Electrical Machine design via Bayesian optimization under uncertainties

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Planning

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- Context and Problematic
- Bayesian Optimization under uncertainty: EFISUR algorithm
- Modified EFISUR algorithm
- Electrical Machine Optimization case
- Conclusions and perspectives

Context and Problematic: Electric vehicles in the news

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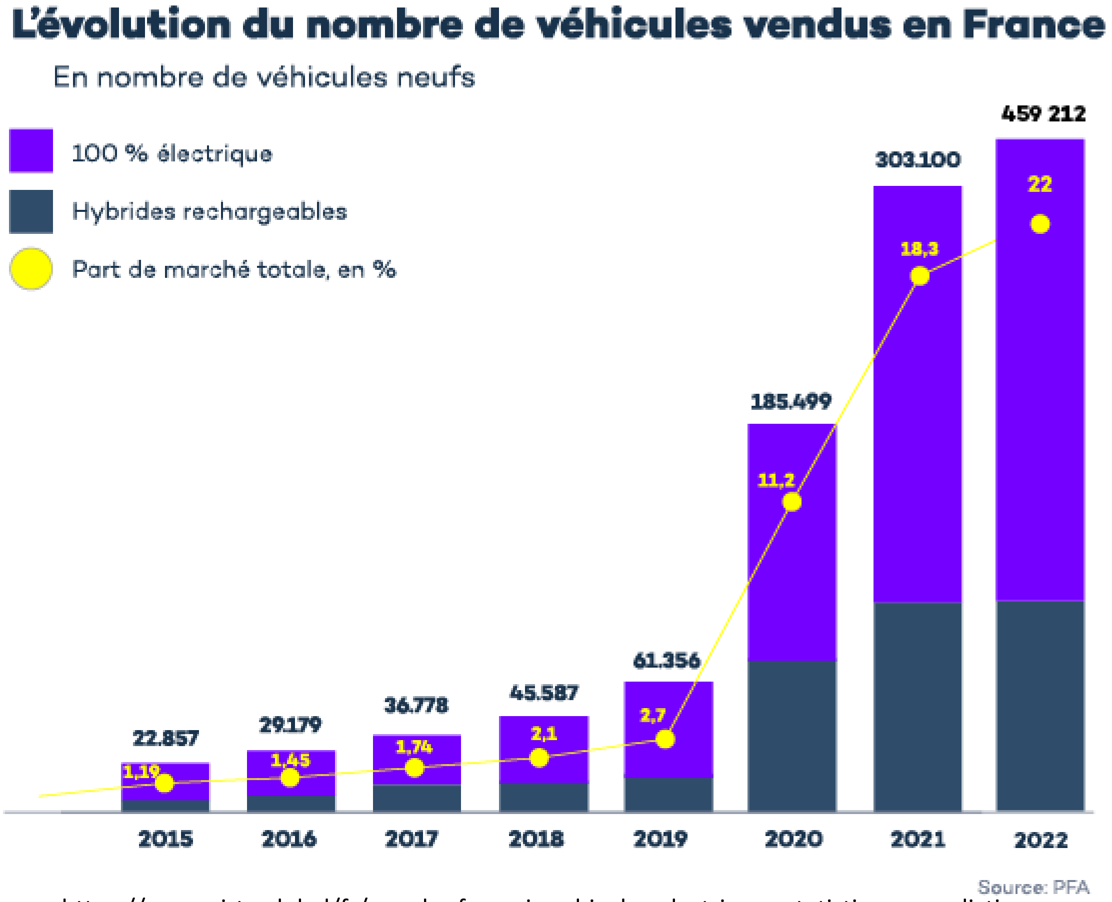
- Context

  - The number of electric and hybrid vehicles (EV, HEV) is growing.

  - Electric motor manufacturing requirements :
    - Minimizing cost
    - Maximizing efficiency
    - Ensure performances and specifications.

