FLANDERS MAKE

Multi-objective optimization of stochastic experiments
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Assembly System Design

Adaptive and Smart assembly system

VCCM

Goal
Efficiently find optimal solutions with a minimal set of computer/physical experiments, and considering
- Multiple objectives
- Uncertainty in outputs
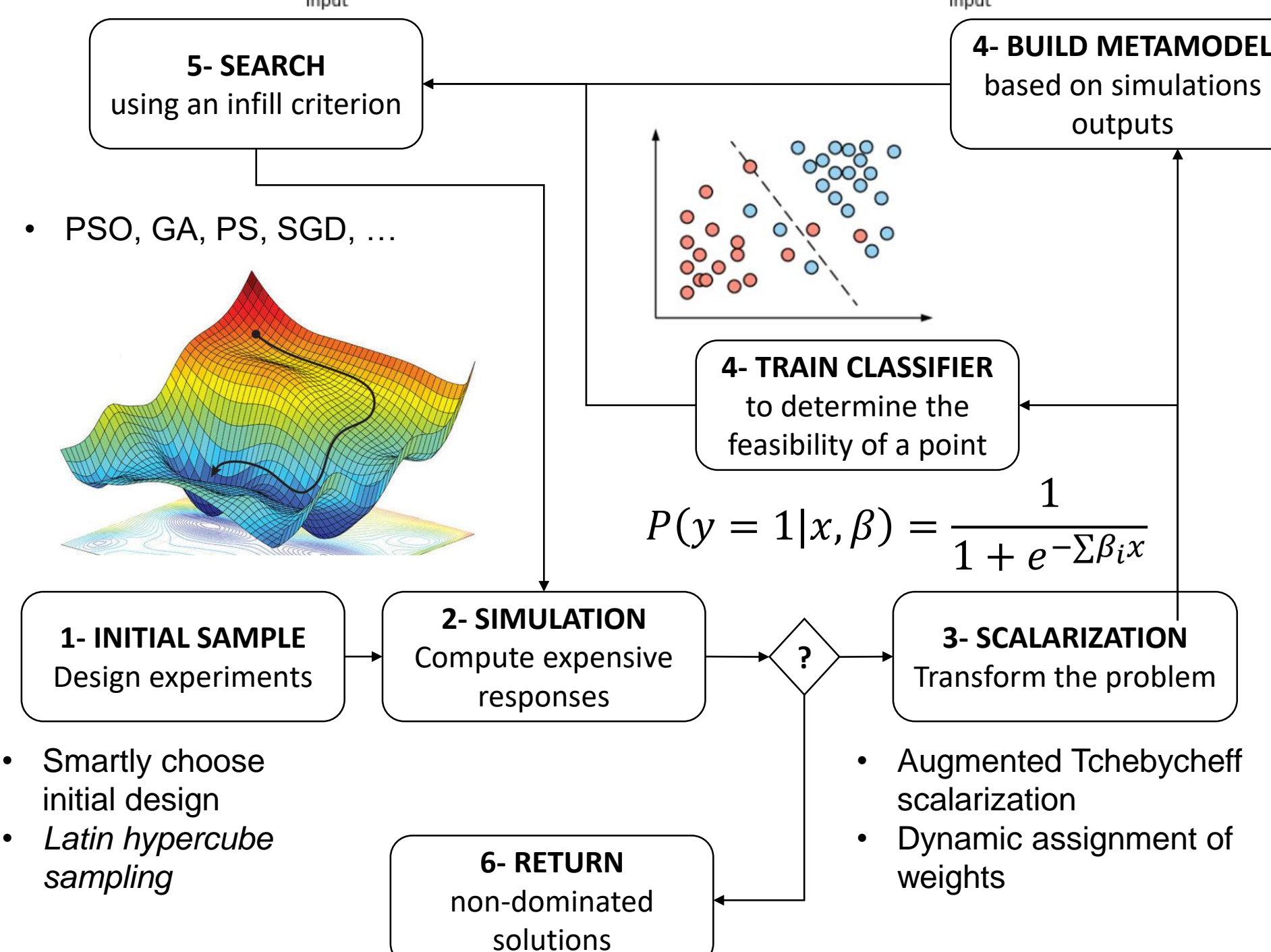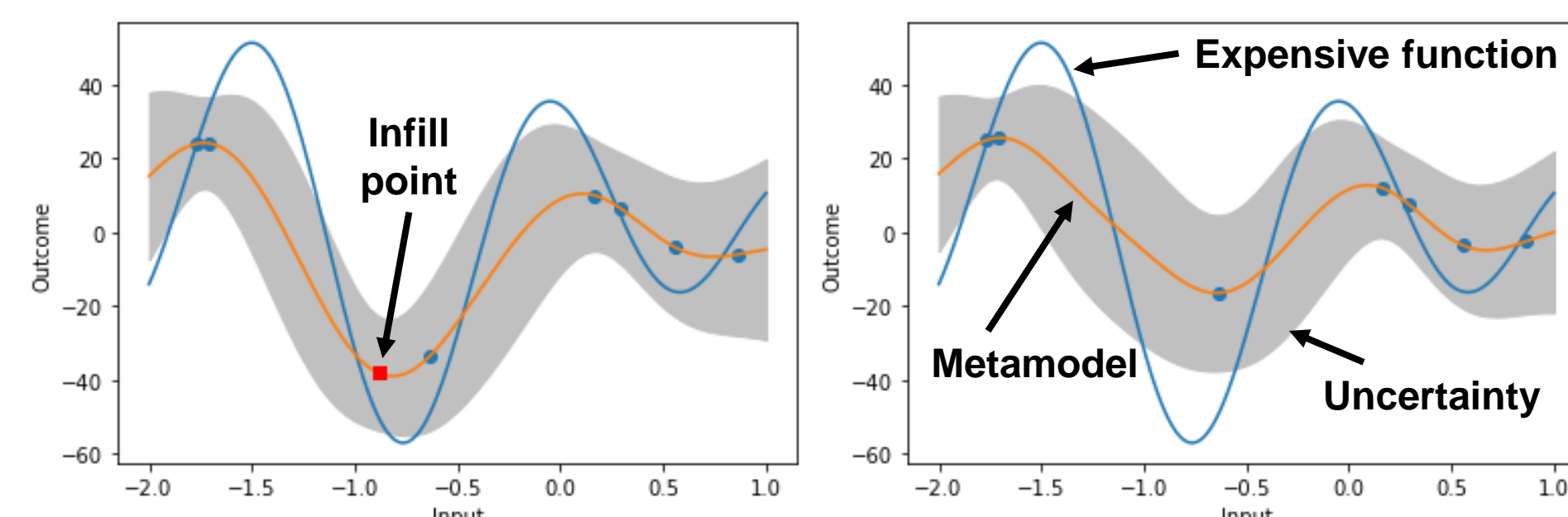- Potential feasibility constraints (on inputs/outputs)

