Preliminary machine learning-based calibration strategy for the ITER Tokamak Systems Monitor

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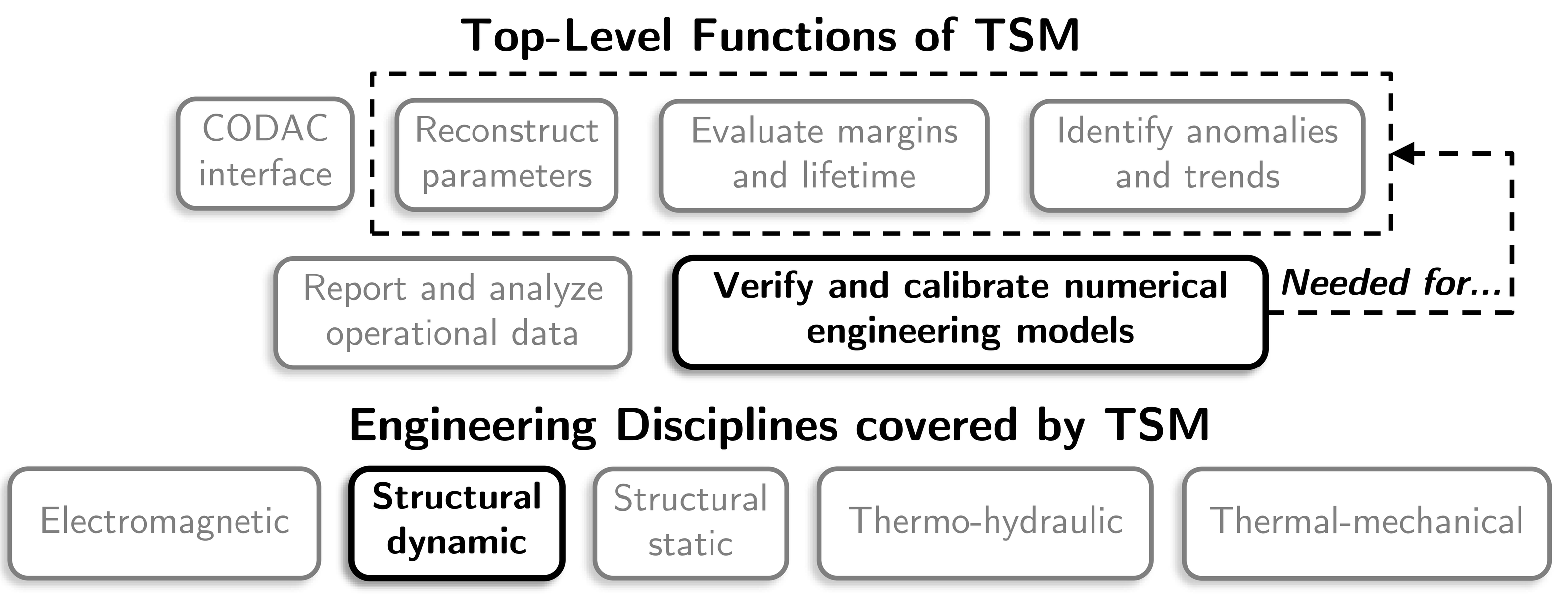
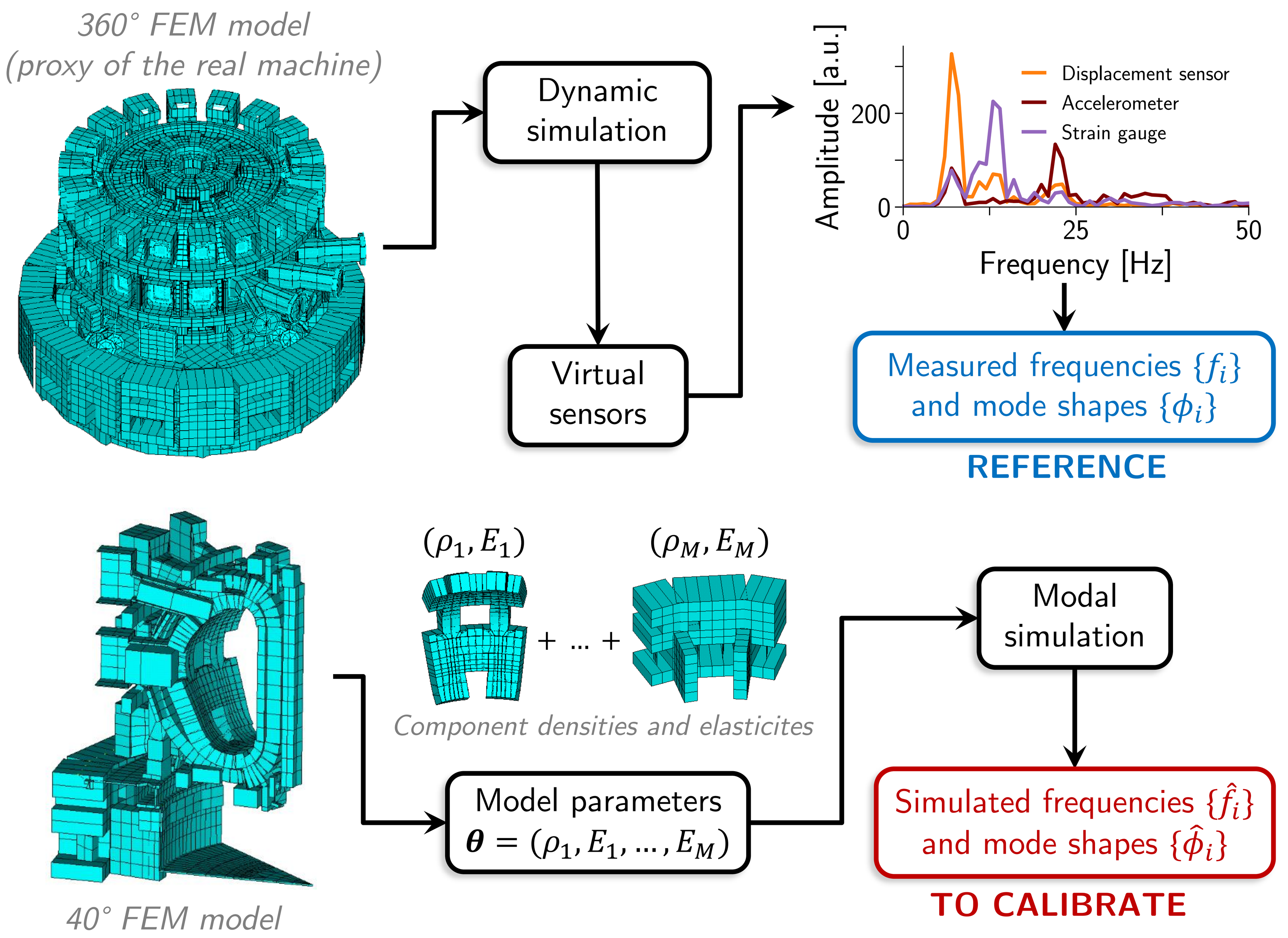
I. TOKAMAK SYSTEMS MONITOR