CONSTRAINED MULTI-OBJECTIVE optimization



https://www.virta.global/fr/marche-francais-vehicules-electriques-statistiques-predictions

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Context and Problematic: optimizing electrical machines

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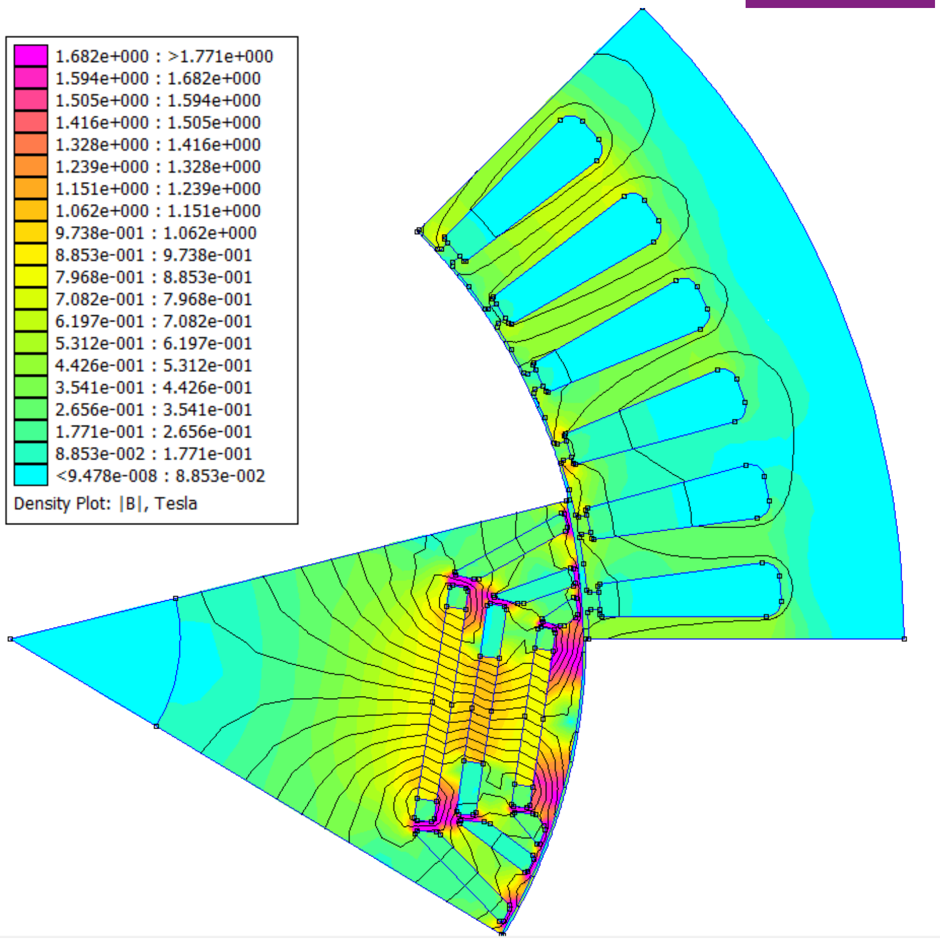
- Electrical machine optimization :

  - Non-linear, generic model -> Finite element simulations (Time consuming).

  - Complex multi-physical system: electromagnetic, mechanical, thermal.