Motivation
- In many real-life systems (engineering design, process design, supply chain design, etc.), the optimization problems studied are **multi-objective** (exhibiting *trade-offs* between individual objectives)**,** and outputs observations are **noisy** (repeated experiments of the same inputs may yield different output observations).

- The input/output relationships for objectives and constraints are often a **black box: experimentation** is required to evaluate them. These (physical or computer) experiments can be **expensive (in terms of cost, time, etc),** and the budget for experimentation is typically constrained.

- The goal then is to detect solutions with very high quality (optimal or near-optimal) **within as few experiments as possible**.

- Traditional optimization heuristics (genetic algorithms, evolutionary algorithms) **are ill-suited** to achieve this goal.

- **Machine learning (ML)** techniques (fit for use in settings with scarce data) combined with **optimization (OR)** insights and/or **statistical learning**, to achieve the goal.

Approach
- Model (expensive, black-box) continuous output functions f using **Gaussian Process Regression (GPR)** with heterogeneous noise (**stochastic kriging**) [1]. This allows us to obtain an estimation of the output value $(\hat{f})$ at unobserved locations, along with an estimator for the **uncertainty** on this value (s^2, also referred to as the MSE). This MSE captures both **metamodel uncertainty** and **stochastic uncertainty**.

- Use **infill criterion (acquisition function)** to select next input combination to sample (**Bayesian optimization**) .

Infill criterion [2]

$$CMEI = \left[(\hat{f}_{min} - \hat{f})\Phi\left(\frac{\hat{f}_{min} - \hat{f}}{s}\right) + s\phi\left(\frac{\hat{f}_{min} - \hat{f}}{s}\right) \right] * P(y = 1|x, \beta)$$

5- SEARCH using an infill criterion

4- BUILD METAMODEL based on simulations outputs

- PSO, GA, PS, SGD, …

4- TRAIN CLASSIFIER to determine the feasibility of a point

$$P(y = 1|x, \beta) = \frac{1}{1 + e^{-\Sigma\beta_i x}}$$

1- INITIAL SAMPLE Design experiments

2- SIMULATION Compute expensive responses

3- SCALARIZATION Transform the problem

6- RETURN non-dominated solutions

- Smartly choose initial design
- *Latin hypercube sampling*

- Augmented Tchebycheff scalarization
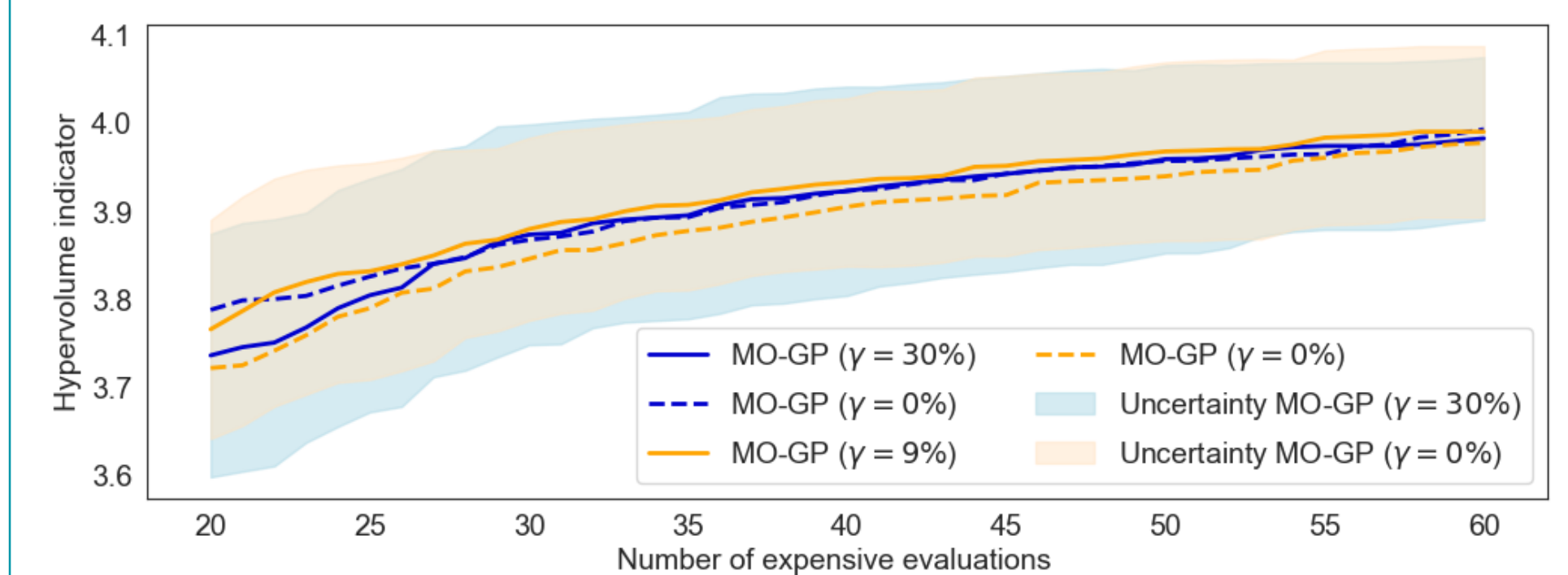- Dynamic assignment of weights

