Digital Design Network+
Case Study 1 Individual Report Template

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| **Institution** | University of York |
| **Team** | Team 3 |
| **Focus** | Better and Faster |
| **Design Process** | Uncertainty quantification |
| **Tools Used** | Sensitivity toolbox TEDS and LLM |
| **Links** | TEDS: https://github.com/longitude-jyang/TEDS-ToolboxEngineeringDesignSensitivity/tree/master<br>Demo: https://github.com/longitude-jyang/D2N_DroneDesign/blob/main/My%20Movie2.mp4 |

## Executive Summary

The primary objective of this project was to bridge Large Language Models (LLMs) with physics-based computational models, to accelerate engineering design under uncertainty.

Traditionally, designing under uncertainty requires computationally expensive Monte Carlo simulations across highly dimensional parameter spaces. By integrating an LLM as an intelligent orchestrator, we created a system where the AI runs the analysis using the TEDS toolbox, and dynamically rewrites the physics models to focus only on the most critical parameters at each design step. This reduces computational overhead drastically while maintaining physics-based rigor.

## Problem

This new AI-guided design tool (combining with the TEDS framework) is designed to overcome several bottlenecks in traditional engineering design, specifically when dealing with complex physics and uncertainty:

- Curse of dimensionality in uncertainty quantification. For example, if a drone design has 20 uncertain parameters, running thousands of physics simulations across all 20 dimensions is often computationally prohibitive.
- The disconnect between AI and physics. For example, AI can provide suggestion to improve the drone design, but often lacks robustness as the solutions are not physical constrained.
- The manual human-in-the-loop bottleneck. Once a traditional sensitivity analysis (like TEDS) identifies the most critical parameters, a human engineer must manually interpret the results and update the simulation code. This is slow and error prone.

## Digital Design Solution

To overcome the bottlenecks of high dimensionality and the disconnect between AI and physics based models, the newly developed digital solution embeds an LLM within a physics based digital twin workflow. This allows the AI agent to autonomously guide the engineering design process from initial simulation to final decision making. See Figure 1 below for an overview.

