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Closed-Loop Identification of Hammerstein Systems with Application to Gas Turbines

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Abstract: Many practical applications, such as the fuel control of a gas turbine engine, can be modeled by a feedback connection of a linear controller in series with a Hammerstein system, where the nonlinearity provides a representation of the control element or actuator. An iterative gradient-based method is proposed to simultaneously identify the nonlinear fuel valve characteristic and a low-order linear plant model in gas turbine applications that leverages *a priori* knowledge of both the nonlinearity and engine dynamics. The identification is a nonlinear prediction error minimization method in a closed-loop Hammerstein model framework. It is applied to data from a high-fidelity simulation of a 5 megawatt *Taurus*^{TM} 60 industrial gas turbine.

Keywords: closed-loop identification, Hammerstein systems, gas turbine

1. INTRODUCTION

The performance of the fuel control system in a gas turbine engine is critical to maintain stability and achieve performance targets. A digital feedback controller meters fuel into the combustion chamber using measurements of shaft speed, stage temperatures, pressures, and power. The fuel control valve(s) typically possess a nonlinear position to flow area relationship. The control system requires knowledge of this nonlinear characteristic to accurately regulate fuel flow. Uncertainty or degradation of the physical fuel valve's flow characteristic can lead to instability or operational limitations of turbine engine. Sources of uncertainty vary from manufacturing variability to contamination due to sulfur deposits on the valve's control surface [Cézac et al. (2008)]. Maximization of machine availability is essential to operators and the cost of unplanned service interruption is typically greater than the cost of preventative maintenance and returning the unit to service. The motivation of this paper is the identification of uncertainty in a nonlinear actuator characteristic in closed-loop operation.

Breikin et al. (2004) demonstrated that low-order linear plant models effectively capture the relationship from fuel flow to output power and Dai and Wang (2006) presented similar results for the relationship from fuel flow to shaft speed. Measurement and simulation data are only available from closed-loop operation. The nonlinear flow control valve, assumptions on linear behavior of the turbine engine over limited operating range, and closed-loop data fit nicely into a closed-loop Hammerstein model framework. The Hammerstein model structure comprises an input nonlinearity in series with a linear dynamic model. This model structure can be used to identify the uncertainty in the actuator nonlinearity and approximate the dynamics of the turbine engine via a linear plant model.

Identification of closed-loop Hammerstein systems has focused on instrumental variable (IV) based methods as they mitigate the bias due to the correlation of output noise and the input and output signals. Laurain et al. (2009) presented an iterative refined IV identification algorithm for LTI systems and later for LPV systems [Laurain et al. (2010)]. Han and De Callafon (2011) applied iterative IV identification to the problem using piecewise triangle basis functions to parametrize the nonlinear function. Laurain states that the IV methods provide a good initialization for use in statistically optimal prediction error methods that are sensitive to the initialization step. The IV methods offer consistent parameter estimates on average, although without optimality properties or convergence guarantees.

Prediction error minimization (PEM) methods offer an alternative. De Bruyne et al. (1999) developed generalized gradient expressions for prediction error minimization in linear closed-loop systems and also noted that exact gradient expressions can be developed for closed-loop nonlinear systems where the controller is smooth and the system is bounded-input, bounded-output (BIBO) stable around a stable trajectory. Van Pelt and Bernstein (2000) used piecewise linear static maps to parametrize the nonlinearities for system identification in open-loop and closed-loop Hammerstein frameworks. Narendra and Gallman (1966) applied an iterative gradient descent algorithm for the open-loop case that motivates the closed-loop formulation here.

Given that that the input nonlinearity (fuel valve) is smooth and partially known and linear dynamic models have been shown to accurately capture the dynamic response of gas turbines over a small operating range during closed-loop control, there is an opportunity to expand the application of systematic closed-loop identification Hammerstein systems. We seek to apply closed-loop Hammerstein system identification that exploits *a priori* knowledge of the input actuator (control valve) for a targeted identification of uncertainty in the flow characteristic of the fuel valve and to evaluate the method on a high-fidelity first principles simulation of a gas turbine generator control system. Results are presented from closed-loop data from a high-fidelity simulation of a *Taurus*^{TM} 60 conventional combustion gas turbine generator.

2. PROBLEM FORMULATION

The objective of this paper is to identify a low order linear dynamic system with possible static nonlinearity in the form of a Hammerstein model to capture the dynamics of a high-fidelity nonlinear turbine model with a non-linear, but static fuel valve characteristic. The nonlinear thermodynamic Matlab/Simulink model of a gas *Taurus*^{TM} 60 turbine generator and feedback control system is used to generate data for use in identification. The high-fidelity model contains a full model of the Brayton cycle that includes each stage of the cycle in addition to the full fuel control, actuator and sensor models. The engine portion of the simulation used in this discussion, depicted in Figure 1, is comprised of the major engine sub-assembly models, i.e. compressor, burner, rotor, power turbine and exhaust, and their interconnections.

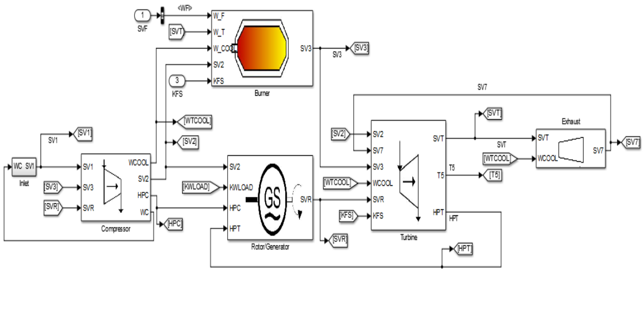

Fig. 1. High-fidelity engine simulation implemented in Matlab / Simulink.

