Advancing Engineering Design: From Robust Multidisciplinary Design Optimization to AI-Driven Collaboration

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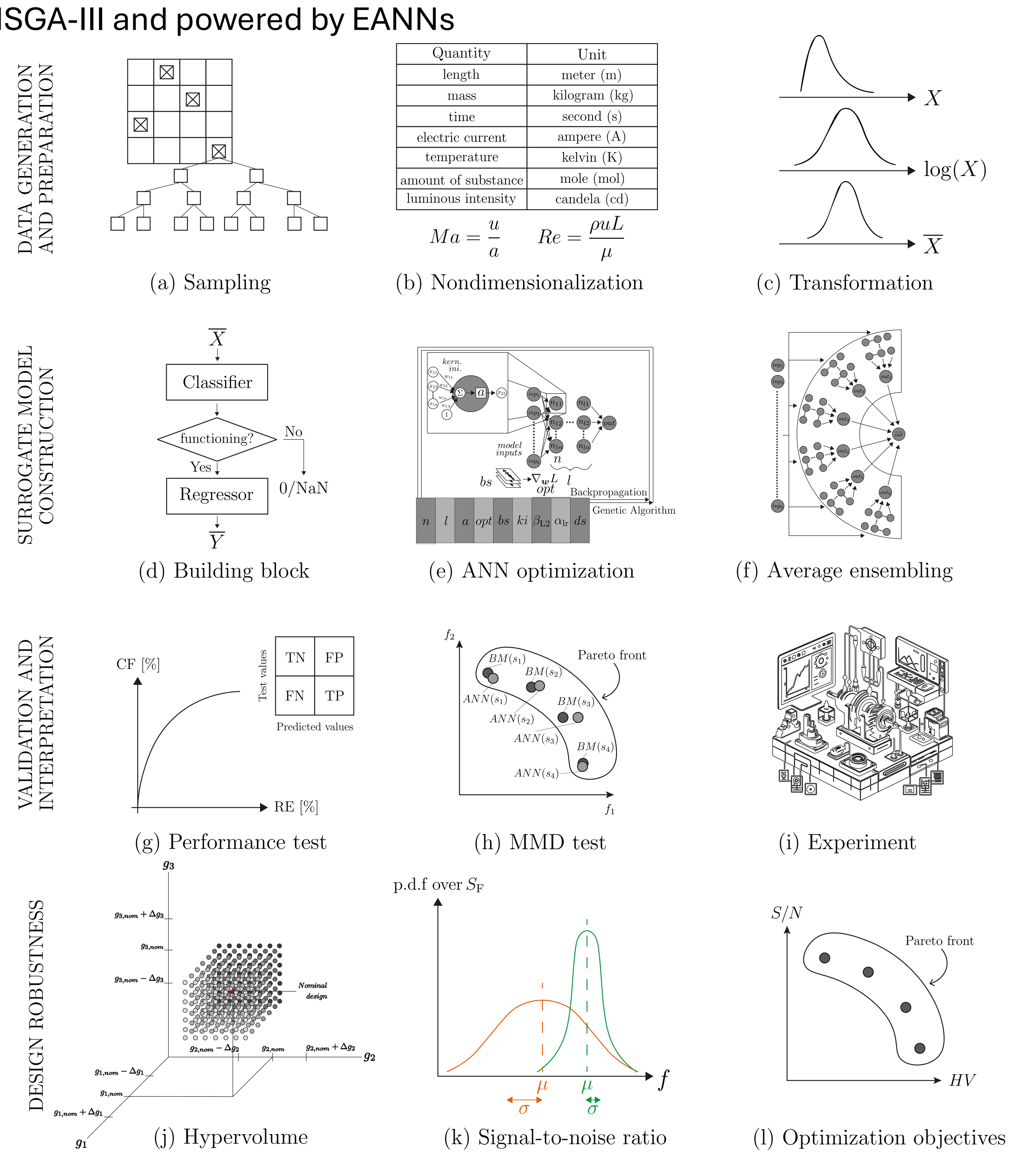
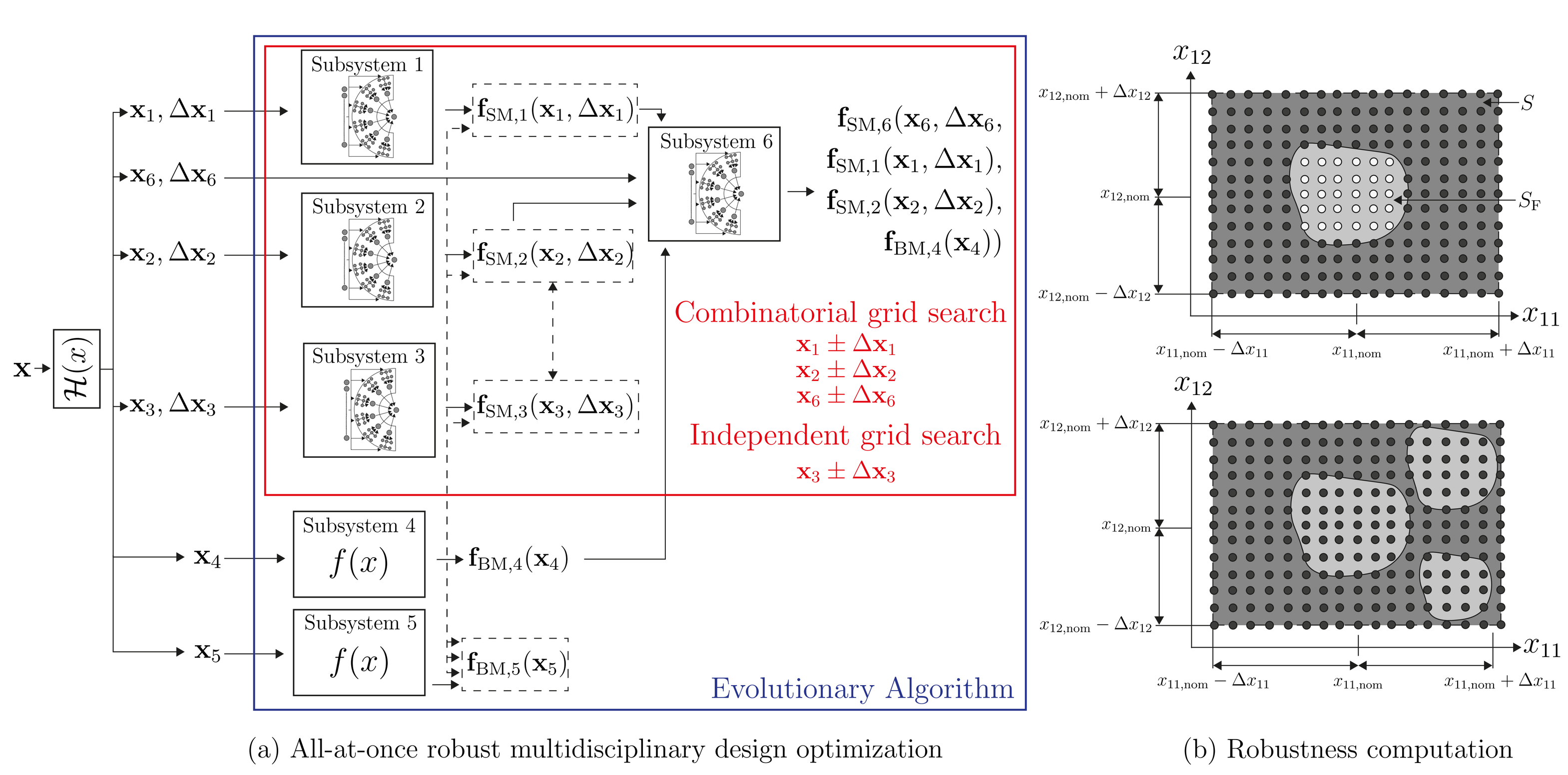
Introduction

