

Nonlinear Model Predictive Control of an Aircraft Gas Turbine Engine[†]

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Abstract

The feasibility of constrained nonlinear model predictive control (NMPC) with state estimation is investigated and applied to a high-fidelity turbojet aircraft engine model. Strong nonlinearities are present in turbojet engines due to the large range of operating conditions and power levels experienced during a typical mission. Also, turbine operation is restricted due to mechanical, aerodynamic, thermal, and flow limitations. NMPC is selected because it can explicitly handle the nonlinearities, and both input and state constraints of many variables in a single control formulation. Due to the computational requirements of NMPC and the fast dynamics of aircraft engines, a Simplified Real Time Model (SRTM) is created that captures all of the relevant dynamics while executing quickly. An Extended Kalman Filter (EKF) is applied to estimate the states in the presence of noise and limited sensor data. This output feedback controller is tested on a high-fidelity model of a military aircraft engine, showing that NMPC based on the simplified model has the potential to achieve better performance than the production controller.

1 Introduction

Gas turbines can be used for propulsion as aircraft engines and for power generation in land based power systems. The gas turbine model considered is a low bypass, two rotor, turbojet with a variable exhaust area typical of military aircraft applications. During normal operation this turbine experiences large changes in ambient temperature, pressure, Mach number, and power output level. For each of these variations the engine dynamics change in a significant nonlinear manner. Careful attention must be paid by the controller during engine operation to ensure that the mechanical, aerodynamic, thermal, and flow limitations of the turbo machinery are maintained. In addition, the control authority is restricted by the actuator rate and saturation limits. Current technology solves this nonlinear constrained problem using many SISO linear controllers in concert that are gain scheduled and min/max selected to protect against engine limits. While this method has many merits we propose solving the problem using NMPC, which handles the MIMO nonlinearities and constraints explicitly and in a single control formulation.

NMPC is model-based, has the capacity to accommodate constraints, and relies on on-line open-loop optimization via a receding-horizon formulation. It is inherently multi-input/multi-output and can be tuned for performance and stability [1,2]. Vroemen [3] has also considered the application of NMPC to a laboratory gas turbine. Here we develop these ideas further by using an Extended Kalman Filter for state estimation and a nonlinear model of the dynamics.

The approach of this paper is to use this application of NMPC to explore the development of a constrained MIMO controller as a replacement for multiple single-loop closures. The objective is for performance while satisfying operational constraints. Because of the sampling speed (10 ms), model

complexity (8 states), and performance focus, this is a demanding task. This application includes the use of an Extended Kalman Filter state estimator as the adjunct to a full-state NMPC. The analysis here explores the use of a simplified model as the predictive core of the NMPC and of the EKF. The performance is based on application to a higher fidelity component level model.

2 Component Level Model

This engine is an aerodynamically coupled, dual rotor machine wherein a low-pressure rotor system (fan and low-pressure turbine) is mechanically independent of a high-pressure (core engine) system. Air entering the inlet is compressed by the fan and then split into two concentric streams. One of these then enters the high-pressure compressor and proceeds through the main engine combustor, high-pressure turbine, and low-pressure turbine. The other is directed through an annular duct and then recombined with the core flow, downstream of the low-pressure turbine, by means of a convoluted chute device. The combined streams then enter the augmentor to a convergent-divergent, variable area exhaust nozzle. Here the flow is pressurized, expands, and accelerated rearward into the atmosphere, generating thrust.

The plant model is a physics based component level model (CLM) of this turbine configuration, which was developed by GE Aircraft Engines. This model is very detailed, high-fidelity, and models each component starting at the inlet, through the fan, compressor, combustor, turbines, and exhaust nozzle.