The **Tokamak Systems Monitor** (TSM) software analyzes data from various sensors across systems to assess the ITER tokamak's health. It reconstructs critical engineering parameters, evaluates operational margins, detects anomalies, and assists physics studies. This work presents the strategy for **calibrating numerical models** that TSM relies upon, focusing on the machine's **structural dynamics**.



II. FINITE ELEMENT MODEL UPDATING

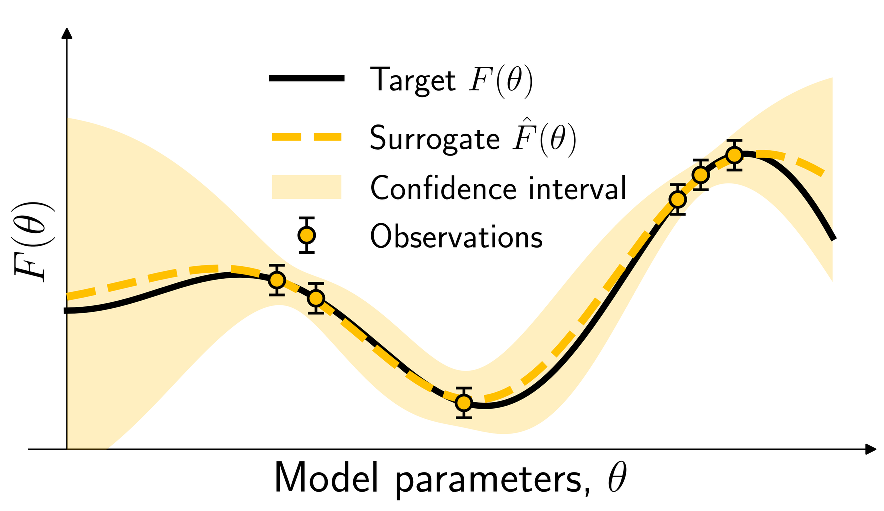
Finite element model updating [1] refines a computational model to match experimental data. Experimental modal analysis identifies a structure's dynamic properties using controlled testing, while operational modal analysis [2] determines these properties from normal operation without artificial excitation. However, in tokamaks, these traditional techniques are often impractical due to limited controlled excitations, sensor integration challenges, and extreme internal conditions. Therefore, calibration must rely on a reduced subset of immovable sensors and minimal modal information extracted from the free vibrations that follow a vertical displacement event.