- **Engineering Design Optimization**: Plays a critical role in sectors like aerospace, automotive, electronics, and energy
- **Traditional Focus**: Historically, centered on cost and efficiency, now also demands robustness against manufacturing deviations and operating conditions
- **Challenges with Traditional Methods**: Traditional designs optimize for nominal conditions, often neglecting real-world variabilities and subsystem interactions, leading to inefficiencies
- **Multidisciplinary Design Optimization (MDO)**: Emerged as a strategy to optimize complex systems holistically by considering the interdependencies between subsystems
- **Increased Complexity**: As systems grow more complex, traditional methods struggle with scaling efficiently, leading to longer development cycles and higher costs
- **Surrogate Models**: While useful in approximating performance, many suffer from limitations in accuracy and representation of the design space
- **CAD Challenges**: Translating optimization outputs into manufacturable CAD models remains costly and time-consuming, especially for complex geometries

Methods

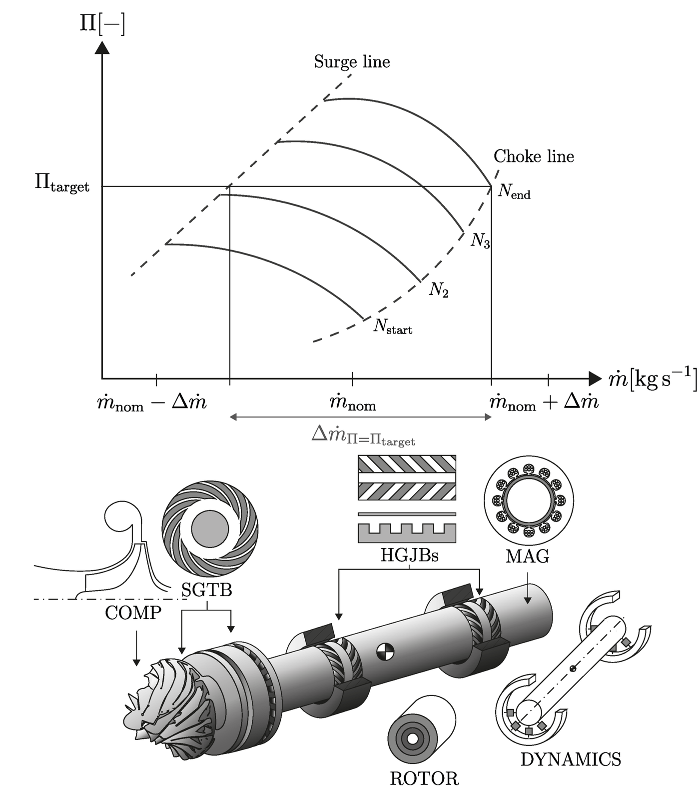
- Training of global surrogate models using ensemble artificial neural networks (EANNs) with dimensionless groups and supervised learning
- Robust metrics of hypervolume *HV* and signal-to-noise ratio *S/N* used as optimization objectives and constraints
- All-at-once robust multidisciplinary design optimization (AAO-RMDO) driven by NSGA-III and powered by EANNs