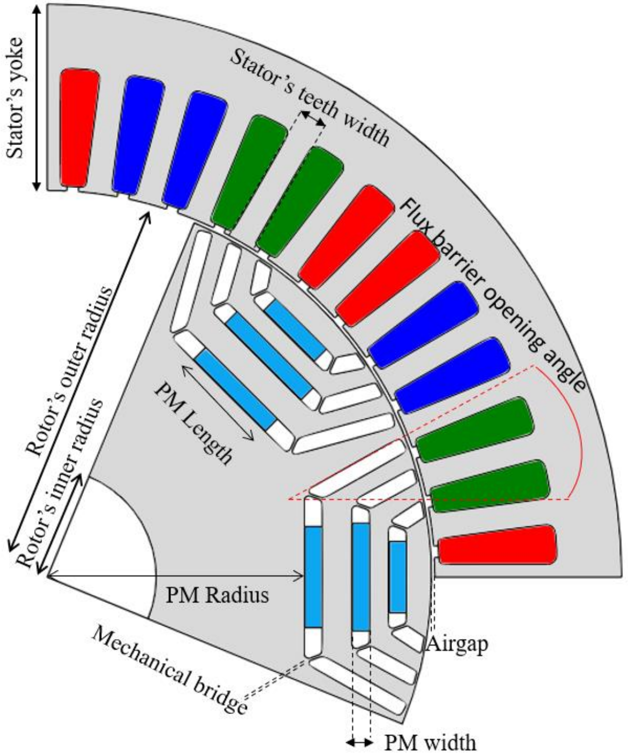


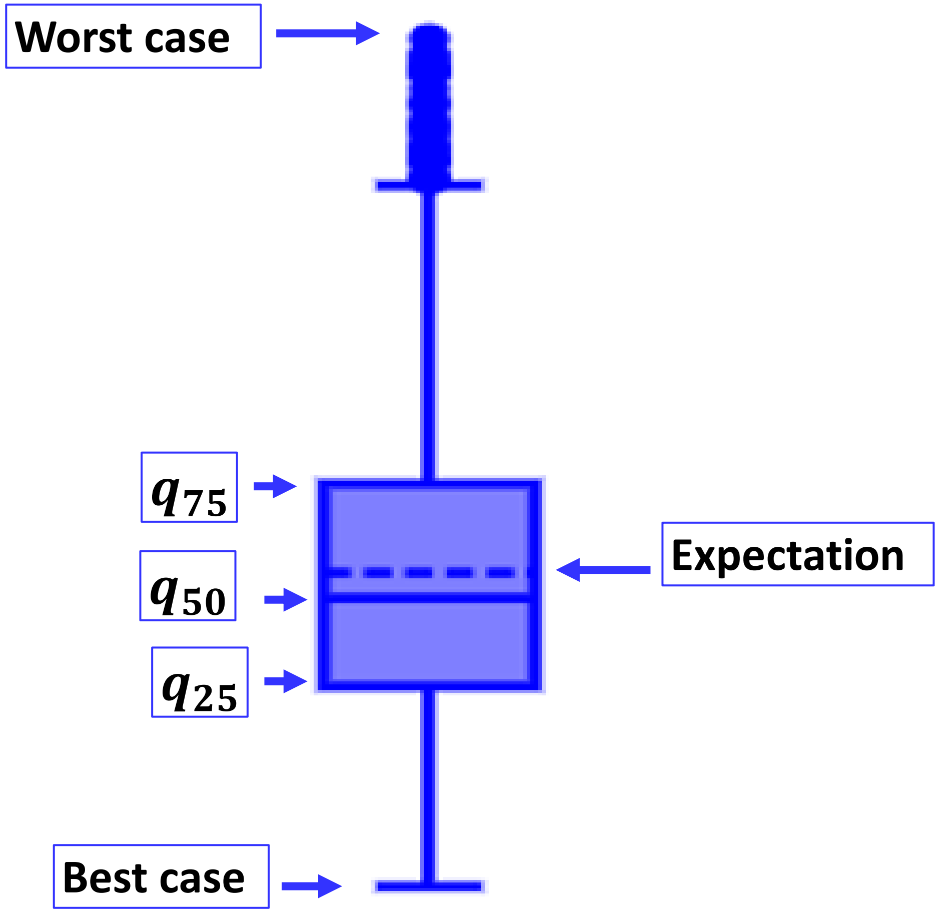
<u>**BLACK-BOX constrained multi-objective optimization**</u>

Context and Problematic: Uncertainties in an electrical machine and their impact on optimal values

Uncertainties:

- Magnetic properties of materials [1].
- Manufacturing tolerances on certain geometric parameters [2].
- Assembly tolerances on certain geometric parameters [3].





Black-box constrained multi-objective optimization UNDER UNCERTAINTY

Context and Problematic: Problem characteristics

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- Complex problem: Black-box, multiple objectives, constraints, input uncertainties
- Parallel computing facilities: several machines can be simulated at once
- Several uncertainties U can be defined as dispersion around controllable variables x.
  - For example, we might optimize permanent magnet dimensions, but there exists uncertainties around its desired dimensions.
- Limited budget of simulations.
- Bayesian Optimization has been successfully employed in a previous study of electrical machine optimization without input uncertainties [4].