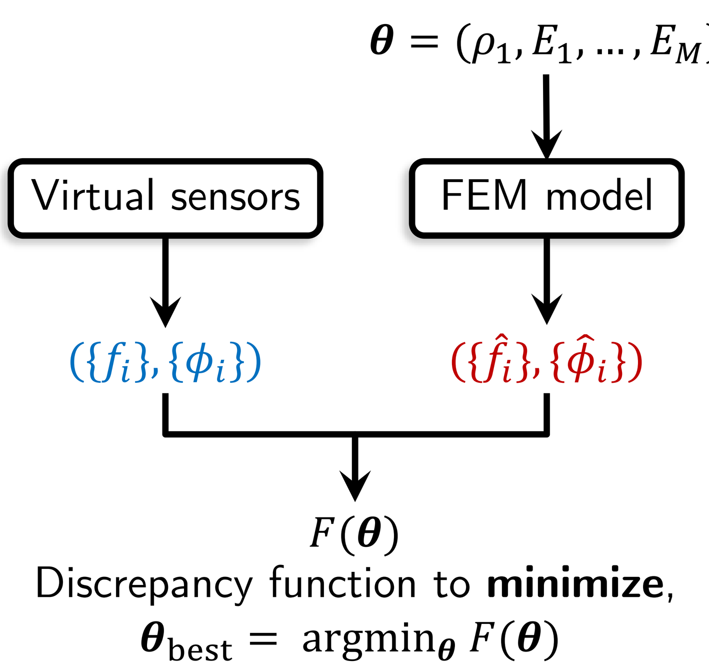
In the absence of experimental data, synthetic sensors signals from the 360° FEM model are used to **emulate operational data** in order to calibrate the 40° FEM model. Eventually, the large 360° FEM model will in turn be calibrated using experimental data.

III. SEQUENTIAL MODEL-BASED OPTIMIZATION

Sequential Model-Based Optimization (SMBO) enables the optimization of a function $F(\boldsymbol{\theta})$ that is expensive to evaluate and lacks a directly computable gradient, using as few observations as possible. **Bayesian optimization**, a common approach within SMBO, uses a **Gaussian Process** (GP) regressor [3] to build a surrogate model $\hat{F}(\boldsymbol{\theta})$ from prior observations $D = \{(\boldsymbol{\theta}_n, F(\boldsymbol{\theta}_n))\}_{n=1}^{N_{\text{obs}}}$. This model not only predicts promising points for further evaluation but also accounts for uncertainties, both in noisy observations of the target function and in the surrogate's predictions. By doing so, it guides the selection of new parameter values $\boldsymbol{\theta}$ and approximates $F(\boldsymbol{\theta})$ across the parameter space.

