Knowledge Transfer Through Machine Learning in Aircraft Design

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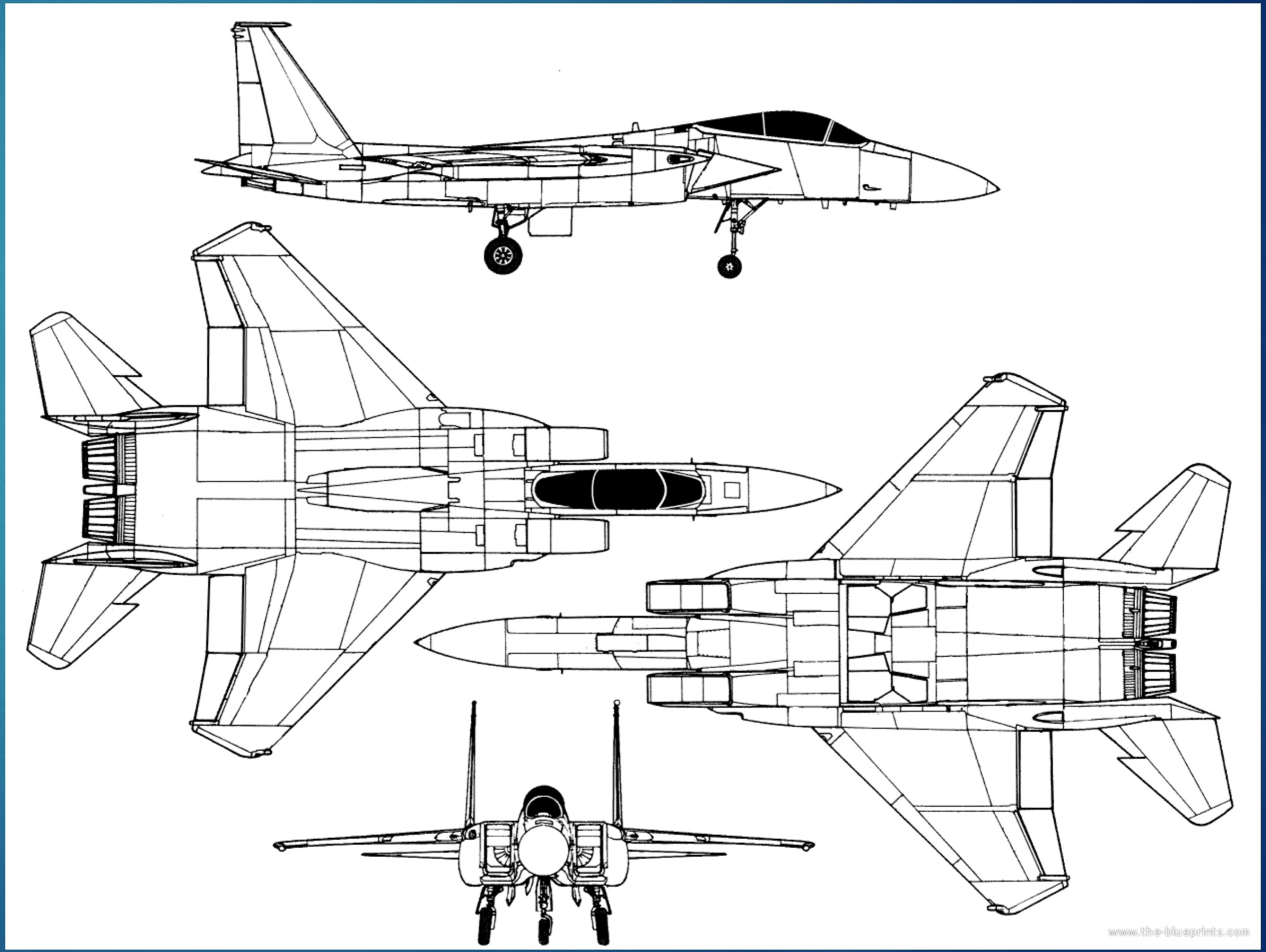
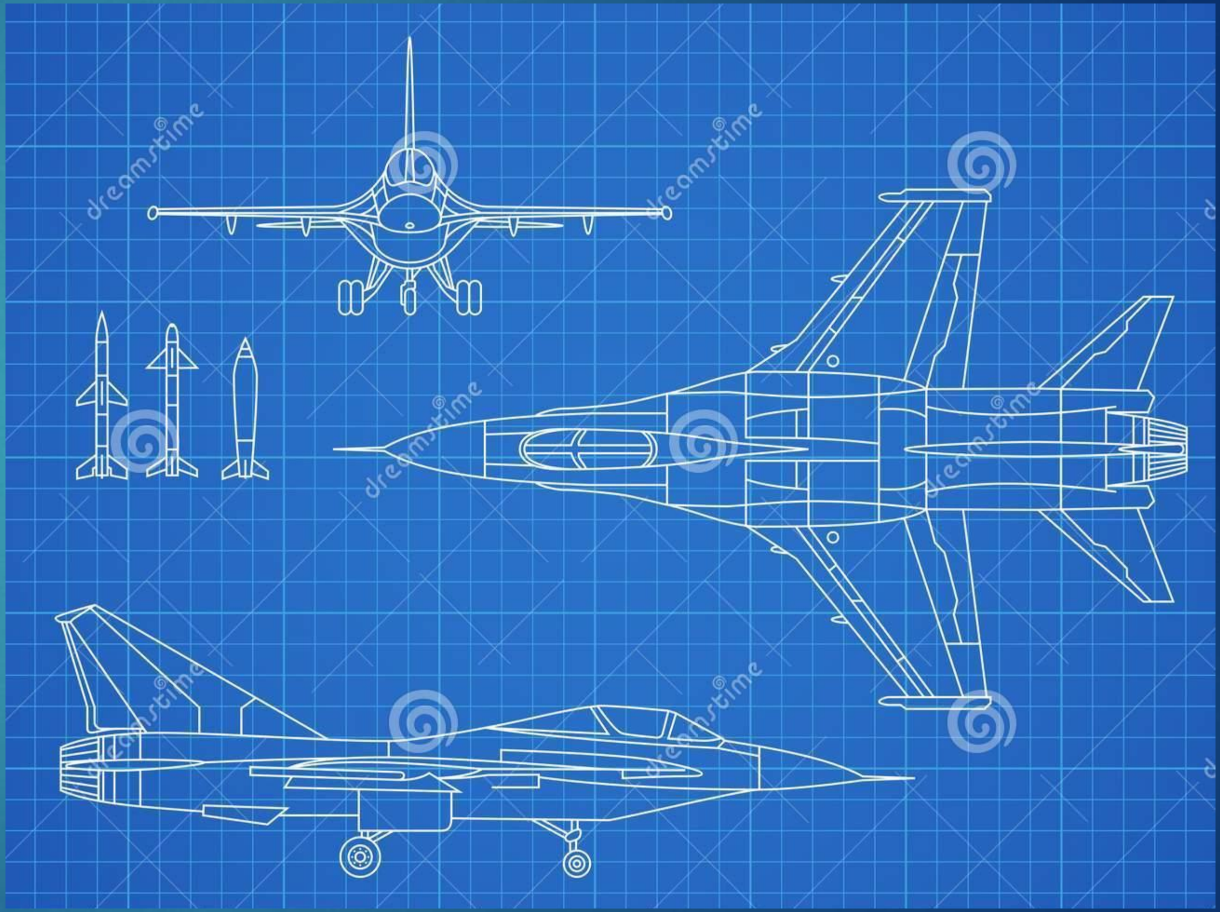