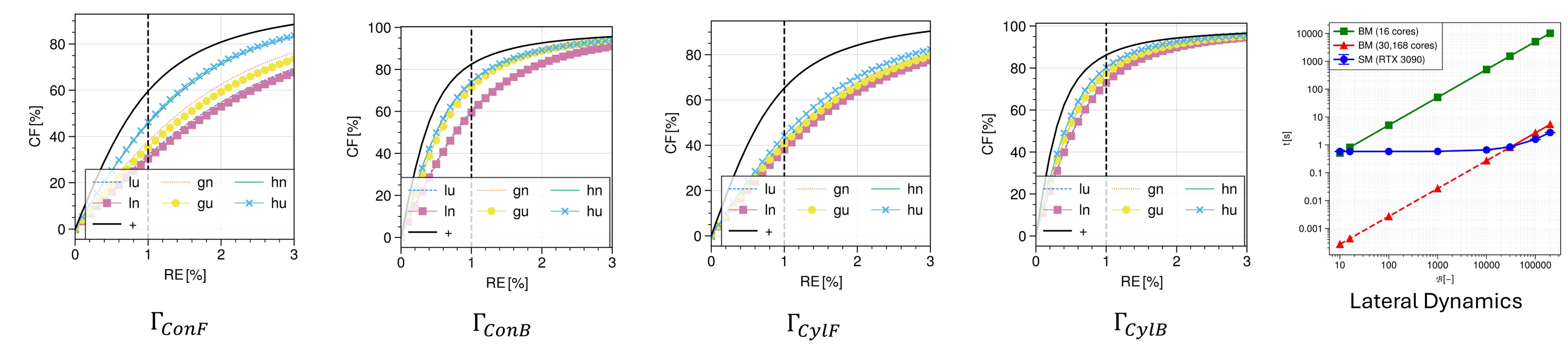


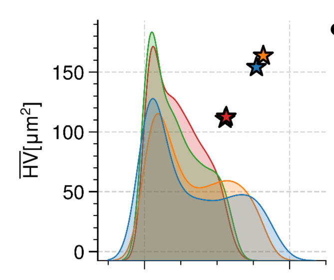
Case Study: Gas-Bearing Supported Turbocompressor

- Aerodynamic Model (COMP): Predicts compressor performance (pressure ratio, efficiency) based on geometry and operating conditions
- Rotor Model (ROTOR): Uses Timoshenko beam elements to predict lateral bending frequencies, mass, moments of inertia, and center of gravity
- Bearing Models (HGJBs, SGTB): Solve lubrication equations to provide stiffness and damping matrices
- Dynamic Analysis (DYNAMICS): Uses bearing stiffness, mass, and inertia to predict rotor's natural frequencies and stability
- Magnet Model (MAG): Sized to deliver mechanical torque for driving the compressor using electromagnetic equation