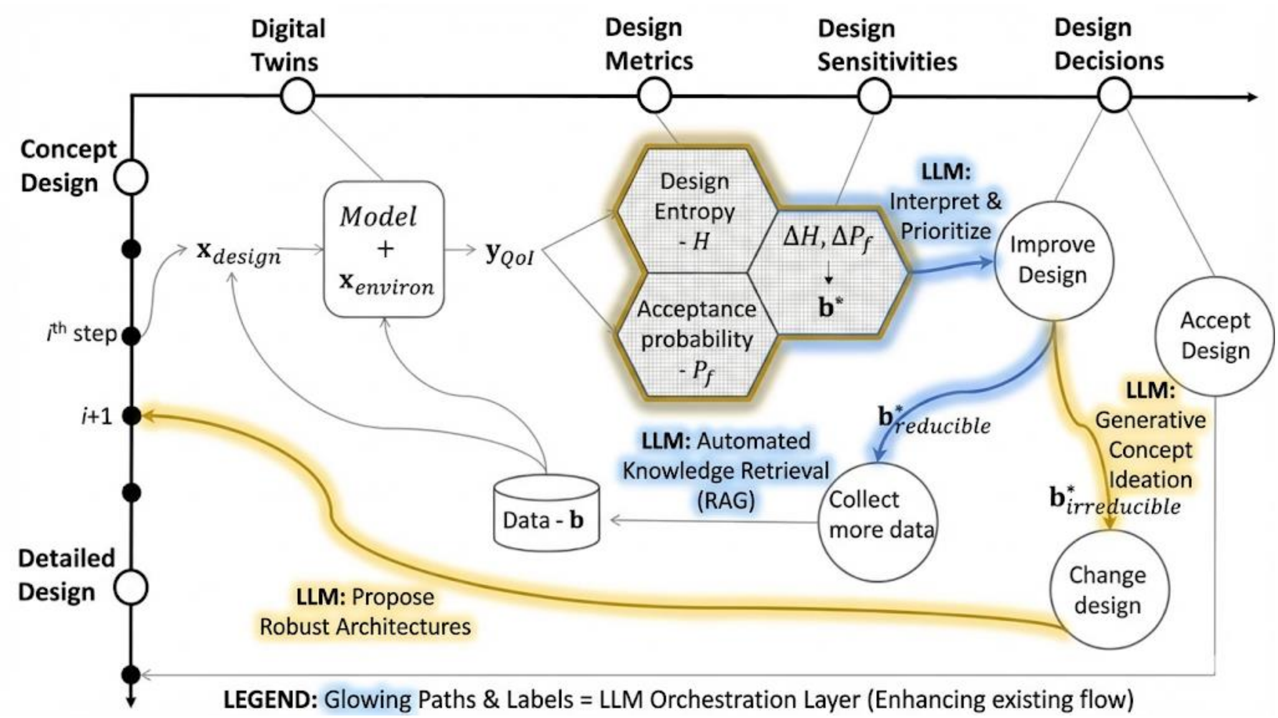



*Figure 1. Sensitivity guided design process under uncertainties with LLM acceleration. Adapted from TEDS-based design process*[1]

More specifically, the system evaluates the design quantifies of interest and identifies the most critical system parameters. The AI agent then uses LLM to interpret and prioritize the key drivers for design improvement, and intelligently routes the decision making process based on the nature of uncertainty. For reducible uncertainties, the agent employs Automated Knowledge Retrieval to gather more data, while for irreducible uncertainties, fundamentally new design is generated by the AI agent. Overall, the AI agent proposes robust architectures that feed directly into the next design iteration, fully automating the transition from conceptual to detailed design while ensuring all decision are grounded in underlying physics.

The integrated design process has been implemented in a chat interface, as shown in Figure 2 below. The AILab dashboard is a modern, split-screen interface that seamlessly blends visual workflow management with AI-driven engineering. The left side features an interactive, node-based canvas where users can drag, drop, and visually connect files to map out complex simulation pipelines. The right side houses a dynamic AI command centre equipped with four distinct operating modes, allowing users to directly execute, intelligently rewrite, or mathematically analyze the currently selected script node.

[1] *Yang, J., Langley, R. S., & Andrade, L. (2022). Digital twins for design in the presence of uncertainties. Mechanical Systems and Signal Processing, 179, 109338.*