3 Simplified Real Time Model

Since NMPC is a model-based control, an internal model is needed to predict the future responses of the plant to control inputs. As the CLM is a very large and complicated model, a new model was developed to be used in the NMPC that has a small number of states, executes quickly, can be analytically linearized, and is accurate to within 20 percent in transient and 5 percent steady state over the area of the flight envelope that is most used. The SRTM has two control inputs; fuel flow demand (WFDMD), and exhaust nozzle area demand (A8DMD), as well as ambient condition inputs; altitude (ALT), Mach (XM), and ambient temperature deviation from ISO (DTAMB). The outputs are; percent core speed (PCN25), percent fan speed (PCN2), engine pressure ratio (PP), compressor discharge static pressure (PS3), high pressure turbine exit temperature (T4B), fan stall margin (SM2), core stall margin (SM25), and thrust (FNAV).

Following the model structure proposed by Shaoji [4], a SRTM of an aircraft engine along with the main fuel-metering valve (MFMV) and variable exhaust nozzle (A8) actuators is developed that meets the above specifications. The model is designed to replicate both transient and steady state performance.

For validation the SRTM is run open loop versus the CLM. The input profiles for the validation are a large step increase in fuel

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at 2 sec., small step decrease in fuel at 4 sec., small step increase in A8 at 6 sec., and a large step decrease in A8 at 8 sec. The results of one such comparison are shown in Figure 1 for PCN2 and PS3. While for this comparison both parameters are within 10 percent transiently and 5 percent steady state, for all of the parameters over all tested points in the defined envelope the maximal deviation transiently is 22 percent and the maximal deviation steady state is 7 percent. These results are just outside of the requirements, but are still quite remarkable given the simplicity of the model structure.

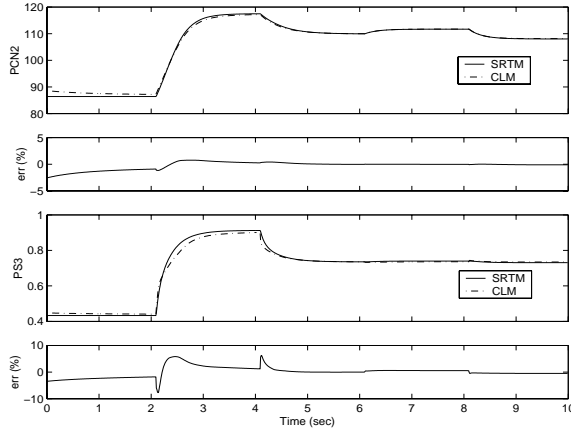


Figure 1 Comparison of the SRTM versus the CLM

4 Nonlinear Model Predictive Control

NMPC is based on the constrained open-loop optimization of a finite horizon objective function. This optimization uses a plant model to describe the evolution of the outputs and commences from an assumed known initial state. At time k the input variables, $\{u(k), u(k+1), \dots, u(k+p-1)\}$, are selected to optimize a performance criterion over the prediction horizon, p . Of the computed optimal control moves, only the values for the first sample, $u(k)$, are actually implemented. Before the next time interval and the calculation of another p input values, $\{u(k+1), u(k+2), \dots, u(k+p)\}$, the initial state is re-estimated from output measurements. This causes the seemingly open-loop strategy actually to implement a closed-loop control.

4.1 Model Hierarchy

The NMPC and the EKF state estimator are both model-based procedures in which a model of the plant is calculated for the generation of state predictions. There is a clear hierarchy of models in this specific problem:

- the real plant, whose dynamics are not fully known,
- the CLM, which is a high-fidelity but computationally complex model which is difficult to linearize,
- the SRTM, which is linearizable and simply iterated as part of the optimization procedure.

Clearly our aim is to generate a controller to perform well on the real plant engine. However, computational demands and knowledge limitations require the use of the SRTM as the basis for both the full-state NMPC calculation and for the EKF state estimate recursion. The initial performance comparison with the existing controllers will be made with this SRTM controller used on the CLM process. Eventual engine tests will be used for final validation of the approach.

