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IFAC-PapersOnLine 48-28 (2015) 461–465

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.

⋆ T. Bogodorova is funded by the EU funded FP7 *iTesla* project. L. Vanfretti is with Statnett SF, Research & Development, Oslo, Norway. L. Vanfretti is supported by Statnett SF, the Norwegian Transmission System Operator, the STandUP for Energy collaboration initiative, the -EU funded FP7 *iTesla* project and Nordic Energy Research through the STRONg^{2}rid project.

10.1016/j.ifacol.2015.12.171

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

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

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

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

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

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

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

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

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

$$y_n = h(x(t_n), t_n, \sigma_n), \quad (8)$$

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:

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

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:

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

The normalizing constant can be evaluated using:

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

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

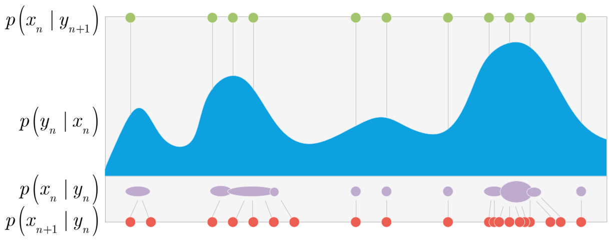

Fig. 1. Particle Filter with importance sampling and resampling

$\{x_n^{(i)}\}$. Each particle is a concrete instantiation of the state (parameter value) at time t.

Algorithm 1 Particle Filter

procedure PF($p_{min}, p_{max}, N_p, \epsilon, \sigma_K, n_{it}$)
  while $n < n_{it}$ and {stop criteria} **do**
    Step 1. Initialization (sampling from uniform prior):
    for $i = 1$ to N_p **do**
      draw the samples $x_n^{(i)} \propto p(x_0)$
      $W_0^{(i)} \leftarrow 1/N_p$.
    Step 2. Importance Sampling:
    for $i = 1$ to N_p **do**
      draw samples $\hat{x}_n^{(i)} \propto p(x_n|x_{n-1}^{(i)})$,
      $\hat{x}_n^{(i)} \leftarrow \{x_{0:n-1}^{(i)}, \hat{x}_n^{(i)}\}$
    Step 3. Weight update with normalization:
    for $i = 1$ to N_p **do**
      $RSSD(y, \hat{y}) \leftarrow \frac{1}{M}\sum_i(\frac{y_i - \hat{y}_i}{y_i})^2$
      $fitness \leftarrow RSSD(y, \hat{y})$
      $W_n^{(i)} \leftarrow 1 - \frac{fitness}{\sum_i fitness}$
    Step 4. Resampling:
    Generate/prune particles $x_n^{(i)}$ from $\{\hat{x}_n^{(i)}\}$
    according to $W_n^{(i)}$/(prune if $W_n^{(i)} < \epsilon$)
    to obtain N_p random samples

where $[p_{min},\ p_{max}]$ - range of parameters' values which define parameter space,
N_p - number of particles used to fill the space of parameter values;
σ_K - covariance of the kernel;
Y - real measurements;
$\hat{Y}$ - estimate;
ϵ - prune threshold (defines which percentage of particles with lowest weight will not survive);
{stop criteria} - set of conditions to finish the particle filtering main cycle
M - number of measurement instances.

The algorithm described above and illustrated in Fig. 1, is a general description of the principle of particle filtering. Variations in the realization of each step lead to different types of particle filters and largely depend on the application.

In the case of the application to the power plant scenario herein, weighting is specific and based on the value of the fitness function (relative squared difference between simulation and real measurements), while resampling is used a well-known and widely applicable (previously for pattern recognition and classification) Gaussian kernel technique Bishop et al. (2006).

2.4 Heuristic optimization concept

The common features of all heuristic optimization (HO) methods is that they start off with a more or less arbitrary initial solution, iteratively produce new solutions by some generation rule and evaluate these new solutions, and eventually report the best solution found during the search process. The execution of the iterated search procedure is usually halted when there has been no further improvement over a given number of iterations (or further improvements cannot be expected); or when the found solution is good enough, or when the allowed CPU time (or other external limit) has been reached Maringer (2005).