INTRODUCTION

- Purpose: Aviation industry generates **big data**, we want to transform this data into **knowledge**, thus improve the **safety**, **security**, and **efficiency** of aviation.
- The modern aircraft has evolved to become an important part of our society. Its design is **multidisciplinary** .... Machine learning has, historically, played a significant role in aircraft design, primarily by approximating expensive physics-based numerical simulations.
- …a major portion of the current efforts are generally built from **scratch** assuming **a zero prior knowledge state**, only relying on data from the ongoing target problem of interest.

FACTS

- Aircraft design is an extremely **complex** task that involves the interactions of a variety of **mutually interdependent systems.**
- Despite advancements, aircraft design remains extremely **laborious** and **time consuming**, taking as much as 6 years from the initial conception to the first product delivery

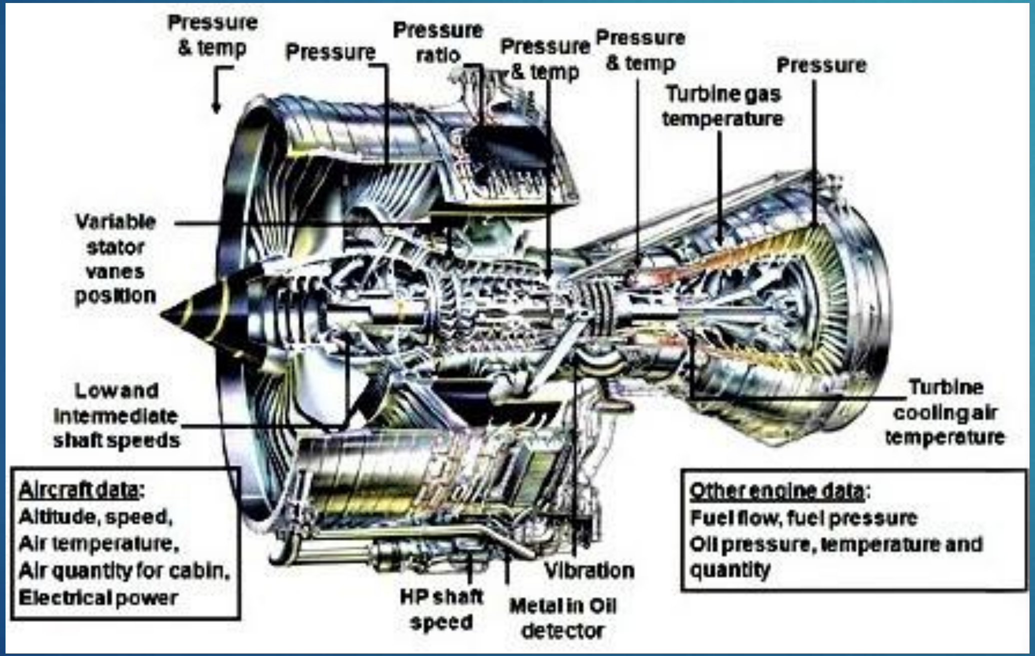


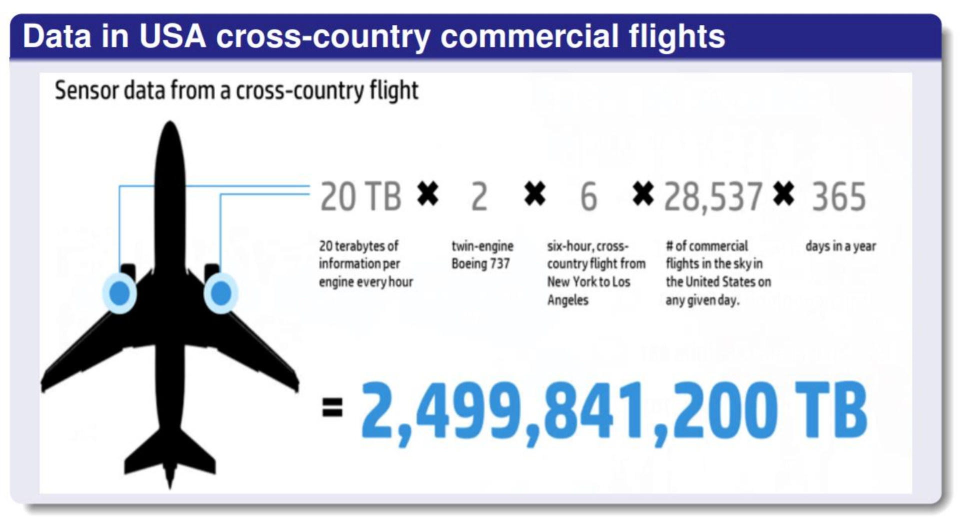
AI IN AIRCRAFT DESIGN

- Generally, aircraft design requires the involvement of groups of specialists and sound mathematical formulations (or architectures) to manage the disciplinary interdependencies.
- In all variants of multidisciplinary design optimization (MDO) architectures, a critical component is the engineering analyses. In the past, these tasks were performed manually using (often oversimplified) analytical theory and/or labor intensive physical experimentation
- With the advent of high-performance computing and the advancements of computational engineering methods, modern analyses heavily utilize physics-based numerical simulations, where mathematical models of physical systems are solved for a discretized domain. However, the significant improvements to accuracy, particularly for large-scale complex systems, come at a price. Computational fluid dynamics (CFD) simulations, for example, can take anywhere from several minutes to several weeks per simulation

MODELLING AND SIMULATION

- Pratt & Whitney's Geared Turbo Fan (GTF) engine comes with 5000 sensors that generate up to 10 GB of data per second





- In aircraft design, machine learning is predominantly used for approximating the expensive physics-based simulations using supervised regression models, or more commonly, surrogate models.

