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Calibration and sensitivity analysis of long-term generation investment models using Bayesian emulation

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ABSTRACT

Investments in generation are high risk, and the introduction of renewable technologies exacerbated concern over capacity adequacy in future power systems. Long-term generation investment (LTGI) models are often used by policymakers to provide future projections given different input configurations. To understand both uncertainty around these projections and the ways they relate to the real-world, LTGI models can be calibrated and then used to make predictions or perform a sensitivity analysis (SA). However, LTGI models are generally computationally intensive and so only a limited number of simulations can be carried out. This paper demonstrates that the techniques of Bayesian emulation can be applied to efficiently perform calibration, prediction and SA for such complex LTGI models.

A case study relating to GB power system generation planning is presented. Calibration reduces the uncertainty over a subset of model inputs and estimates the discrepancy between the model and the real power system. A plausible range of future projections that is consistent with the available knowledge (both historical observations and expert knowledge) can be predicted. The most important uncertain inputs are identified through a comprehensive SA. The results show that the use of calibration and SA approaches enables better decision making for both investors and policymakers.

1. Introduction

There is a growing concern over capacity adequacy in future power systems due to a number of risks that may discourage investment in generation capacity [1–4]. These risks exposed to investors range from policy (e.g., VOLL pricing, CO_2 prices and renewable targets) and market (e.g., fuel cost, demand forecast and electricity price) risks, to technology (e.g., capital cost) and finance (e.g., hurdle rate) risks [4] and they create uncertainty (*i.e.*, imperfect knowledge) in the financial returns of an investment. One prominent feature in future power systems is that market risks increase with the amount of variable wind power that contributes to higher price volatility and lower (on average) and more uncertain load factors for thermal power plants [5].

Various long-term generation investment (LTGI) models have been developed for predicting real-world generation projections and hence guiding investment decisions and the design of energy policy [6–13]. From the perspective of policymakers, who wish to adequately account for uncertainty around future generation projections related to the real world, it becomes increasingly important to consider two main sources of uncertainty existing in these models. One is input uncertainty representing investment risks and/or model assumptions that affect or shape the direction of investment decisions [4]. The other one is structural uncertainty which concerns the discrepancy between the model and the real-world complex investment decision-making process. Questions regarding validation and understanding of these LTGI models need to be carefully addressed before model outcomes can be interpreted and applied.

Calibration or *history matching* is a valuable tool for validating a model and linking it to the real world when historical observations are available. This typically involves calibration of a subset of uncertain model parameters against historical observations of the model output whilst modeling the discrepancy between the model and the real system. Uncertainty of calibration parameters, which may be specified ex ante as a probability distribution based on the prior beliefs of the model user or other experts, can be reduced through calibration (*i.e.*, by identifying values of calibration parameters that are plausible with respect to prior beliefs and historical

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Nomenclature

Sets and functions

$\mathcal{T}$	Set of planning years of interest, indexed by t.
$\mathcal{P}$	Set of past planning years.
$\mathcal{F}$	Set of future planning years.
G	Set of generation technologies, indexed by g.
J	Subset of input variables, indexed by i, j.
ρ	Set of fuel types including uranium, coal, gas, and carbon.
$f(\cdot), \tilde{f}(\cdot)$	Functions of the simulator and the emulator, respectively.
$h_i(\cdot)$	Functions of the main modules within the simulator.
$\mathcal{GP}(\cdot,\cdot)$	Gaussian process function.
$p(\cdot)$	Probability distribution function.