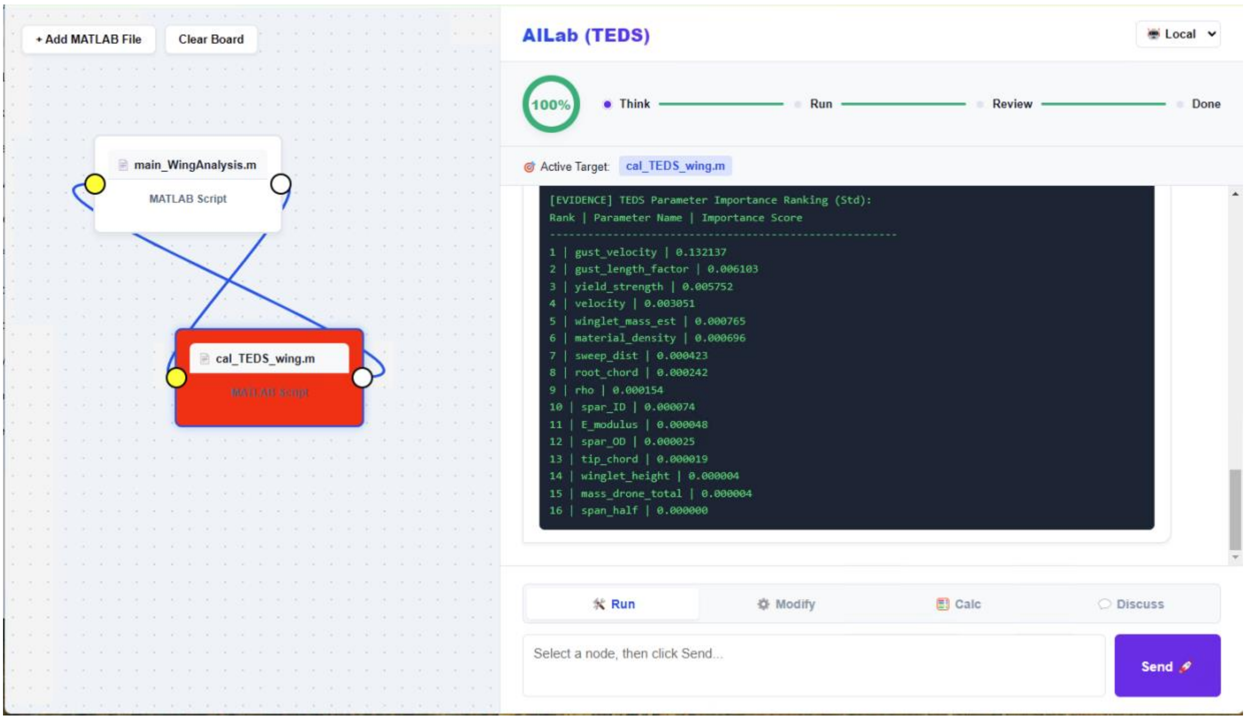



*Figure 2 AI lab dashboard.*

## How it makes Digital Design Better, Faster and/or With Less

**Faster**: it reduces the computational time by reducing the dimensionality of the parameter space. For example, for a design with only 6 uncertain parameters, 1 million simulation is required if the design test 10 variations per parameter. This reduces to only 100 runs, once the AI agent identifies the top 2 dominant parameters. In addition, with LLM, the AI agent autonomously updates the scripts and these further speeds up the iteration.

**Better**: it improves the robustness of the decision making by enforcing physics in the workflow. Different from many black-box approaches, the AI agent only updates parameters that possess high mathematical influence on the design, therefore reducing the most uncertainties with reduced resources.

