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Bayesian calibration of power plant models for accurate performance prediction

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ABSTRACT

Gas turbine combined cycles are expected to play an increasingly important role in the balancing of supply and demand in future energy markets. Thermodynamic modeling of these energy systems is frequently applied to assist in decision making processes related to the management of plant operation and maintenance. In most cases, model inputs, parameters and outputs are treated as deterministic quantities and plant operators make decisions with limited or no regard of uncertainties. As the steady integration of wind and solar energy into the energy market induces extra uncertainties, part load operation and reliability are becoming increasingly important. In the current study, methods are proposed to not only quantify various types of uncertainties in measurements and plant model parameters using measured data, but to also assess their effect on various aspects of performance prediction. The authors aim to account for model parameter and measurement uncertainty, and for systematic discrepancy of models with respect to reality. For this purpose, the Bayesian calibration framework of Kennedy and O'Hagan is used, which is especially suitable for high-dimensional industrial problems. The article derives a calibrated model of the plant efficiency as a function of ambient conditions and operational parameters, which is also accurate in part load. The article shows that complete statistical modeling of power plants not only enhances process models, but can also increases confidence in operational decisions.

1. Introduction

Electricity production, and energy in general, play a pivotal role in every modern society, as energy is required for fulfilling almost all basic needs, such as food, water, transportation, shelter, and security. To ensure the availability of energy for future generations, a collective effort is undertaken to decrease the dependency on conventional energy resources, such as oil, natural gas, and coals, of which the future supply is limited. There is a need for alternative and sustainable energy resources. The more mature sustainable technologies are wind and solar energy.

Given the currently available technologies, electricity cannot yet be stored in large quantities. It is a product that should be delivered momentarily, and on demand. A national grid authority is responsible for maintaining the power balance on the electricity grid. The power producing companies usually have a fleet of power plants with varying characteristics, and power is dispatched from the plant with the lowest estimated incremental costs. El-Naggar et al. [1] shows that the fuel cost function (i.e., efficiency as a function of ambient conditions and operational parameters) plays an important role in the economic deployment of power plants.

While these mechanisms are intended to maintain the balance on the electricity grid, power plants based on sustainable technologies are increasingly added to the grid to comply to the Kyoto protocol, which requires the reduction of CO_2 emissions. However, the most mature sustainable technologies, wind and solar, are not available on demand, so that their production rates cannot be controlled. Despite efforts in predicting the behavior of wind (e.g., [2]), and solar energy (e.g., [3]), a certain amount of uncertainty remains present, where the uncertainty increases with the forecast lead time.

Gas turbine combined cycles (GTCC), are expected to play an important role in keeping the grid in balance, because of their relatively short start-up and shut down times. They are expected to be operated increasingly as reserve capacity [4] and thus at lower load factors (ratio of averaged power output to maximum power). Accordingly, reliability, predictability and flexibility play an important role in the operation of these plants, and part load operation is becoming increasingly important. It is highly recommended to keep accurate track of the performance of these units.

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Nomenclature

δ	Model discrepancy	LP	Low pressure
ϵ	Noise	LPST	Low pressure steam turbine
$\hat{\theta}$	Hypothetical true value of model parameters	LPT	Low pressure gas turbine
ρ	Probability density	MCMC	Markov Chain Monte Carlo
θ	Unknown model parameter	OTC	Once through cooler
COMP	Compressor	RBC	Rankine Bottoming Cycle
DOE	Design Of Experiments	SEV	Sequential environmental vortex (burner)
EV	Environmental vortex (burner)	TAT1	Low pressure gas turbine exit temperature
GPMSA	Gaussian process models for simulation analysis	TAT2	High pressure gas turbine exit temperature
GSP	Gas turbine simulation program	TIT1	Turbine inlet temperature of first combustor
GT	Gas turbine	TIT2	Turbine inlet temperature of second combustor
GTCC	Gas turbine combined cycle	VIGV	Variable inlet guide vane
HP	High pressure	y	Model output
HPT	High pressure gas turbine	x	Model output
LHS	Latin Hypercube Sampling	y^*	Measured output
LHV	Lower heating value		

The increasing uncertainty on the supply side of the electricity market, combined with the usual fluctuations on the demand side, result in an increasing need for uncertainty analysis in the field of power plant management. Uncertainties can exist in the various aspects of plant design, operation, and management. Metaxiotis et al. [5] provides an overview of the application of advanced computational techniques for electric load forecasting. Li and Huang [6], Dong et al. [7] demonstrate how electric power system planning can be done, taking into account uncertainties in energy demand and supply, conversion technology, and costs/benefits, among others.