AIM

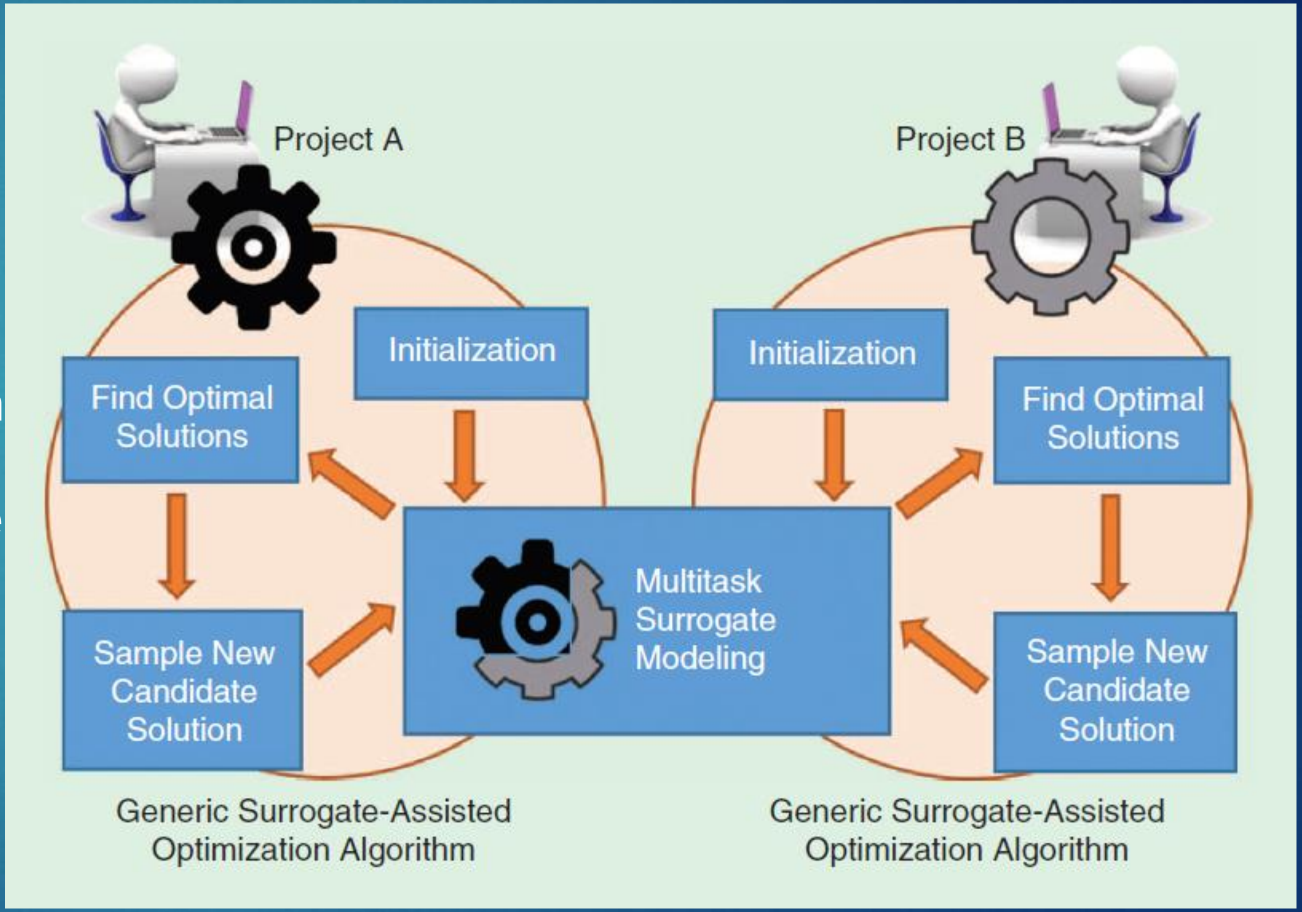
- Aim is to unveil metamachine learning as a promising approach to enhance the efficiency of aircraft design and facilitate the realization of a more *agile* design process
- Rapid adaptation to change, lower development costs, and shorter time-to-market.