Bayesian optimization under uncertainty: EFISUR algorithm (Expected Feasible Improvement with Stepwise Uncertainty Reduction sampling)

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Problem Definition :

$$\min_{\mathbf{x}\in D_x} \mathbb{E}_{\mathbf{U}}[f(\mathbf{x},\mathbf{U})] \text{ s.t. } \mathbb{P}_{\mathbf{U}}\left(g_i(\mathbf{x},\mathbf{U}),\ \ i=1,\dots,l) \le 0\right) \ge 1-\alpha$$

Assumption: objective functions f and g as realizations of Gaussian processes :

$$F(\mathrm{x},\mathbf{u}) \sim \mathcal{GP}\left(m_F(\mathbf{x},\mathbf{u}), k_F\left(\mathbf{x},\mathbf{u},\mathbf{x}',\mathbf{u}'\right)\right)$$
$$\forall i=\{1,\dots,l\}, G_i(\mathrm{x},\mathbf{u}) \sim \mathcal{GP}\left(m_{G_i}(\mathrm{x},\mathbf{u}), k_{G_i}\left(\mathbf{x},\mathbf{u},\mathbf{x}',\mathbf{u}'\right)\right)$$

For the objective, the expectation of a Gaussian process (conditioned at any time t) is still a Gaussian process :

$$Z^{(t)}(\mathbf{x}) = \mathbb{E}_{\mathbf{U}}\left[F^{(t)}(\mathbf{x},\mathbf{U})\right]$$

For constraints, the probability of a Gaussian process is not a Gaussian process, but we can always define the following process whose realizations can be simulated :

$$C^{(t)}(\mathrm{x}) = 1-\alpha-\mathbb{E}_{\mathrm{U}}\left[\mathbb{1}_{\cap_{i=1}^{l}}\left\{G_i^{(t)}(\mathrm{x},\mathrm{U}) \le 0\right\}\right]$$

Bayesian optimization under uncertainty: EFISUR algorithm

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As in every Bayesian Optimization Algorithm, an infill criterion is needed. In the case of EFISUR, this criterion is divided in two, one to obtain x^{t+1}, and other one to obtain u^{t+1} [5].

The first one is the Expected Feasible Improvement (EFI):

$$\mathrm{x}^{t+1} = \arg\max_{\mathrm{x}\in D_x} \mathrm{EFI}^{(t)}(\mathrm{x})$$

$$EFI^{(t)}(x) = \mathbb{E}\left[FI^{(t)}(x)\right] = \mathbb{E}\left[\mathbb{1}_{\{C^{(t)}(x)\leq 0\}}\left(z_{\min}^{\text{feas}} - Z^{(t)}(x)\right)^{+}\right] = \mathbb{P}(C^{(t)}(x) \leq 0)\mathbb{E}\left[\left(z_{\min}^{\text{feas}} - Z^{(t)}(x)\right)^{+}\right]$$

To obtain u^{t+1}, a criterion based on Stepwise Uncertainty Reduction (SUR) is proposed and has the following expression:

$$\mathbf{u}^{t+1} = \arg\min_{\tilde{u}\in D_U} S\left(\mathbf{x}^{t+1}, \tilde{u}\right)$$

$$S\left(\mathbf{x}^{t+1}, \tilde{u}\right) = \mathbb{VAR}\left(\left(z_{\min}^{\text{feas}} - Z^{(t+1)}\left(\mathbf{x}^{t+1}\right)\right)^{+}\right)\int \mathbb{VAR}\left(\mathbb{1}_{\{G_i^{(t+1)}(\mathbf{x}^{t+1},\mathbf{u})\leq 0\}}\right)\rho_{\mathbf{U}}(\mathbf{u})d\mathbf{u}$$

Variance of future improvement

Variance of the variable quantifying constraints satisfaction

Our modified EFISUR algorithm

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$$\min_{\boldsymbol{x} \in D_x} \mathbb{E}_{\boldsymbol{U}}[f(\boldsymbol{x}, \boldsymbol{U})]$$
$$s.t.\ \mathbb{P}_{\boldsymbol{U}}(g_i(\boldsymbol{x}, \boldsymbol{U}) \leq 0, i = 1, \dots, l) \geq 1 - \alpha$$

Transition to the (x+U) formulation and individual probability constraints :

$$\min_{\boldsymbol{x} \in D_x} \mathbb{E}_{\boldsymbol{U}}[f(\boldsymbol{x} + \boldsymbol{U})]$$
$$s.t.\ \mathbb{P}_{\boldsymbol{U}}(g_i(\boldsymbol{x} + \boldsymbol{U}) \leq 0) \geq 1 - \alpha_i$$
$$i = 1, \dots, l$$

- Many controllable variables in an electrical machine also carry uncertainties -> Reduction of input dimension

Switching to a multi-objective formulation:

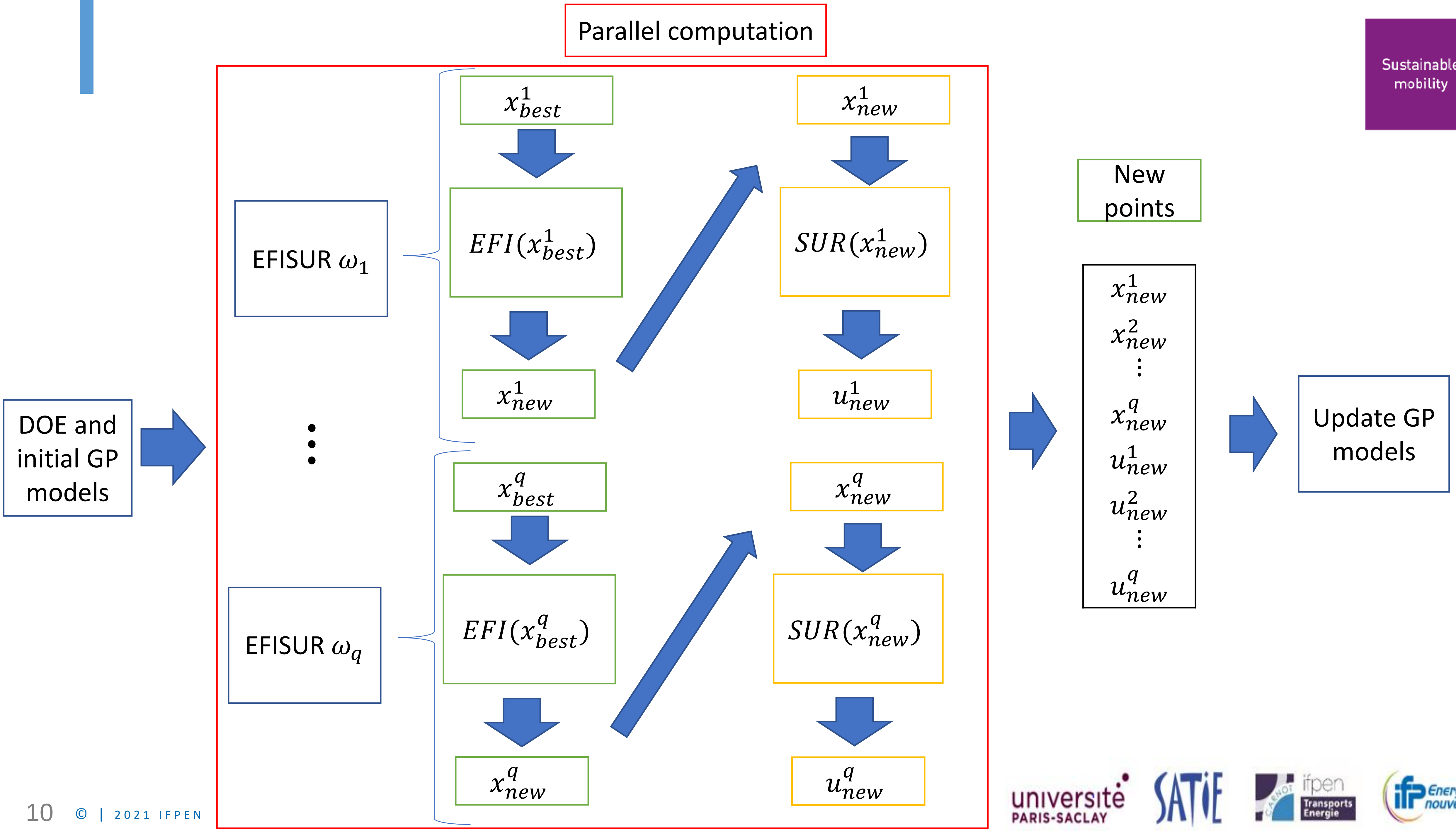
$$\min_{\mathbf{x} \in D_x} \mathbb{E}_{\mathbf{U}}\left[\sum_{j=1}^{k} w_j f_j(\mathbf{x} + \mathbf{U})\right]$$
$$s.t.\ \mathbb{P}_{\boldsymbol{U}}(g_i(\boldsymbol{x} + \boldsymbol{U}) \leq 0) \geq 1 - \alpha_i, i = 1, \dots, l$$

- By doing this the insides of the EFISUR algorithm rest unchanged

Switching to a q-batch algorithm :

Thanks to the weighted sum approach, we can solve several problems (each one with a different vector of weights) in parallel -> q-batch algorithm

- Each of the new q points enriches all the GPs.