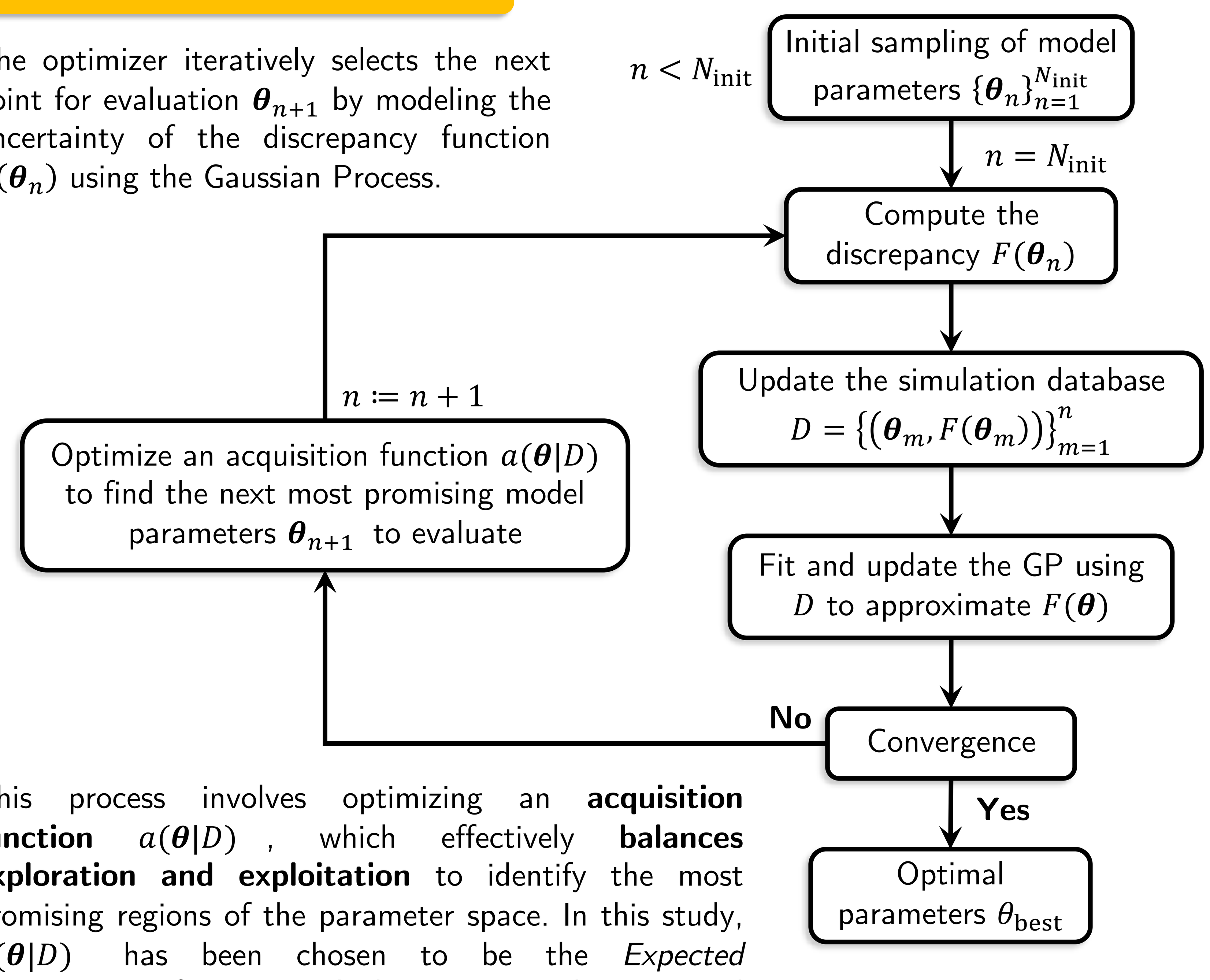


One-dimensional example of a Bayesian optimization using a Gaussian Process ($N_{\text{obs}} = 6$)



IV. CALIBRATION WORKFLOW

The optimizer iteratively selects the next point for evaluation $\boldsymbol{\theta}_{n+1}$ by modeling the uncertainty of the discrepancy function $F(\boldsymbol{\theta}_n)$ using the Gaussian Process.



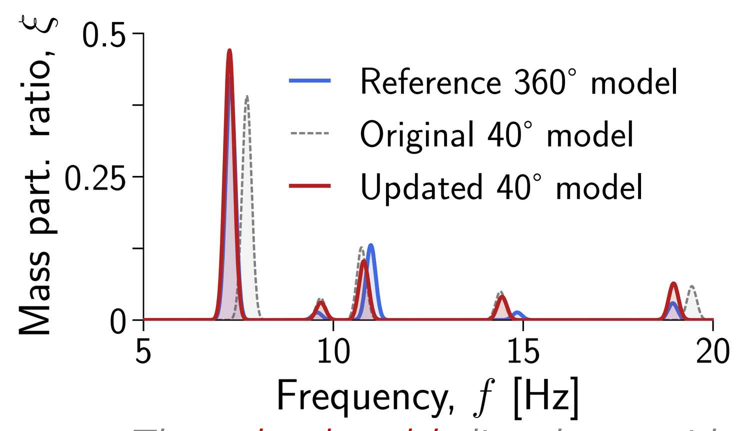
This process involves optimizing an **acquisition function** $a(\boldsymbol{\theta}|D)$, which effectively **balances exploration and exploitation** to identify the most promising regions of the parameter space. In this study, $a(\boldsymbol{\theta}|D)$ has been chosen to be the *Expected Improvement* function, which estimates the expected gain over the current best observation of $F(\boldsymbol{\theta})$.