AIRCRAFT DESIGN INSIGHTS

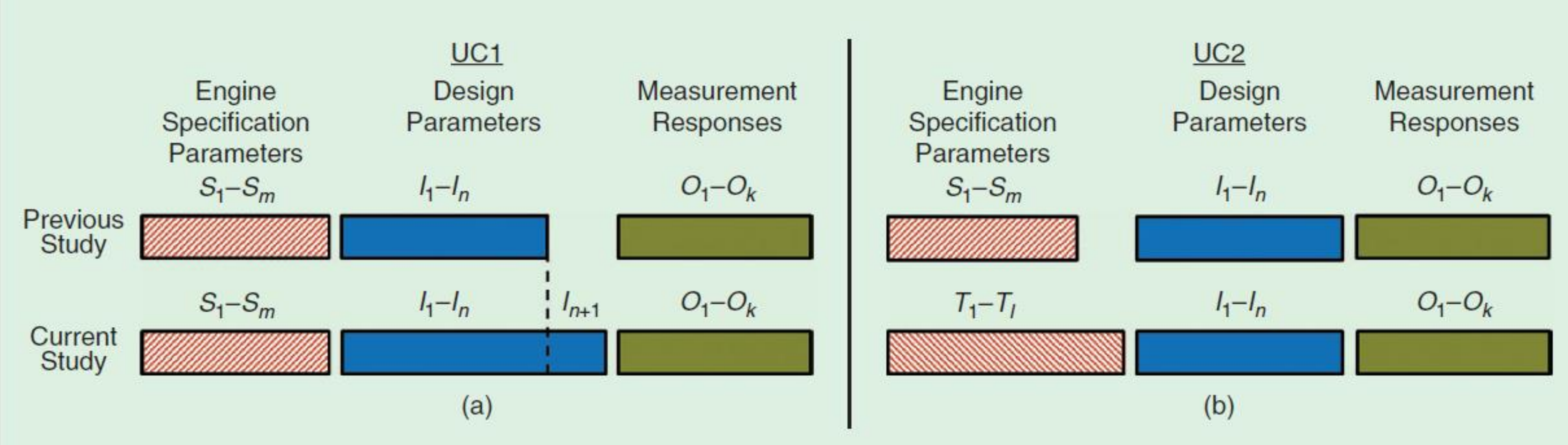
- Data-driven surrogate models of physical phenomena
- Machine-learning complemented physics simulations. Computational fluid dynamics(CFD)
- Regression Models used:
  - Polynomial regression (the 2^{nd} order variant in particular)
  - Neural networks
  - Gaussian process (or kriging)
  - Co-kriging ,
  - Support vector regression
  - Radial basis functions.

TRANSFER LEARNING

- The development of complex designs draws heavily from prior knowledge
- While prior knowledge incorporation can occur through appropriate problem formulations, the optimization algorithm itself is conducted from scratch i.e. without reusing knowledge (e.g. data or regression models) gathered from previous optimization efforts.



CASE STUDY



The previous study is carried out with 5 input parameters, while the current one has 6 parameters!

CASE STUDY

TABLE 1 List of the input and output parameters for the previous and current study datasets for UC1 and UC2. For similarly labeled parameters, the subsystem where it affects is indicated inside the parenthesis.

INPUT PARAMETERS			OUTPUT PARAMETERS
UC1 CURRENT STUDY	**UC1 PREVIOUS STUDY**	**UC2 PREVIOUS AND CURRENT STUDIES**	**UC1 & UC2 PREVIOUS AND CURRENT STUDIES**
ALTITUDE-FT	ALTITUDE-FT	ALTITUDE-FT	O1: NET THRUST
FAN BYPASS RATIO	FAN BYPASS RATIO	–	O2: FNET/W
PRESSURE RATIO (COMPRESSOR)	PRESSURE RATIO (COMPRESSOR)	PRESSURE RATIO (COMPRESSOR)	O3: FUEL FLOW
PRESSURE RATIO (BURNER)	PRESSURE RATIO (BURNER)	PRESSURE RATIO (BURNER)	O4: TSFC
EFFICIENCY (TURBINE)	EFFICIENCY (TURBINE)	EFFICIENCY (TURBINE)	O5: CORE AIRFLOW
A8/A2 (NOZZLE)	–	A8/A2 (NOZZLE)	O6: WEIGHT

The previous study is carried out with 5 input parameters, while the current one has 6 parameters!

CASE STUDY

- 300 engine configurations are simulated for the source (previous study) dataset, and 500 configurations are sampled for the target (current study of interest) dataset
- Gaussian process regression (GP)
- Naïve-Transfer Gaussian process regression (NT-GP)
- Each dataset is sampled using a latin hypercube design of experiment (DOE) procedure and rescaled to a mean of zero and a standard deviation of one.