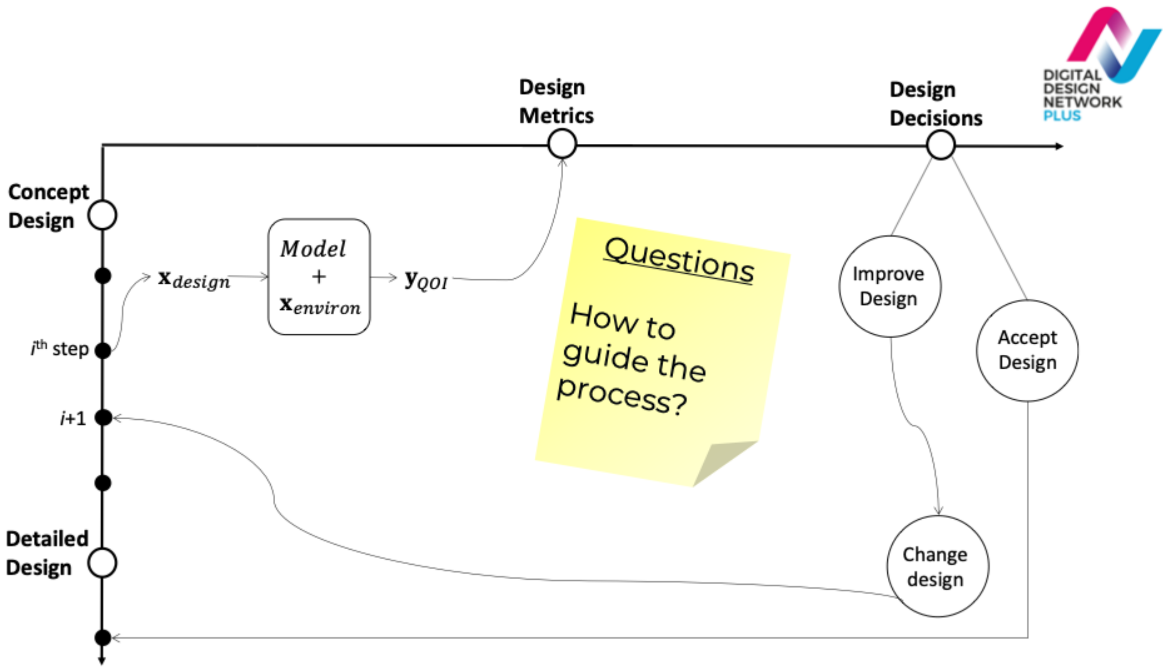
## Reflections

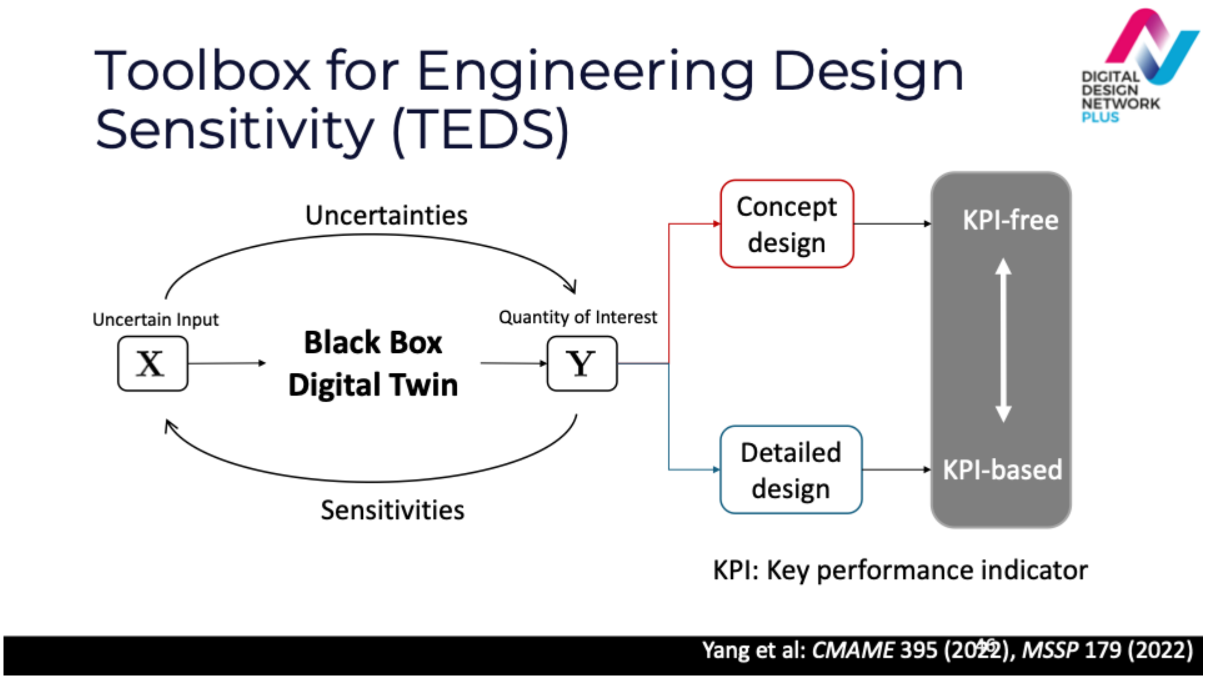
- Tool development: the role of LLM and physics engines should be separated, to ensure a robust autonomous framework
- Challenges: A lean approach is adopted in this work, where I learn with the team by doing together. The probabilistic AI agent must be further validated by physics-based evidence.