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Electrical Machine Optimization : Problem definition

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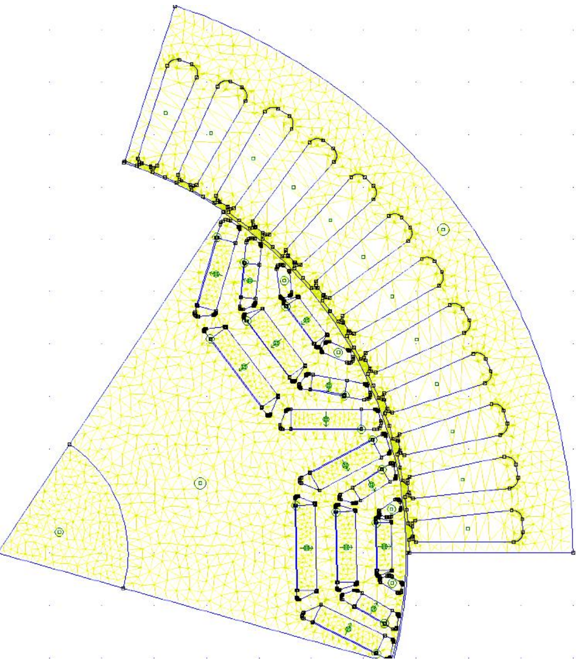

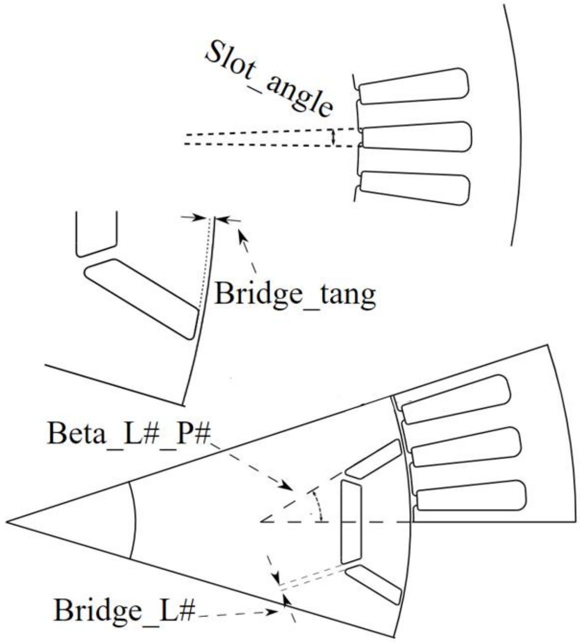

Objective function $\mathbb{E}_U[f_1(x+U)]$	Maximize the mean torque expectation
Objective function $\mathbb{E}_U[f_2(x+U)]$	Minimize the torque ripple expectation
Constraint $\mathbb{P}_U[f_1(x+U) \geq 420] \geq 1-\alpha$ $\alpha \in \{0.01,0.03,0.05,0.07,0.10\}$	Achieve a mean torque superior to 420 N.m with a probability greater or equal to {99%,97%,95%,93%,90%}
Initial DOE size	140 points LHS maximin
Number of iterations and points added per iteration	19 iterations and 5 points per iteration: A total 95 points

- Number of controllable variables $\boldsymbol{x}$: 11
- Number of uncertain variables U : 7
  - 5 (dispersions for 5 x, called U_g) → $x + U_g$,
  - 2 magnetic properties of materials → U_m