CASE STUDY

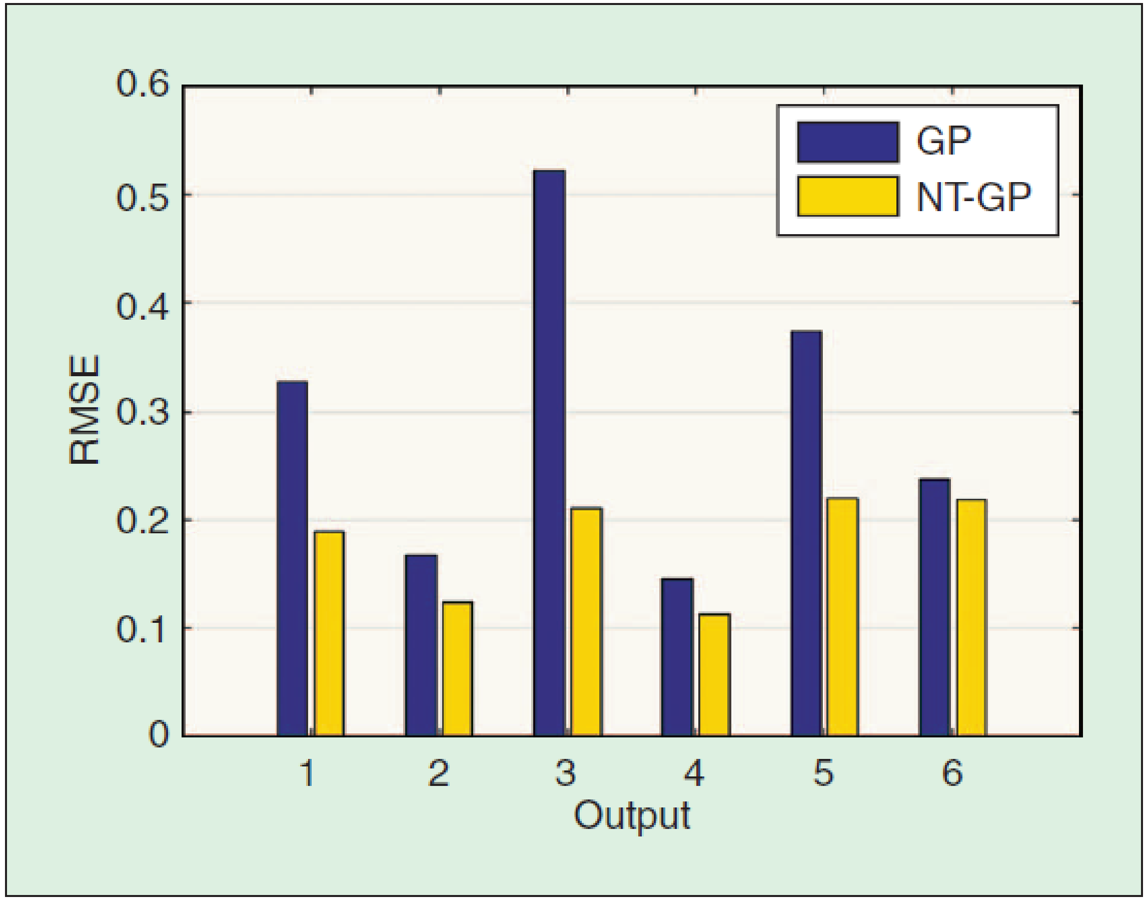


FIGURE 5 *RMSE* values of GP and NT-GP for each output on UC1.

