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DYNAMIC CALIBRATION OF DIGITAL TWIN VIA STOCHASTIC SIMULATION: A WIND ENERGY CASE STUDY

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ABSTRACT

We present a framework to dynamically calibrate a digital twin to support decision-making in systems operating under uncertainty. The framework integrates nested input models that accommodate nonstationarity in independent and response variables with a physics-based model to capture evolving system dynamics with a stochastic simulation. Calibration is formulated as a simulation-optimization problem with an evolving feasible region at each stage to maintain temporal dependence within the calibration parameter. We apply our previously established root-finding strategy to solve this problem with a Gaussian metamodel. As a case study, we apply the framework to forecast the short-term power deficit, known as the wake effect, in wind farms using real-world data and demonstrate the robustness of the proposed framework. Besides advancing the digital twin research, the presented methodology is expected to advance wind farm wake steering strategy by enabling accurate short-term wake effect prediction.

1 INTRODUCTION

Digital twins are virtual representations of physical systems that support real-time monitoring and control. In many applications, operational decisions need to be made in advance, before future state of the system is known. One example is in wind farms operations, where the yaw angle of the turbine could be adjusted in a way to maximize the power generation for the upcoming wind conditions. This decision can be empowered by a digital twin whose accuracy heavily depends on an unobservable parameter known as the wake effect. Previous work establishes sample-efficient algorithms to learn a global wake parameter that aligns the digital twin to the entire historical data (Jain et al. 2023; Jain et al. 2024). However, digital twins may need to be continuously calibrated to account for the evolving state of the real-world system. For this, we present a dynamic calibration framework that incorporates a data-driven stochastic simulation to generate replications of the future system state based on the data-driven probabilistic model.

2 DYNAMIC CALIBRATION WITH STOCHASTIC SIMULATION

We formulate the dynamic digital twin calibration task as a simulation-optimization problem, where the goal is to update the key model parameters $\theta \in \Theta$ at time step t by minimizing the discrepancy between the system response Y_t and digital twin outputs $h(X_t, \theta)$ generated given the independent variables X_t using a stochastic simulation. However, a) expected temporal evolution of the calibration parameters, b) potential nonstationarity, and c) noise in the observations introduce significant challenges for the calibration task.

To address these challenges, we first account for the temporal dependence of the calibration parameter by constraining its updates at each time step. However, as the system may experience unknown amount of abrupt shifts, we instead solve the dual of the problem that seeking for the nearest parameter to the most recent estimate θ_{t-1} that sufficiently reduces the expected discrepancy. This leads to an optimization problem having a deterministic objective with a stochastic constraint:

$$\min_{\theta \in \Theta} \ |\theta_{t-1} - \theta| \quad \text{s.t.} \quad g_t(\theta) := \mathbb{E}_{X_t}\left[\mathbb{E}_{Y_t|X_t}\left[d(Y_t, h(X_t, \theta))\right]\right] \leq \kappa_{t,\alpha}(\mathbb{P}^{Y_t|X_t}\mathbb{P}^{X_t}). \tag{1}$$

The stochastic constraint in (1) is evaluated using the simulation replications that instantiate the probabilistic models fitted to the historical data. We hypothesize that the response variables exhibit more stable behavior when conditioned on the independent variables that represents the environmental changes in the future state. A nested structure at the outer level generates replications of the independent environmental variables X_t (which can be nonstationary), and generates response variables Y_t from the fitted conditional probability models at the inner level. While the framework deliberately keeps this flexible, in our case study, we use a Gaussian process regressor with a finely-tuned training window size for $\mathbb{P}^{X_t}$ and first-order autocorrelation structure to model the short-term persistence (inertia) in the system response $\mathbb{P}^{Y_t|X_t}$.

The next feature of our framework is to enable the constraint's threshold $\kappa_{t,\alpha}(\cdot)$ to vary over time, based on the range of residuals (the smallest and largest possible) that one could attain from the simulation. This dynamically updated threshold governs what constitutes sufficient reduction in the expected discrepancy at each time t. This is particularly important in dynamic calibration, as the range of discrepancies and their heteroskedasticity may vary over time—a crucial phenomenon in many applications, including wake models. The threshold also incorporates a hyperparameter $\alpha \in [0, 1]$, which controls the degree to which rapid fluctuations are considered plausible in a given application. For instance, in the wind farm applications, this hyperparameter (α) may be chosen closer to one that restrict the drastic changes in the wake effect due to physical limits, even when the noisy data itself might otherwise suggest such behavior.

3 IMPLEMENTATION AND COMPUTATIONAL CONSIDERATIONS

The stochastically constrained problem in (1) is challenging as estimating the discrepancy for any θ requires running the nested stochastic simulation and the physics-based model for multiple replications. Moreover, estimating $\kappa_{\alpha,t}$ practically entails an inner optimization task during the evaluation of every θ. In our former work, we developed a Bayesian Optimization (BO) algorithm that attempts root-finding instead of minimization by exploiting the signed discrepancy (Jeon and Shashaani 2024). Implementing this algorithm requires an approximation by replacing the average discrepancy with the discrepancy of the averages to track the change in the signed values. While the solution to this approximate problem may differ from that of the original formulation, root-finding substantially reduces the search space and allow us to obtain better solution within a fixed total number of simulation replications. Besides the accelerated search advantages, the metamodel that we construct in that algorithm can also provide an estimate for $\kappa_{t,\alpha}$, since it captures the overall structure of the discrepancy function from the evaluated design points. With the estimated sufficient reduction threshold $\kappa_{t,\alpha}$, we recommend the closest feasible design to θ_{t-1} as optimal.

4 NUMERICAL RESULTS AND CONCLUDING REMARKS

We conducted two experiments on a yearly real-world wind farm with multiple turbines. Our dynamically calibrated wake model achieves 3–6 % lower test loss compared to a global θ (Jain et al. 2024) and compared with the strategy that relies on the most recent data points (x_{t-1}, y_{t-1}) deterministically. We then used the calibrated parameters in the digital twin for decision-making—i.e., finding the yaw angle that maximizes power generation; where we found 50% greater proximity to the theoretical upper bound (maximum achievable power generation if future conditions were exactly known). In summary, the methodology and implementation suggest that this framework can fill an important gap in the digital twin research and enable impactful real-world outcomes.

REFERENCES

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