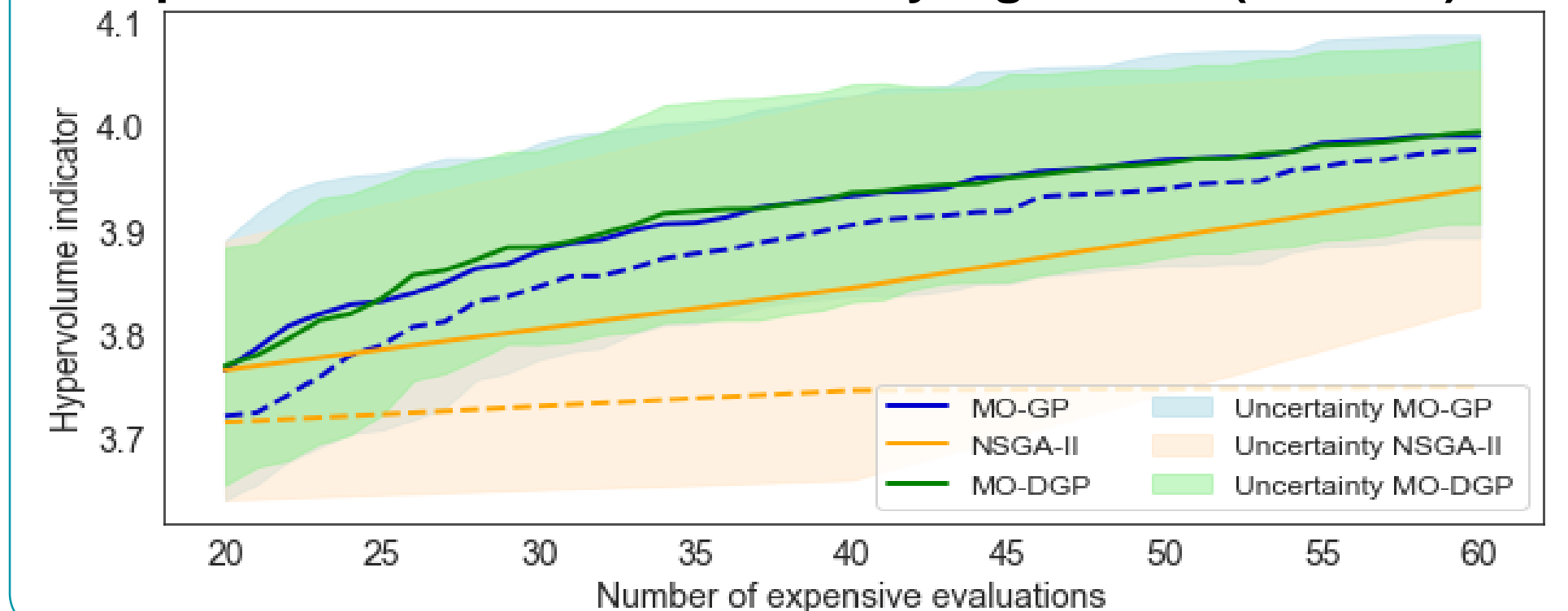*Algorithm based on the work presented in [3]*

Results
Parameter optimization for plasma process in adhesive bonding application (JMLab, Flanders Make)
- Maximize break strength and minimize production costs (bi-objective) by tuning 6 parameters
- Avoid configurations that lead to adhesive failure or visual damage of the sample

Results MO-GP for low and moderate noise levels (γ)

Outperforms common evolutionary algorithms (NSGA-II)

Key take-aways
- Efficient and effective search for solutions to expensive optimization problems with noise
- Proposed (Bayesian) approach is shown to be robust to the noise level and clearly outperforms the well-known NSGA-II

Further reading
[1] https://doi.org/10.1287/opre.1090.0754
[2] https://doi.org/10.1080/0740817X.2012.706377
[3] https://doi.org/10.1016/j.ejor.2019.12.014