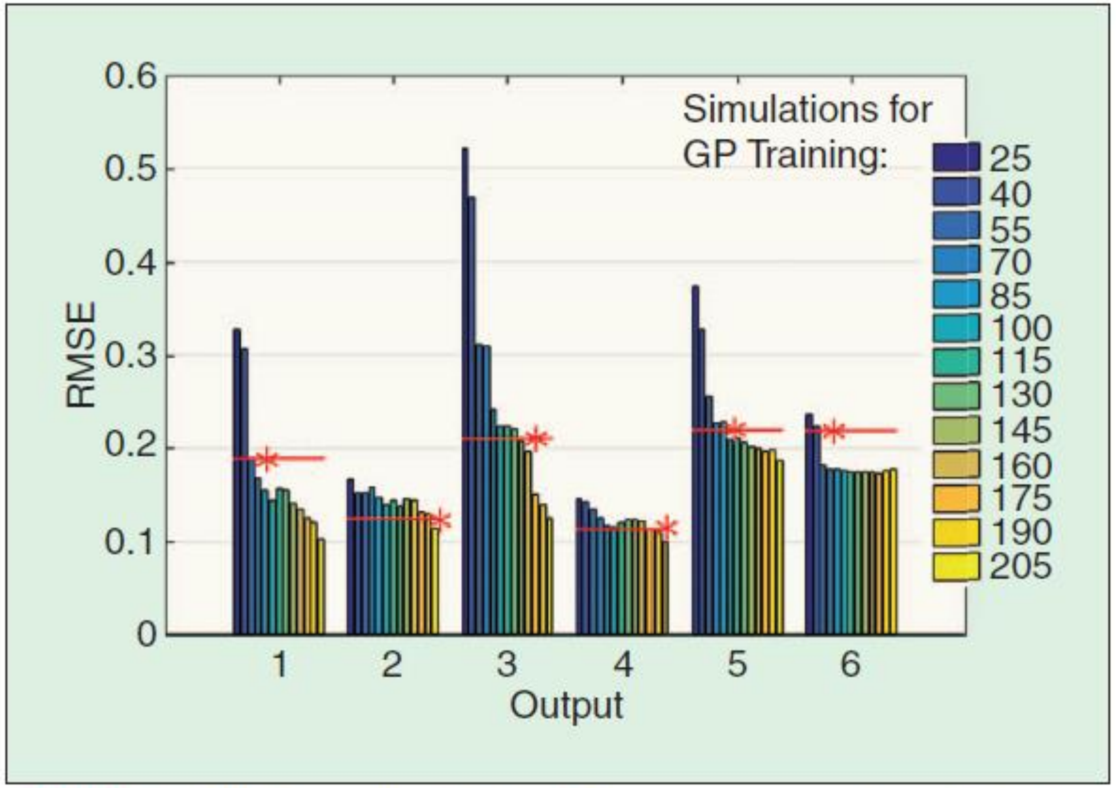


FIGURE 6 *RMSE* for each output with increasing number of simulations for training a GP model. The red segments show the *RMSE* of NT-GP trained with 20 (target) simulations, and the red stars highlight the points where GP starts outperforming NT-GP.

CASE STUDY-2

- Gaussian process regression (GP)
- Naïve-Transfer Gaussian process regression (NT-GP)
- Adaptive Transfer Gaussian Process (AT-GP)
- Metaheuristic-based Instance Selection for Transfer (MIST)
- *!!* **negative transfer** may occur if the naïve combination of those datasets results in adulterated samples from the source distribution that misleads the GP.

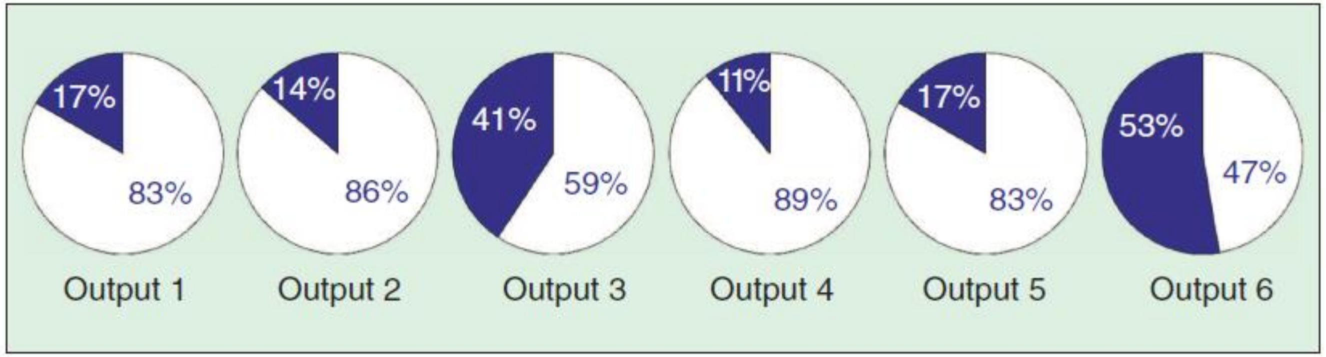


FIGURE 8 Percentage of source data employed (dark colored) for training an NT-GP model with MIST for each output in UC2.