An important issue is the quantification of uncertainties within process models. The method of Bayesian inference [8] represents a way to estimate unknown model parameters and quantify the uncertainties in these parameters. Measurements are used to calibrate the model. This method has been applied to various cases in plant and engine diagnostics, such as [9,10].

A specific case of Bayesian inference is the Kennedy and O'Hagan framework for model calibration [11]. This method not only calculates most likely model parameters and their probability, but also estimates the systematic bias of models with respect to reality. This framework has been applied to implosion modeling [12], structural modeling [13], and gas turbine performance modeling [14], among others.

However, the Kennedy and O'Hagan Bayesian framework has not yet been applied to the modeling of GTCC plants. With this method, it is possible to statistically predict important output quantities, such as plant power output and efficiency, taking into account the uncertainties in estimated model parameters. The present article applies this method for quantifying the various sources of uncertainty in GTCC modeling.

After the introduction, a brief overview is given of Bayesian calibration and the Kennedy and O'Hagan framework. A gas turbine performance model of the GT26, described in Appendix A, is then calibrated using the framework. Unknown parameters of the gas turbine model represent the influence of variable inlet guide vanes, turbo machinery map inadequacy, and some aspects of the cooling flow distribution. The parameters are estimated from measurements recorded during normal operation of the Alstom KA-26-1 plant situated in Lelystad, The Netherlands. The calibration framework is then applied to a steam cycle model of the same plant, described in Appendix B. Unknown parameters of the steam cycle model include low pressure steam turbine design point efficiency. Among the calibration results are calibrated predictors of the gas turbine and steam cycle respectively.

The gas turbine and steam cycle models were created in two different modeling environments: GSP [15] and Thermoflex [16] respectively. Two methods are proposed to integrate these models for predicting overall plant efficiency. The first of these methods uses the outputs of a calibrated gas turbine model as inputs to a separately calibrated steam cycle model, to predict plant behavior: the integration is done after calibration. The second method integrates the models before calibration, so that, during the calibration, a single plant model is created.

The resulting integrated plant model can be applied to predict the plant efficiency as a function of ambient conditions and load setting, the so called fuel cost function. The models are shown to accurately predict part load performance of the plant. This type of models can be regularly updated with recent measurements, so that the resulting predictions become more reliable, and the information about plant performance is always up-to-date.

2. Bayesian analysis and model calibration including model bias estimation

2.1. Introduction to Bayesian analysis

In Bayesian statistics [8], probability density functions can describe the present knowledge about physical as well as non-physical quantities. Unknown model parameters (θ) are considered as random variables, whose probability distribution can be calculated from the probability distribution of measured output variables (y_i), using Bayes'rule:

$$\rho(\theta_i|y_i) = \frac{\rho(y_i|\theta_i)\rho(\theta_i)}{\rho(y_i)}, \tag{1}$$

where $\rho(\theta_i|y_i)$ is called the posterior, $\rho(y_i|\theta_i)$ represents the likelihood function, and $\rho(\theta_i)$ is the prior. $\rho(y_i)$ is independent of the parameters θ and serves as a normalization constant. The aim of Bayesian statistics is to represent the complete state of knowledge rather than a (subjective) part of it.

2.2. Outline of the Kennedy and O'Hagan framework

Within the context of Bayesian analysis, Kennedy and O'Hagan [11] proposed a model calibration method that estimates unknown or partially known physical parameters especially in high dimensional models. If $\hat{\theta}_i$ are the hypothetical 'true' values for the model