4.2 Constrained Optimization

For this study the controlled inputs are fuel flow demand (WFDMD) and exhaust area demand (A8DMD). The references for this engine are fan speed (ref1) and engine pressure ratio (ref2). While trying to run to these two references

the control is constrained by other operating limitations like maximum T4B, min and max PS3, minimum and max N25, max N2, rotor speed acceleration, and rotor speed deceleration. Also, both actuators are rate limited and have minimum and maximum slew positions.

The objective function J to minimize in the NMPC framework is defined over the prediction horizon p .

$$J = \sum_{i=1}^p (PCN2R_i - ref1_i)^2 + \gamma \sum_{i=1}^p (PP_i - ref2_i)^2 + \rho_1 \sum_{i=1}^p \Delta Wf_i^2 + \rho_2 \sum_{i=1}^p \Delta A8_i^2 + \delta_1 \sum_{i=1}^p (e^{(Ps3_{max} - Ps3_i)})^2 + \delta_2 \sum_{i=1}^p (e^{(PCN2_{max} - PCN2_i)})^2 + \delta_3 \sum_{i=1}^p (e^{(T4B_{max} - T4B_i)})^2 + \delta_4 \sum_{i=1}^p (e^{(PCN25_{max} - PCN25_i)})^2 + \dots \quad (2)$$

Where γ , ρ , and δ are weighting factors. The SRTM is used as the predictor to obtain the turbine cycle parameters' response over the prediction horizon.

The control goal is the constrained optimization,

$$\min_u J \text{ subject to } x \in X, u \in U. \quad (3)$$

Where x is the vector of p future states and u is the vector of p future control inputs WFCMD, A8CMD. This optimization is accomplished using a gradient descent method based on central differences with projection for input constraints U and penalty functions for state constraints X .

5 Extended Kalman Filter

NMPC is a full state feedback controller and hence all states need to be measured or estimated from available measurements. Typically not all states are measured because of the cost or availability of sensors. Moreover sensors have dynamics, delays, and noise. Hence a dynamic observer is necessary to reconstruct the states and reduce noise. An Extended Kalman Filter is used for this purpose [5,6].

6 Simulations and Results

The EKF and SRTM are wrapped into the NMPC logic and this is connected to the CLM. Figure 2 displays a block diagram representation of how all of the components are connected. The assembled control process starts with the EKF using the SRTM to determine the current state of the engine. This information is used as the initial condition for the predictions used in the gradient calculation. The SRTM is then run over the prediction horizon for each control input and sample. The sample time is 10 mseconds for each time step. Each run corresponds to a perturbation at a different point in the control horizon. This information is assembled into the gradient and a search path is followed in the negative gradient direction.

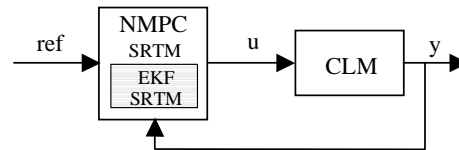


Figure 2 Simulation configuration

This simulation configuration with the NMPC control algorithm is run for a step demand in power from the pilot. This is a critical simulation that would be used to replicate an aircraft takeoff, combat, or ground avoidance maneuver. Figure 3 shows the results of the control and engine response versus time for a step in power demand at 0.3 seconds (note: the magnitude

of each of the plotted parameters is scaled to protect proprietary information).

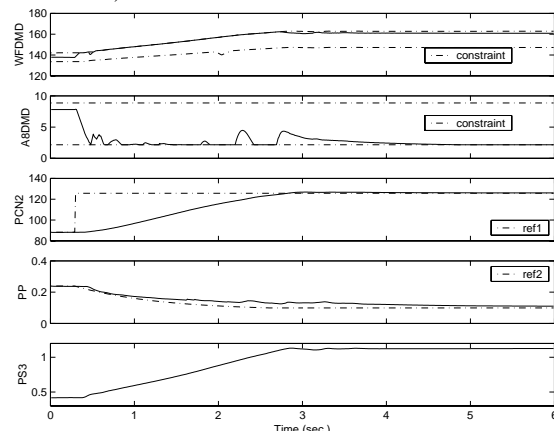


Figure 3 Step in power demand at 0.3 sec with input constraints on WFDMD and A8DMD