## Appendix

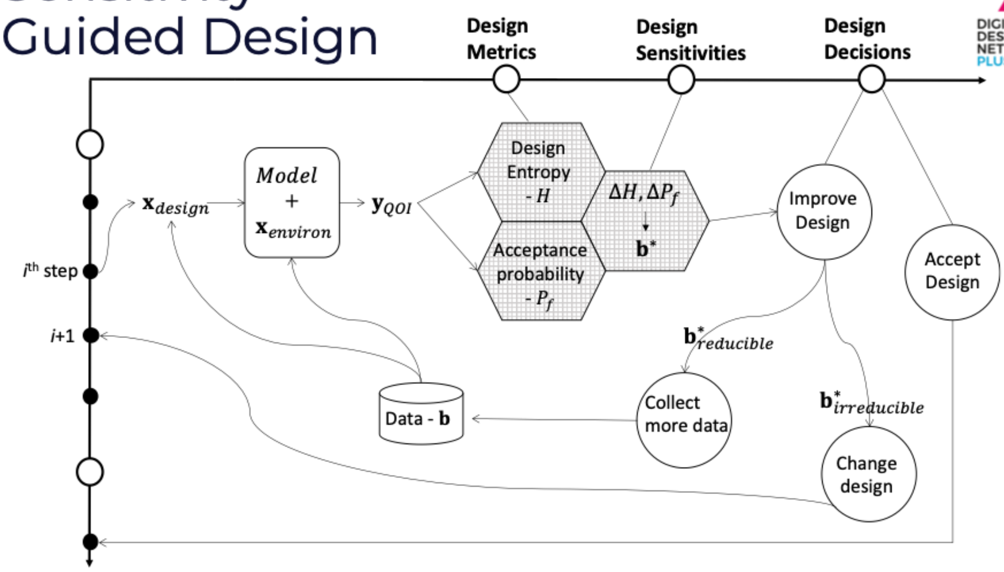
Before integrating with LLM, we have conduced validation of the sensitivity guided design process (TEDS-based sensitivity method). The validation was conducted via a digital twinning process of a floating column, which represents an offshore floating platform. The physical system would subject wave excitations and there is nonlinearity in the fluid-structure interaction. Different from many conventional sensitivity methods, TEDS is design-tailored and well suited to the iterative nature of a typical engineering design process.

Below we briefly explain the validation results, where the digital representation has been efficiently updated with sensitivity guided design. More importantly, this process is much more robust. This enables the AI agent to be integrated with confidence for a much broader application. More details of this validation process can be found in this paper: [Use of truncated Fisher sensitivity analysis for design verification of mechanical systems under uncertainty]