2.5 Particle Swarm Optimization

The particle swarm optimization (PSO) is an heuristic optimization method based on the natural behavior of animal groups Nedjah and de Macedo Mourelle (2006). Each potential solution is assigned a randomized position vector, and the potential solutions called particles, move through the potential values of the parameter space seeking the objective function's optimal values. Particles change their direction based on the combination of their own experience and the best experience of the group. In each iteration, the particles are updated with swarm motion equations which include a particle's own experience, and experience of the group of particles to choose the way of movement for each particle towards the optimum with some random deviation:

$$V_t = \alpha_1 R_1 V_{t-1} + \alpha_2 R_2 (P_b - X_{t-1}) + \alpha_3 R_3 (p_b - X_{t-1})$$
$$X_t = X_{t-1} + V_t \tag{12}$$

where
α_1- multiplier on the contribution of the last sample of the particle's speed to it's next sample;
α_2- multiplier on the contribution of the distance to the particle's personal best position to the next sample of the speed;
α_3- multiplier on the contribution of the distance to the swarm's overall best position to the next sample of the speed;
P_b- particle's previous best state;
p_b- the globally best location of the moving group;
$R_{1,2,3}$- randomly generated noise.

3. NUMERICAL TESTS

The RaPId toolbox for parameter identification developed by Vanfretti et al. (2014) has been equipped with Particle Filter method in addition to previously implemented PSO algorithm.

Due to complexity of heuristic and Bayesian algorithms and the use of high-order models (e.g. the Greek power plant) for parameter identification, the methodology used for experiment setup can be described in two main steps:
Step 1. Execute the stochastic (Bayesian) Particle Filter or Particle Swarm Optimization (PSO) for a few iterations.

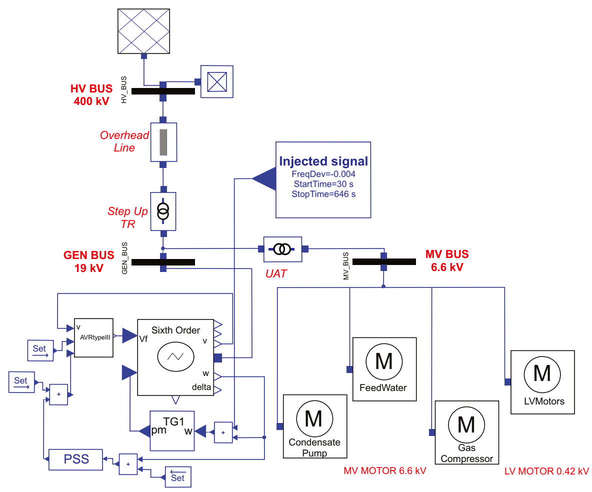

Fig. 2. iGrGen greek power plant model

Step 2. Start from the solution found in Step 1 (which is close to the optimum solution) with a simple optimization method (gradient descent-based (naive) or simplex (Nedler-Mead method Lagarias et al. (1998)) in order to find an optimal solution.

At each iteration of the algorithms, RaPId launches the simulation of a Modelica model for each particle of the PSO and Particle Filter. The model used for the experiments is shown in Fig. 2. This Greek power plant (iGrGen) is a combined cycle power plant containing a gas turbine, a steam turbine and a synchronous generator in a single shaft arrangement. A speed governor is used to control the system frequency.

The measurement data used for parameter identification was obtained from staged tests performed on the turbine governor. The purpose of the experiment is to demonstrate the response of turbine to system frequency deviations, thus the measured data is the turbine mechanical power output p_m. The turbine parameters of the iGrGen system model which influence the power output the most are droop (R) and governor time constant (T_s). Hence, they were chosen for estimation. The steam turbine in the power plant does not contribute initially to the primary frequency control because of its large thermal inertia.

For each test (experiment) the power plant was operated at different power dispatch levels by varying the initial power p_{in}^* (1). The initial power was measured in percentage of the so-called Maximum Continuous Rating (MCR) which refers to the gas turbine output at which it enters into the temperature limit control regime under present air temperature/humidity ambient conditions. An incremental signal ($\Delta\omega = \pm 0.2\,Hz\,(0.004\,p.u)$) is injected to the frequency reference input of the governor to mimic the effect of a variation of system frequency.

The numerical results of the turbine governor parameter estimation are shown in Table 1. Two kinds of optimization algorithm combinations are used, and the performances are evaluated by comparing the Averaged Relative Summed Squared Difference (ARSSD).
Graphical comparisons of the measurement data and simulation results of the iGrGen system model using the estimated values obtained from the estimation process are shown in Figs. 3 - 8.