Parameters and variables

x	Vector of input variables.
u, θ, ω	Vector of control inputs, calibration parameters and forcing inputs, respectively.
I	Total number of input variables.
$y^B_{g,t}, y^M_{g,t}, y^D_{g,t}$	Investment, mothballing and de-mothballing of generation capacities of type g at year t, respectively.
$y_{g,t}$	Installed generation capacity of type g in operation at year t.
y_{obs}	Vector of historical observations of elements $y_{obs,t}$ over $\mathcal{P}$.
$F_{\rho,t}$	Fuel price of type ρ at year t.
MR_ρ	Reference trend level of annual fuel prices of type ρ.
P_ρ	Multiplier applied to the trend level of fuel type ρ.
$P_{markup,t}$	Hourly price markup payment at year t.
θ_{markup}	Markup cut-in point where the markup approaches zero.
ND_t	Hourly net demand (demand minus wind generation) at year t.
$AG_{g,t}$	Hourly available thermal capacity subject to forced outages at year t.
CM_t	Hourly capacity margin (hourly available thermal capacity minus hourly net demand) at year t.
$VOLL$	Value of lost load (VOLL).
$P_{e,t}$	Energy prices at year t.
$C_{g,t}$	Generation cost of generation type g at year t.
$LOLE_t$	Loss-of-load expectation at year t.
$RT_{g,t}$	Retirement of existing generators of type g at year t.
V_t	Net Present Value (NPV) of an investment at year t.
τ_f	The furthest simulation year ahead of the current decision year.
$V_{VaR,t}$	Value at Risk (VaR) of V_t.
θ_{VaR}	Assumed level of risk aversion.
β, σ^2, γ	Hyperparameters in the Gaussian Process model.
δ	Model discrepancy function.
D	Design points of chosen input variables.
K_f	Principal component basis vectors of elements $k_1, \ldots, k_{p_f}$.
d_i	The ith basis function for model discrepancy.
ϑ_i	Weight of the ith basis function for model discrepancy.
λ_ϑ	Hyperparameter in the model discrepancy.
p_δ	Total number of basis functions for model discrepancy.
S_J	Measure of sensitivity to a subset of inputs x_J.
SV_J	Variance of the main effect of a subset of inputs x_J.
Var(y)	Total output variance.

observations of the model output). To the best of our knowledge, no such formal calibration of LTGI models has previously been done. If a calibration against historical observations is not performed, this severely limits the conclusions which can be drawn regarding investment decisions and policy design in the real system.

Sensitivity analysis (SA) is also often applied to LTGI models in order to understand how model outputs react to changes in model inputs. SA in [11,6,9,14,13,15] was carried out using a simple one-at-a-time method, where each uncertain parameter is varied independently across a range of possible values while all others are held constant. The one-at-a-time method fails to treat the analysis with sufficient care (*i.e.*, no formal weight or probability is attached to each outcome), and is incapable of taking into account interactions among different inputs. Multi-way SA can identify the combined effects of two or more inputs, through varying the inputs together using a large and highly structured set of simulator runs [16]. Probabilistic SA is an alternative approach to multi-way SA that can address interactions and nonlinearities. The input uncertainty is explicitly described as a scenario tree with associated probabilities (discrete) or a probability distribution (continuous) in probabilistic SA while it is treated only implicitly in the preceding methods. A wide ranging review of uncertainty and sensitivity analysis in the context of power system planning may be found in [17].

A conventional way to conduct a formal calibration or a probabilistic SA is the Monte Carlo (MC) method of drawing random configurations of inputs from their uncertainty distributions, running the model for each input configuration to obtain the set of outputs, and constructing the output distribution (which can in principle be evaluated to any desired accuracy). Computationally intensive models associated with large studies tend to have high-dimensional inputs. The MC-based method may require thousands of (if not more) individual evaluations in order to avoid sparse coverage of the model input space. It may be practically impossible for complex models to achieve very dense coverage of input space even if very large computer resource is available [17]. For example, a single run of a LTGI model may take many hours [18,6] or even many days or weeks with more detailed modeling of short-term operations of power plants [19,20]. In addition, the outputs of interest (e.g., generation projections) for a LTGI model are often high-dimensional due to the long planning horizon; this adds to the complexity of calibration and SA. Even where a very large number of runs may be possible by acquiring additional computing resource, the approach adopted in this paper allows results to be obtained in a systematic way with a smaller computing resource.

This paper will carry out calibration and probabilistic SA of a computationally intensive LTGI model (*i.e., the simulator*) with careful management of two sources of uncertainty—input uncertainty and structural uncertainty. A highly-efficient Bayesian approach described in [21–24] is employed. Fig. 1 shows a diagram of the proposed Bayesian framework, which is based on a Gaussian process model (*i.e., the emulator*) that is built as an approximation of the simulator using a limited number of simulation runs (*i.e., training data*). The emulator can efficiently deal with the tasks of: *calibration*; *probabilistic SA*; *prediction*—estimation of model outputs at input configurations that have not been tested; and *uncertainty analysis* that is most relevant when those outputs provide guidance in the making of some decision (such as using a LTGI simulator in setting VOLL for maintaining the LOLE target).

The main contributions of this paper can be summarized as follows.

(1) Use of Bayesian emulation to manage uncertainties arising from the limited number of runs that are possible and consequent sparse coverage of the input space; this is the first time that such emulation techniques have been used to manage these uncertainties when performing model calibration and uncertainty analysis associated with generation investment.