limitations the sample time was limited to 1.2 s. We find that MPC is a challenging, new control strategy for turbomachinery. The performance of the implemented MPC configuration is good. Both steady state set-point variations and transient tracking of reference trajectories are performed well. Constraint limits are observed and the influence of MPC tuning parameters like weighting factors and length of horizons is well understood. The presence of model mismatches and disturbances is handled correctly by the filter although limited filter performance is responsible for temporary violations of the temperature constraint during fast transients. Anticipation is a powerful control tool, but the undesired phenomenon of inverse response can only be avoided by computationally demanding long control horizons.

To make the advantages and opportunities of model based control available to industrial turbomachinery configurations, more research, both in simulations and in experiments is required.

The following suggestions for future research are made. First, based on advanced hardware, the sample time should be decreased, allowing faster control, this should be combined with the introduction of fast and accurate control valves and new filter implementations. Second, more emphasis is needed on the development of accurate control-oriented models for combustion and especially dynamic combustion efficiency. Third, an extension of the MPC algorithm towards a *mixed integer optimization*, Bemporad [8], should be aimed for. This strategy includes the optimal selection of discrete events like turning machines in or out into the performance criterion of the continuous optimization. An interesting application is reported for load balancing of compressor stations in Essen [1] and Smeulers [9]. Finally, the concept of hierarchical controller implementation, where MPC is not used as the primary controller, but only computes the (optimal) set-points for local controllers, seems promising to maintain the overall optimizing properties of MPC and simultaneously reduce the required computation time.

Acknowledgment

The authors gratefully acknowledge TNO-TPD at Delft, The Netherlands, for their support.

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