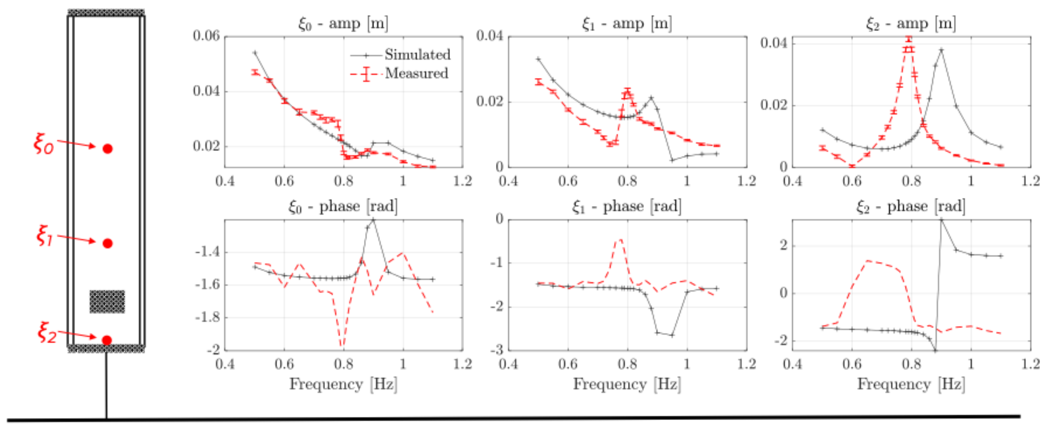


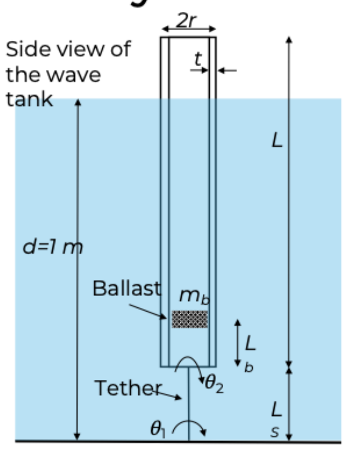
# Sensitivity Guided Design

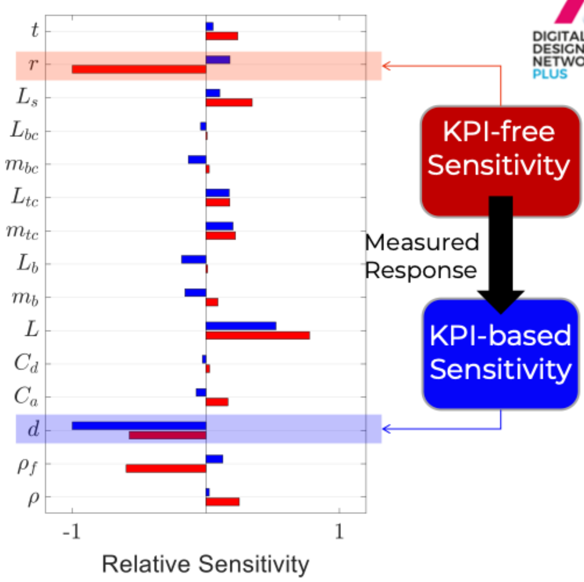



# Experimental Verification

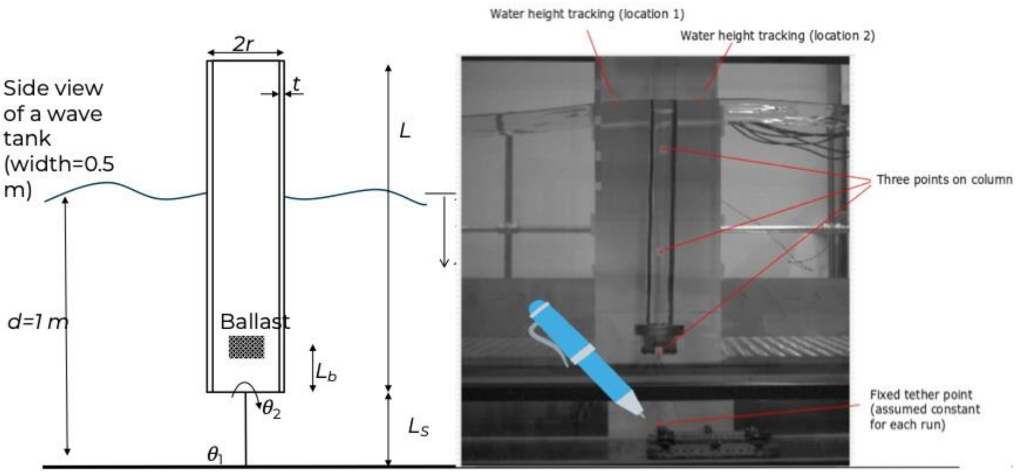



# Sensitivity Analysis

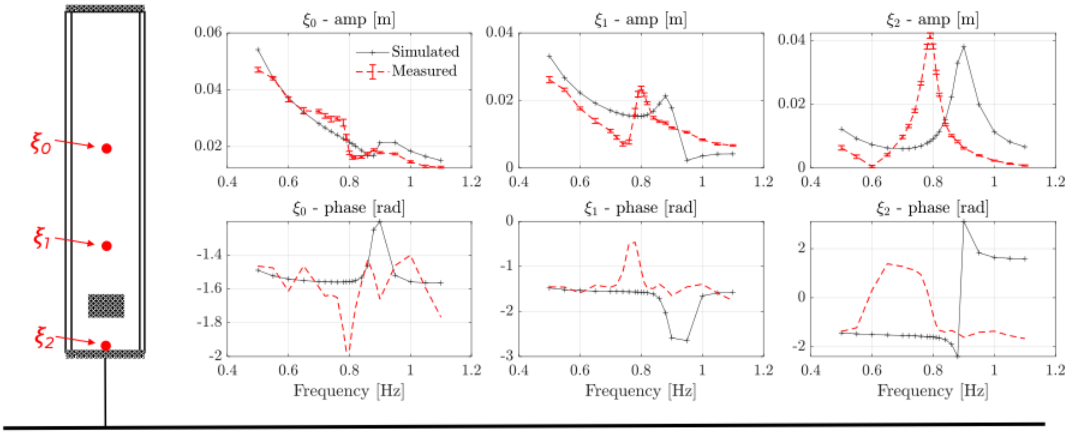


# Tether offset – 60 mm




## Before update ...




## Updated with sensitivity analysis ...