Table 1. Parameter and fitness values for the simulated model

	Exp. Name	R	T_s	Fitness
1	PSO_{10} + NM	0.0558	1.5397	1.4659e-004
	PF_{10} + NM	**0.0547**	7.4021	**1.0137e-004**
2	PSO_{10} + NM	0.0672	14.4695	9.0661e-005
	PF_{10} + NM	0.0672	14.2693	9.0661e-005
3	PSO_{10} + NM	0.0469	1.2551	2.6791e-004
	PF_{10} + NM	**0.0461**	12.9999	**1.5908e-004**
4	PSO_{10} + NM	0.0571	1.4008	3.0166e-004
	PF_{10} + NM	**0.0560**	1.6019	**3.0123e-004**
5	PSO_{10} + NM	0.0686	1.8506	7.4265e-005
	PF_{10} + NM	**0.0681**	3.4113	**6.7935e-005**
6	PSO_{10} + NM	0.0703	1.0762	5.1476e-005
	PF_{10} + NM	**0.0691**	0.8929	**5.0014e-005**
7	PSO_{10} + NM	0.0696	0.9581	5.1442e-005
	PF_{10} + NM	**0.0689**	1.1808	**4.9343e-005**
8	PSO_{10} + NM	0.0600	0.7849	8.3462e-005
	PF_{10} + NM	**0.0660**	1.0685	**4.8372e-005**

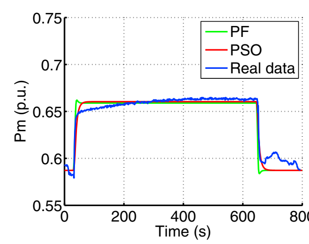

Fig. 3. Test 1 (MCR 60%, $\Delta\omega = -200\,mHz$)

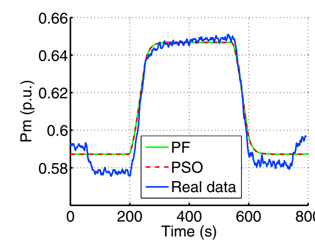

Fig. 4. Test 2 (MCR 60%, $\Delta\omega = -200\,mHz$)

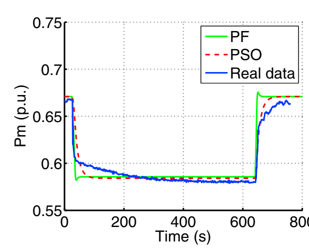

Fig. 5. Test 3 (MCR 60%, $\Delta\omega = +200\,mHz$)

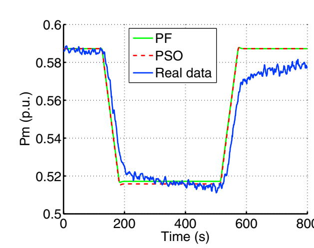

Fig. 6. Test 4 (MCR 60%, $\Delta\omega = +200\,mHz$)

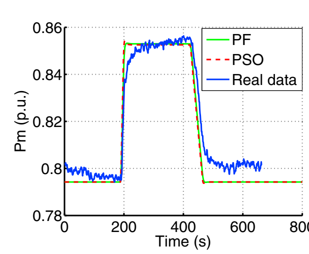

Fig. 7. Test 5 (MCR 80%, $\Delta\omega = -200\,mHz$)

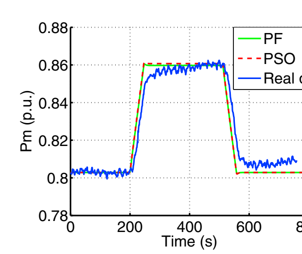

Fig. 8. Test 6 (MCR 80%, $\Delta\omega = -200\,mHz$)

4. DISCUSSION

The results on estimation of the turbine governor parameters in Table 1 show faster convergence using the combination of PF and NM methods in contrary to the PSO and

NM methods. The results, as expected, lie within a range of physically valid parameter values. This demonstrates the potential to use these algorithms to facilitate routine parameter calibration.

The comparisons in Fig. 3 - 8 show the ability to estimate the parameters which allow the model to reproduce the systems dynamic behavior. The turbine governor requires longer time to restore the frequency to the nominal value, which results power variance in the process of real experiment.

The reason for divergence from the real system response is uncertainty in the model structure. The dynamics of the rise and fall period during the frequency change are hard to estimate due to insufficient information for more detailed modeling. However, using a turbine governor model of higher order brings additional complexity to estimate transient time constants. This is specially difficult because the tests performed in the plant did not heavily excite transient dynamics, and thus, cannot be observed in measurement data. This causes a large divergence in the estimates of T_s for Test 1 and 3.

5. CONCLUSION AND FUTURE WORK

The numerical experiments obtained show good performance of the methodology proposed in the paper. The ability to estimate the turbine governor time constant is uncertain due to modeling adequacy and dynamics observability in the measurements. Nevertheless, overall fitness of the simulations to the real data is sufficient for practical purposes.

Future work will be focused on enhancing the RaPId toolbox to include other Bayesian methods. More experimental tests and real data are needed to evaluate different methodologies for parameter identification. In addition, further work with include the use of more complex models of the plant, as well as larger power systems for the aforementioned aims.

ACKNOWLEDGEMENTS

The authors are thankful to George Antonopoulos of IPTO who kindly provided measurements and plant structure information. Le Qi has contributed to the development of the Modelica model during her Master thesis project. Her contributions are sincerely appreciated.

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