V. PRELIMINARY RESULTS

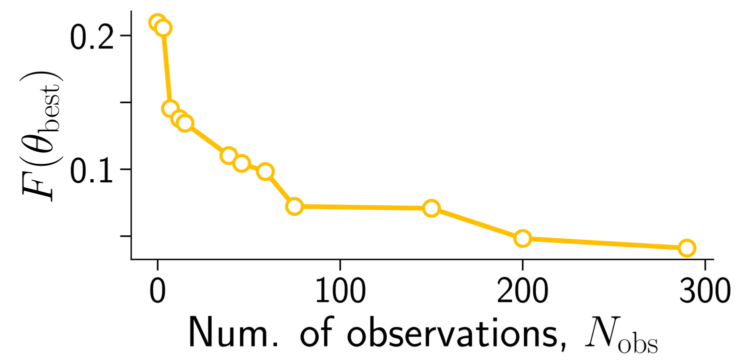
Using a simple form of the discrepancy function that only focuses on minimizing the distance between **measured frequencies** and **simulated frequencies**,

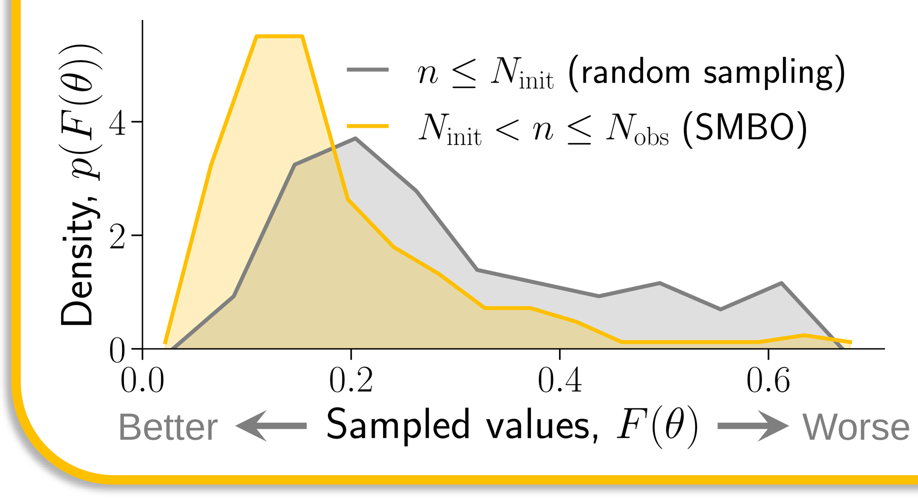
$$F(\boldsymbol{\theta}) = \frac{1}{N}\sum_{i=1}^{N}\left(f_i - \hat{f}_i(\boldsymbol{\theta})\right)^2,$$

the **SMBO procedure** explores the parameter space efficiently and iteratively finds new values of $\boldsymbol{\theta}_{\text{best}}$ that decrease the value of $F(\boldsymbol{\theta})$. In this study, a small subset of $|\boldsymbol{\theta}| = 10$ model parameters are varied, consisting only of the densities ρ and elasticities E of components predefined in the FEM model. A total of $N_{\text{obs}} = 300$ modal simulations were run, including $N_{\text{init}} = 100$ for the initial random sampling.



The updated model aligns better with the reference model after calibration





During the initial random sampling, values of $F(\boldsymbol{\theta})$ are higher on average than in the SMBO phase, where Bayesian optimization explores the parameter space more efficiently, showing its potential for autonomously finding optimal model parameters with fewer observations.

VI. FUTURE WORK

- Perform a more robust identification of the most influential model parameters $\boldsymbol{\theta}$ to vary during the optimization.
- Incorporate more modal information into the discrepancy function F (*e.g.*, mode shapes, mass participation) and consider regularization techniques (*e.g.*, *Lasso*, *Ridge*).
- Include uncertainties on the reference frequencies and mode shapes $(\{f_i\}, \{\phi_i\})$.
- Implement *Sequential Domain Reduction* [4] to dynamically reduce the search space.
- Leverage dimensionality reduction techniques or *SAASBO* [5] to allow for a larger number of tunable parameters $|\boldsymbol{\theta}|$ and make the procedure more scalable.
- Improve the initial sampling phase using *Latin Hypercube Sampling*, *Importance Sampling*, etc.
- Expand this strategy to define the calibration workflow of other systems and engineering displicines covered by TSM.

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33rd SOFT, September 2024

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