The PCN2 reference (ref1) is stepped up to increase the resulting thrust. PP reference (ref2) is reduced to maintain sufficient fan stall margin. Both PCN2 and PP try to follow the references for the first 4 seconds with PCN2 reaching the reference and PP resulting in a steady state error. The response time of PCN2 to the reference is limited mainly by the changing maximum constraint on WFDMD. This maximum constraint is used in the production control as an acceleration limiter to protect against compressor surge or stall. The PP steady state error is due to the A8CMD hitting the minimum constraint and PCN2 being weighted more heavily in the objective function. The results of the production control to the same step input are within 4 percent in transient and 0.2% steady state.

The same maneuver is accomplished again, but this time an output constraint on PS3 is applied. This constraint protects against combustor case structural limits when operating at high Mach numbers at low altitudes and would be a higher priority than reaching either of the two references. Figure 4 shows that PS3 never violates the maximum constraint and as PS3 is approaching the constraint at around 2 seconds, PP and PCN2 are forced to stop trying to reach their references.

While data is presented here on only one active output constraint (maximum PS3), many other transients were run that showed that all of the limits used in the production control work well when applied using NMPC and can all work in concert together as conditions change.

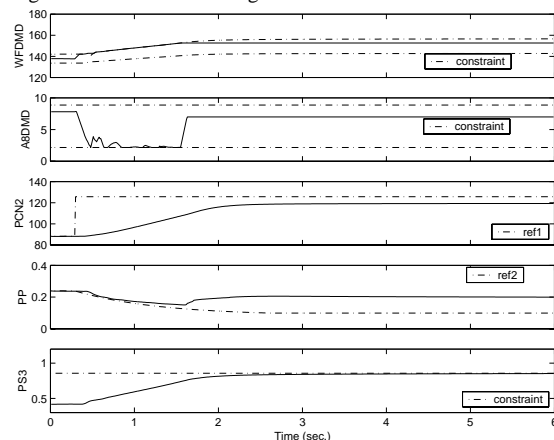


Figure 4 Step in power demand at 0.3 sec with input constraints on WFDMD and A8DMD and output constraint on PS3.

7 Conclusions

This study provided data to show the feasibility of applying NMPC to solve the nonlinear, multi-input/multi-output, and multiple constraints problem on a fast system. The time scales involved in this process are orders of magnitude faster than the typical petrochemical plant run by NMPC. Since we are pushing the computational limits of NMPC we have to rely on approximate simplified models like the SRTM. One of the key features of using NMPC and EKF is that both preserve the linear design rules and ideas from their LQG background. This gives experience and insight into how to tune both algorithms.

The average execution time for this algorithm running in Matlab[®] and Simulink[®] in an uncompiled state on a Pentium[®] III 600 MHz with 512 MB of ram is 700 msec. This is a factor of 70 or greater than the 10 msec. required to command the fuel loop on this engine. The first step we will take is to recode all of the algorithms in C or Fortran in preparation for application to a real engine. If the execution times are still too long, then faster optimisation solvers like quadratic programming will be implemented as a replacement for the gradient optimisation to see if the execution time is reduced. If necessary, further investigation into execution times and shorter prediction horizons while guaranteeing stability will be investigated to obtain the 10 msec. In addition a faster computer could be used to reduce the execution times.

The SRTM has thus far proven to be a reliable and robust model of the process. While the SRTM has been validated open loop over the most used portion of the flight envelope and all power ranges, the control has only been exercised for all power ranges on a limited portion of the flight envelope. Future work will involve looking at the control performance over the flight envelope and determining what modifications are required to obtain acceptable robust performance. Once the technology is proven on the model, the final step is to get the NMPC algorithm to run on a production engine.

While NMPC can recreate the current production control, using this technology may unlock many potential benefits. Using the model based properties of NMPC can lead to running to other more attractive references like thrust and stall margin. The open architecture of NMPC allows for many extensions and variations that may allow for further improvements.

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