CASE STUDY-2

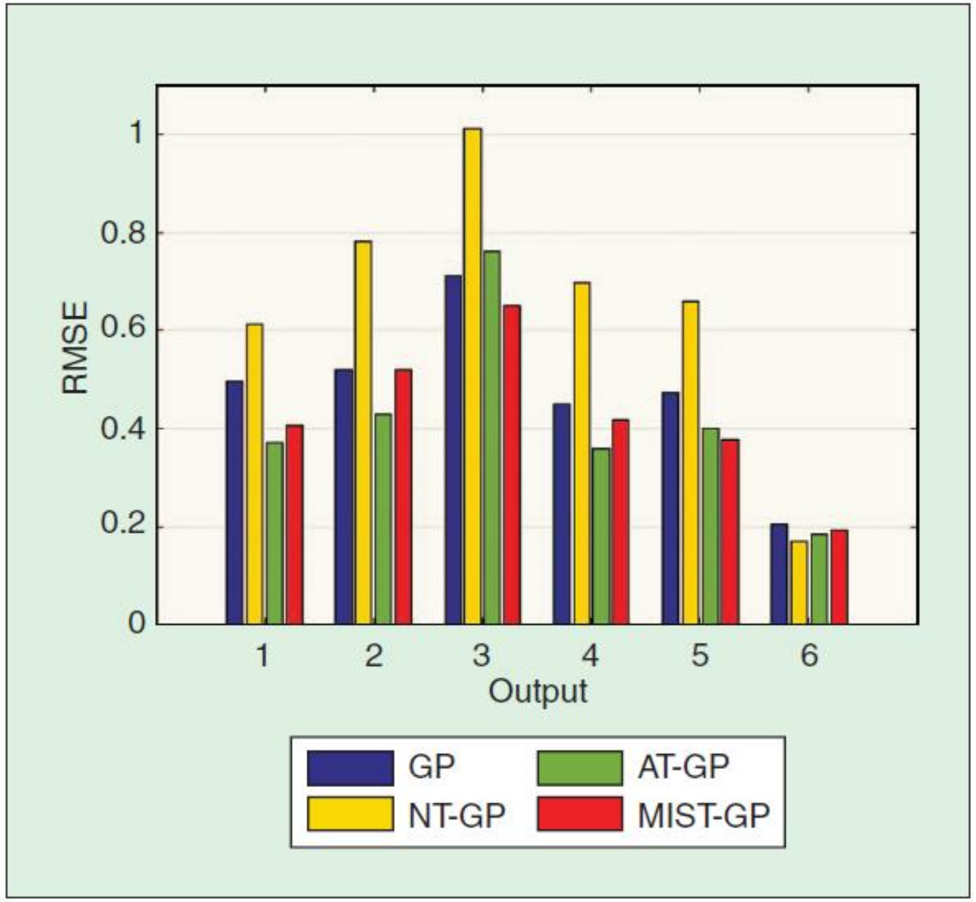


FIGURE 7 *RMSE* values of GP, NT-GP, AT-GP and MIST-GP, for each output on UC2.

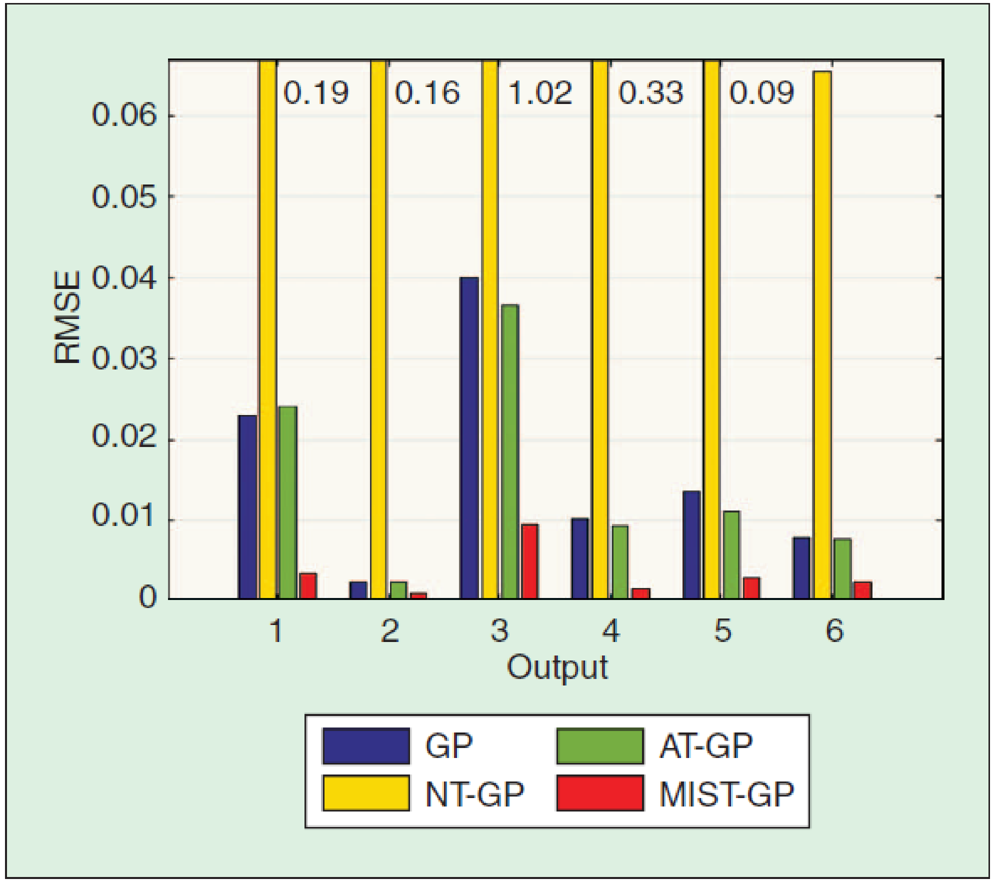


FIGURE 9 *RMSE* for GP, NT-GP, AT-GP, and MIST-GP for each output in UC2 of the real-world data. The numbers within the figure window represent the actual values of the yellow bars that extend outside the figure.

REFERENCES

- MACHINE LEARNING IN AVIATION, Computational Intelligence Group Artificial Intelligence Department Technical University of Madrid, Spain, 2013
- Knowledge Transfer Through Machine Learning in Aircraft Design, IEEE Computational intelligence magazine, 2017