Electrical Machines Optimization : Results

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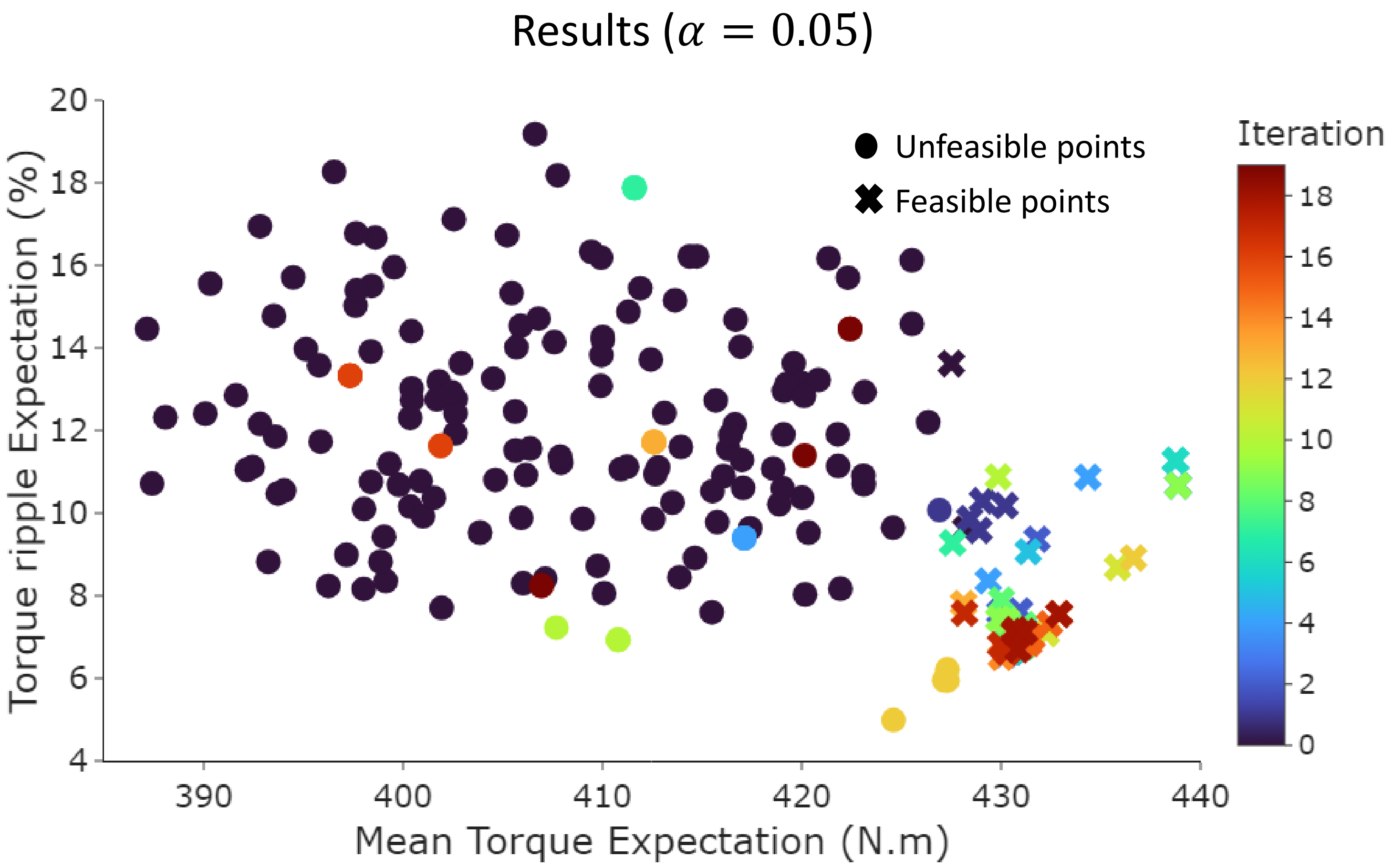

- This figure shows the expectations (predicted by GPs) of all the simulated points through algorithm iterations

- None of the points in the initial design of experiments satisfies the constraint of having a mean torque of at least 420 N.m with a probability of at least 95%.

- On the other hand, the modified EFISUR algorithm proposes several feasible promising points.