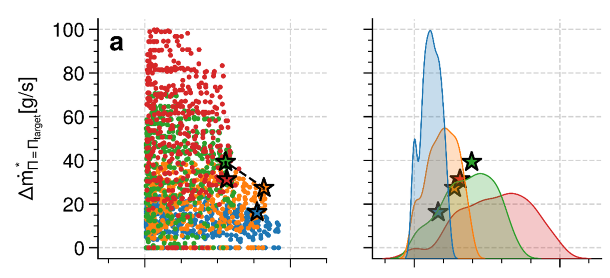


Results and Discussion

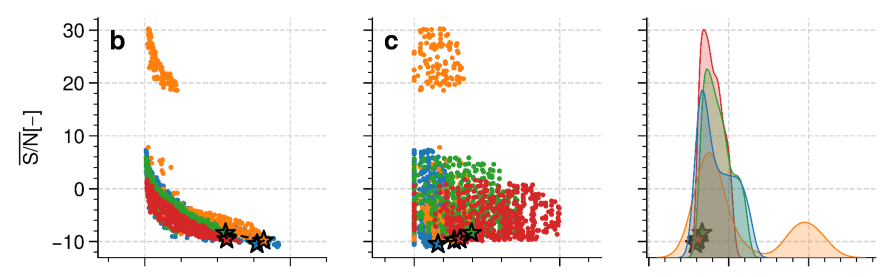




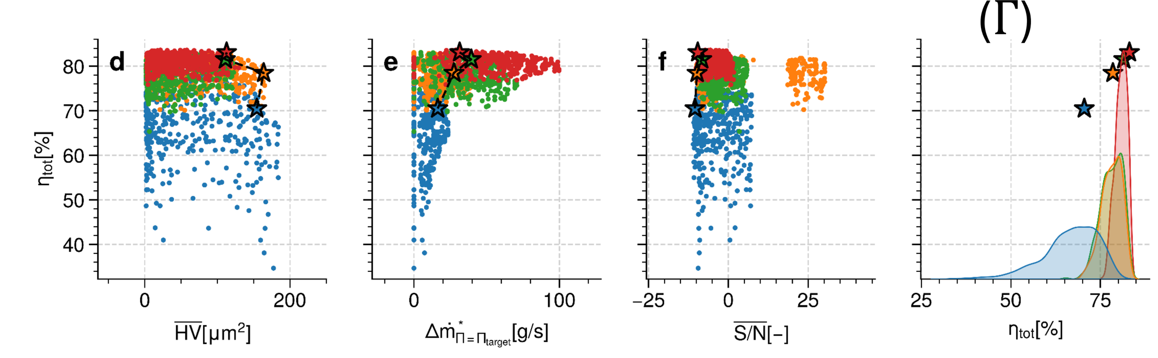
- **Speed**: Processed 1.5 billion samples in under two days using GPU hardware, optimizing speed and scalability. Surrogate models (SM) on GPU faster than baseline models (BM) on entire university cluster

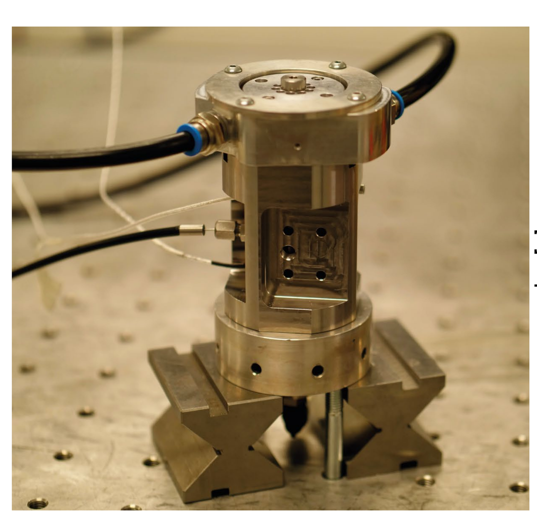


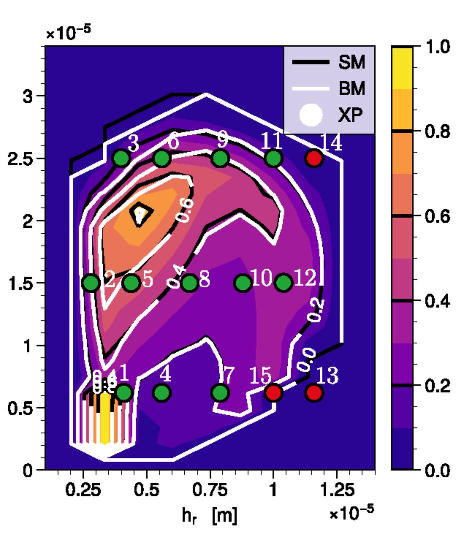
- **Scalability Challenge**: Robustness decreases with larger mass flows, highlighting scalability issues as compressor power increases



- **Validation**: Reliable predictions validated across 500,000+ test samples for compressor performance (η, Π) and dynamics (Γ)







- **Experimental Campaign**: Robustness strategy and surrogate models' accuracy validated experimentally with air-driven Pelton turbine rotors, up to 100 kRPM or until sub-synchronous instability

Future Work

- Can the engineering tasks of interpreting scope of specifications, mapping to a functional decomposition, selecting and modeling the systems, optimizing the complete system be taken over by artificial agents?
- Large language models (LLMs) may be of interest to power these agents. Yet, they remain probabilistic models to predict the next tokens given a certain context. Can they properly formulate a plan without a true understanding of the world, and to what complexity can they execute it?
- How can the intrinsic iterative nature of design, from its early stage to production, be addressed when LLMs have limited context length?

Acknowledgments

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