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Bayesian Parameter Estimation of Power System Primary Frequency Controls under Modeling Uncertainties ⋆

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Abstract: Nonlinear Bayesian filtering has been utilized in numerous fields and applications. One of the most popular class of Bayesian algorithms is Particle Filters. Their main benefit is the ability to estimate complex posterior density of the state space in nonlinear models. This paper presents the application of particle filtering to the problem of parameter estimation and calibration of a nonlinear power system model. The parameters of interest for this estimation problem are those of a turbine governor model. The results are compared to the performance of a heuristic method. Estimation results have been validated against real-world measurement data collected from staged tests at a Greek power plant.

Keywords: Nonliner Systems; Parameter Estimation; Electric Power Systems; Recursive filters; Monte Carlo Method.

1. INTRODUCTION

Mathematical modeling and parameter estimation of electrical power systems are of the great importance for power system operators. Model uncertainties and deviations from reality deeply affect the ability of operators to predict large blackouts Kosterev and Davies (2010). Speed governors play a major role in power system security and dynamic performance. They are responsible for primary frequency control in the power grid.

Heuristic algorithms to identify of the steam turbine speed governor model parameters have been successful Tao et al. (2012), Stefopoulos et al. (2005). In addition, these algorithms have been used to solve other estimation problems in power systems Lee and El-Sharkawi (2008). The nonlinear recursive least squares method has been applied to estimate parameter values optimizing the measurement and simulation difference in voltage and current through time Pourbeik (2009). Extended Kalman filtering was successfully applied for generator parameter estimation from real measurements in Huang et al. (2013).

The application of particle filters in power systems has been recently investigated for dynamic state estimation of a synchronous machine Zhou et al. (2015). Due to its non-requiring assumptions about the state-space model or the state distributions, there is great potential to exploit Bayesian filtering approach for parameter identification and model validation.

There are technical issues related to identification problems in power systems. First, there is a lack of measurement data due to several reasons. Experimental testing is limited, as it requires the switching of components or part of the network, which is costly. From the other hand, confidentiality issues are always present, so an operator may be able to provide measurements, but not to provide the model, or vice versa. Second, even when the model and measurements are provided, there is always ambiguity and uncertainty in these data. Some details about the network are not documented properly or are a trade secret.In addition, time-series data may contain different number of samples and usually has to be processed before estimation algorithms can be applied.

The contribution of this paper consists in evaluating methods from different frameworks - the Bayesian framework (Particle Filter (PF)) and heuristic optimization (Particle Swarm Optimization (PSO)) in combination with naive (gradient descent) or simplex search (Nelder-Mead (NM) method) using real measurements from staged tests in a Greek power plant.

The remainder of this article is structured as follows. Section 2 describes the algorithms applied for parameter estimation and the turbine speed governor model in the Greek power plant. Numerical tests and simulation results are shown in Section 3, and further discussed in Section 4.

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Finally, conclusions were drawn and future work is outlined in Section 5.

2. MODELING AND METHODOLOGY

The Greek power plant which will be used in this paper was not modeled for dynamic simulation before this study and relatively little information was available about the dynamic characteristics of the equipment. Complete modeling of the plant has been carried out using Modelica Fritzson (2011), in Bogodorova et al. (2013), Qi (2014), however, in this paper only the turbine-governor system is described in detail.

2.1 The dynamic model of the turbine-governor

The model TG Type I, Milano (2005), was used to represent the dynamics of the real turbine governor in the Greek power plant, as follows

$$p^*_{in} = p_{ref} + \frac{1}{R}(\omega_{ref} - \omega) \tag{1}$$

$$p_m = x_{g3} + \frac{T_4}{T_5}\left(x_{g2} + \frac{T_3}{T_c}x_{g1}\right) \tag{2}$$

$$\dot{x}_{g1} = (p_{in} - x_{g1})/T_s \tag{3}$$

$$\dot{x}_{g2} = \left(\left(1 - \frac{T_3}{T_c}\right)x_{g1} - x_{g2}\right)/T_c \tag{4}$$