3. MODEL DESCRIPTION

For the sake of the approximation problem formulated in this paper, the fuel control of a gas turbine is represented by the closed-loop BIBO stable nonlinear system model $\mathcal{M}$, shown in Figure 2. The known controller $K(q)$, and static nominal actuator mapping $f_0(\cdot)$, with output $w(t)$ is explicitly included in the model. The uncertain static memoryless nonlinearity $\delta(\cdot)$, in the series connection of $f_0(\cdot)$ with linear dynamics $G(q)$ *jointly* capture any deviation of the fuel valve characteristic from $f_0(\cdot)$ and nonlinear behavior of the gas turbine. The problem is to identify the unknown nonlinear map $\delta(\cdot)$, and linear dynamics $G(q)$. For identification, an additive and persistently exciting reference signal is applied to the shaft speed set point $r(t)$. The data set contains the uniformly sampled input-output signals of $r(t)$, $u(t)$, and $y(t)$ with sampling time T_s over N samples. System identification applies a two stage iterative gradient-descent procedure within a prediction error minimization framework to estimate $\delta(\cdot)$ and a low-order linear dynamic plant $G(q)$.

Since $\delta(\cdot)$ jointly captures uncertainty in $f_0(\cdot)$ and the nonlinearity of the turbine plant, we introduce $\delta_w(t)$ in the series connection of the static nonlinearity and linear plant dynamics to be identified. The noise $v(t)$, is assumed as inherent to the physical system and in this context, the noise model is not important to the identification objective. Since an output error (OE) model structure is used for identification, the noise is assigned a zero mean sequence $v(t) \sim N(0, \lambda)$ as a matter of convention and a noise model is not estimated, i.e. $H_0(q) = 1$. The signal $w(t)$, represents the flow area of the control valve is a known function of the controller output $u(t)$ that is given by,

$$w(t) = f_0(u(t)). \tag{1}$$

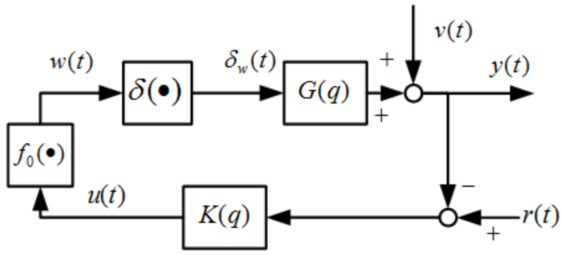

Fig. 2. Closed-loop Hammerstein system model $\mathcal{M}$.

To facilitate parameter estimation, $\delta(\cdot)$ is approximated by a set of orthogonal basis functions that allow $\delta_w(t)$ to be written

$$\delta_w(t) = \sum_{j=1}^{M} \rho_j(w(t))\mu_j. \tag{2}$$

The linear dynamic process $G(q)$ is the linear time invariant plant,

$$G(q) = q^{-t_d}\frac{B(q)}{A(q)}, \tag{3}$$

of polynomials $A(q)$ and $B(q)$, with the time shift operator q^{-1}, and input time delay t_d. Similarly, the controller may be written

$$K(q) = \frac{D(q)}{C(q)}. \tag{4}$$

The following assumptions apply throughout the discussion:

- A1: The reference input $r(t)$ is known, control output $u(t)$, and noisy output $y(t)$ are measured for identification.
- A2: The system is closed-loop BIBO stable.
- A3: The nominal $f_0(\cdot)$ in (1) is a known, monotonic, continuously differentiable function.
- A4: The input time delay t_d, to the linear plant is known.
- A5: The reference input $r(t)$, is persistently exciting for the identification of $G(q)$.

Note: It is not assumed that $u(t)$ excites the full input range of the static nonlinearity $\delta(\cdot)$ and plant. We will specifically use the series connection of $\delta(\cdot)$ and $G(q)$ to identify $\delta(\cdot)$ over a limited range.

4. PARAMETRIZATION

4.1 Static nonlinearity

The nonlinear mapping in (2) is written as a linear combination of orthogonal basis functions $\rho_j(w(t))$, with weights μ_j. The weighting vector μ, of function $\delta(\cdot)$, in this basis is an M-vector parameter to be identified. The basis uses the grid

$$m = [\, m_1 \ \cdots \ m_M \,]^T, \tag{5}$$

to define the center locations of the basis functions and satisfies $[m_1 \le w(t) \le m_M]$, $\forall\, t \in [1..N]$. In practice, the entire range of $u(t)$, and therefore $w(t)$, may not be able to be excited due to operational constraints on the physical system. The choice of the M-vector of basis functions $\rho(w(t))$, is closely related to the identification objective and structure of the nonlinearity. A basis that facilitates a good approximation with parsimony in the parameters is desirable. Han and De Callafon (2011), for example, apply a set of piecewise triangular basis functions to the problem. In this study, we seek specifically to locally identify $\delta(\cdot)$ in the series connection of a smooth valve characteristic $f_0(\cdot)$, and linear dynamics $G(q)$. Lippmann (1991) discusses