$$\dot{x}_{g3} = \left(\left(1 - \frac{T_4}{T_5}\right)\left(x_{g2} + \frac{T_3}{T_c}x_{g1}\right) - x_{g3}\right)/T_5 \tag{5}$$

$$p_{in} = \begin{cases} p^*_{in} & \text{if } p^{max} \geq p^*_{in} \geq p^{min} \\ p^{max} & \text{if } p^*_{in} > p^{max} \\ p^{min} & \text{if } p^*_{in} < p^{min} \end{cases} \tag{6}$$

where
ω_{ref} - reference speed [p.u];
R - droop [p.u.];
p_{max} - maximum turbine output [p.u.];
p_{min} - minimum turbine output [p.u.];
T_s - governor time constant [s];
T_c - servo time constant [s];
T_3 - transient gain time constant [s];
T_4 - power fraction time constant [s];
T_5 - reheat time constant [s];

This model was chosen because of its simplicity and ability to reproduce the main dynamics of the governor and steam turbine. It is a very simple approximation of the real dynamics, which brings deviation of the model behavior from the real system response.

A droop governor response is used in turbine generator controls to help maintaining an electrical grid at constant frequency. If the grid frequency drops below rated frequency, the turbine will be commanded to increase its power output. If the grid frequency increases above the rated frequency, the turbine will be commanded to reduce its power output. In other words the primary frequency response is aimed to automatically change of the gas turbine load to compensate for change in grid frequency.

2.2 Bayesian filtering concept

Bayesian filtering is one of the most popular methods to solve inverse problems. It recursively estimates a belief in the unmeasured states/parameters $\{x_n\}$, Kramer and Sorenson (1988), by using all available information about the system's structure

$$\frac{dx}{dt} = f(x(t), t) \tag{7}$$

$$y_n = h(x(t_n), t_n, \sigma_n), \tag{8}$$

where σ_n- measurement noise; and $y_{1:n} = \{y_i, i = 1..n\}$ are measurements. Assuming that the initial probability distribution function (pdf) (prior), $p(x_0|y_0) = p(x_0)$, is given, one has to construct the posterior pdf, $p(x_n|y_{1:n})$. This process is recursive and may be performed in two stages: *prediction* and *update*.

At the *prediction* step the Chapman-Kolmogorov equation, Doucet et al. (2001), is applied:

$$p(x_n|y_{1:n-1}) = \int p(x_n|x_{n-1})p(x_{n-1}|y_{1:n-1})dx_{n-1} \tag{9}$$

At the *update* step when the measurements y_n have been received, the Bayes' rule is exploited to update the prior to the posterior pdf given the measurements y_n:

$$p(x_n|y_{1:n}) = \frac{p(y_n|x_n)p(x_n|y_{1:n-1})}{p(y_n|y_{1:n-1})} \tag{10}$$

The normalizing constant can be evaluated using:

$$p(y_n|y_{1:n-1}) = \int p(y_n|x_{n-1})p(x_n|y_{1:n-1})dx_n \tag{11}$$

The likelihood function $p(y_k|x_k)$ is represented trough measurement equation, where the properties of the measurement noise are known.

In Bayesian inference, all of uncertainties are treated as random variables. Bayesian filtering is optimal in a sense that it seeks the posterior distribution which uses all of available information expressed by probabilities (assuming they are quantitatively correct). However, as time proceeds, one needs infinite computing power and unlimited memory to calculate the optimal solution, except in some special cases (e.g. linear Gaussian or conjugate family cases). Hence, in general, we can only seek a suboptimal or locally optimal solution Chen (2003).

2.3 Particle Filter

The particle filter is an nonparametric implementation of the Bayes filter. The particle filters approximate the posterior pdf by a finite number of parameters. The key idea of the particle filter is to represent the posterior pdf $p(x_{n+1}|y_n)$ by a set of random samples drawn from the posterior. Instead of representing the distribution in parametric form (exponential function for a normal distribution), particle filters represent a distribution by a set of samples drawn from this distribution. Such a representation is approximate, but it is nonparametric, and therefore can represent a much broader space of distributions than, for example, Gaussians. Another advantage of the sample based representation is its ability to model nonlinear transformations of random variables, as shown in Fig. 1. The samples of a posterior distribution are called particles