- The same behavior was observed for the other probability thresholds

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Electrical Machines Optimization : Results

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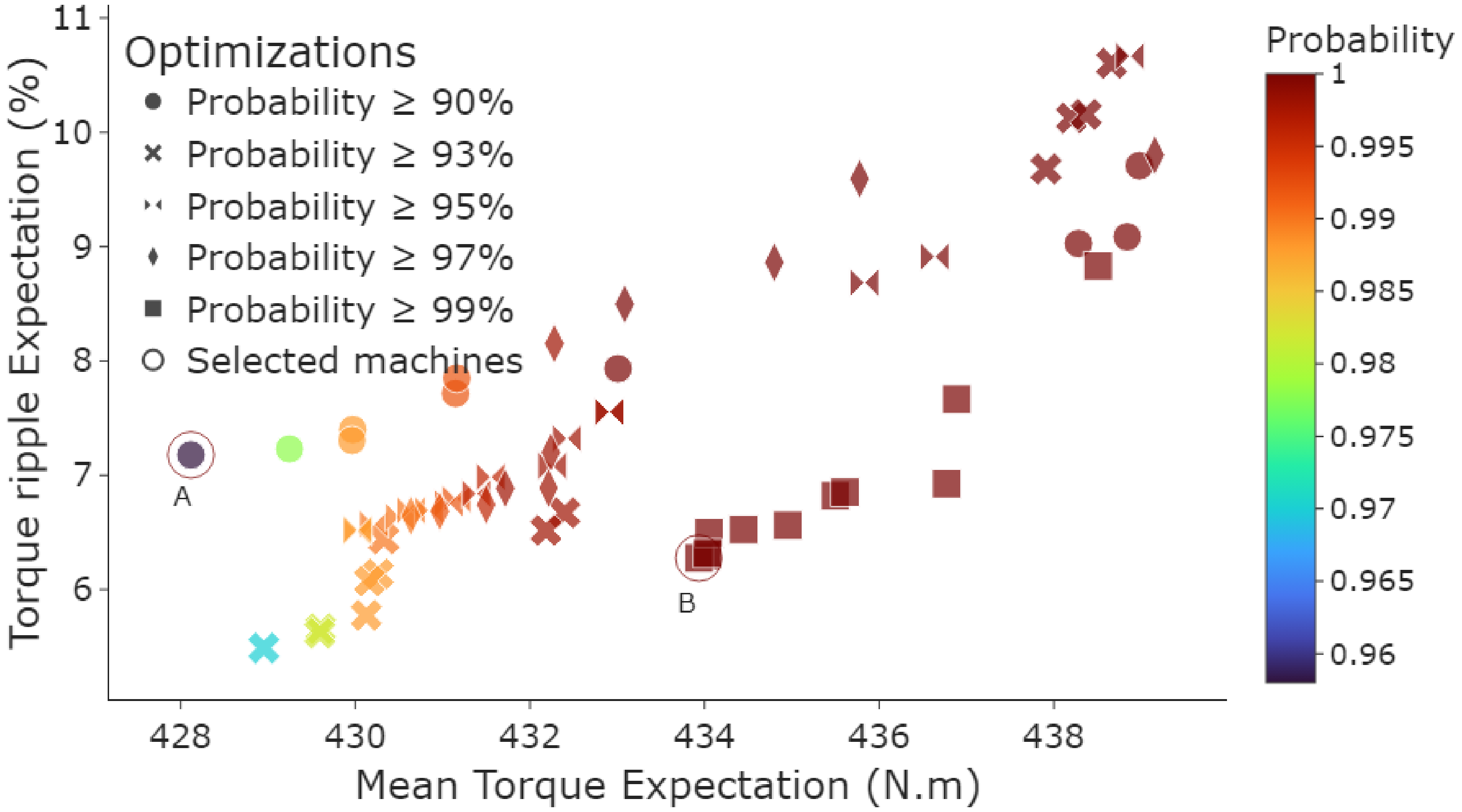
Results from robust optimizations



- This figure shows Pareto fronts for different probability thresholds

- Higher probability levels (e.g. 99%) results in a shorter Pareto front. This is somehow expected, higher the probability of passing 420 N.m, higher the expectation value.

- Machines A and B were selected for further analysis (see Table below for their designs).

Input	Slot_angle	Beta_L1P1	Beta_L1P2	Beta_L2P1	Beta_L2P2	Beta_L3P1	Beta_L3P2	Bridge_L1	Bridge_L2	Bridge_L3	Bridge_Tang
Machine A	2,47°	27,03°	38,65°	31,04°	47,04°	**36,99°**	**59.7°**	2,6 mm	**1,18 mm**	0,5 mm	**0,6 mm**
Machine B	2,47°	27,03°	38°	31,16°	47,07°	**33,7°**	**63°**	2,6 mm	**0,9 mm**	0,5 mm	**0,4 mm**

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Electrical Machines Optimization : verification by simulations

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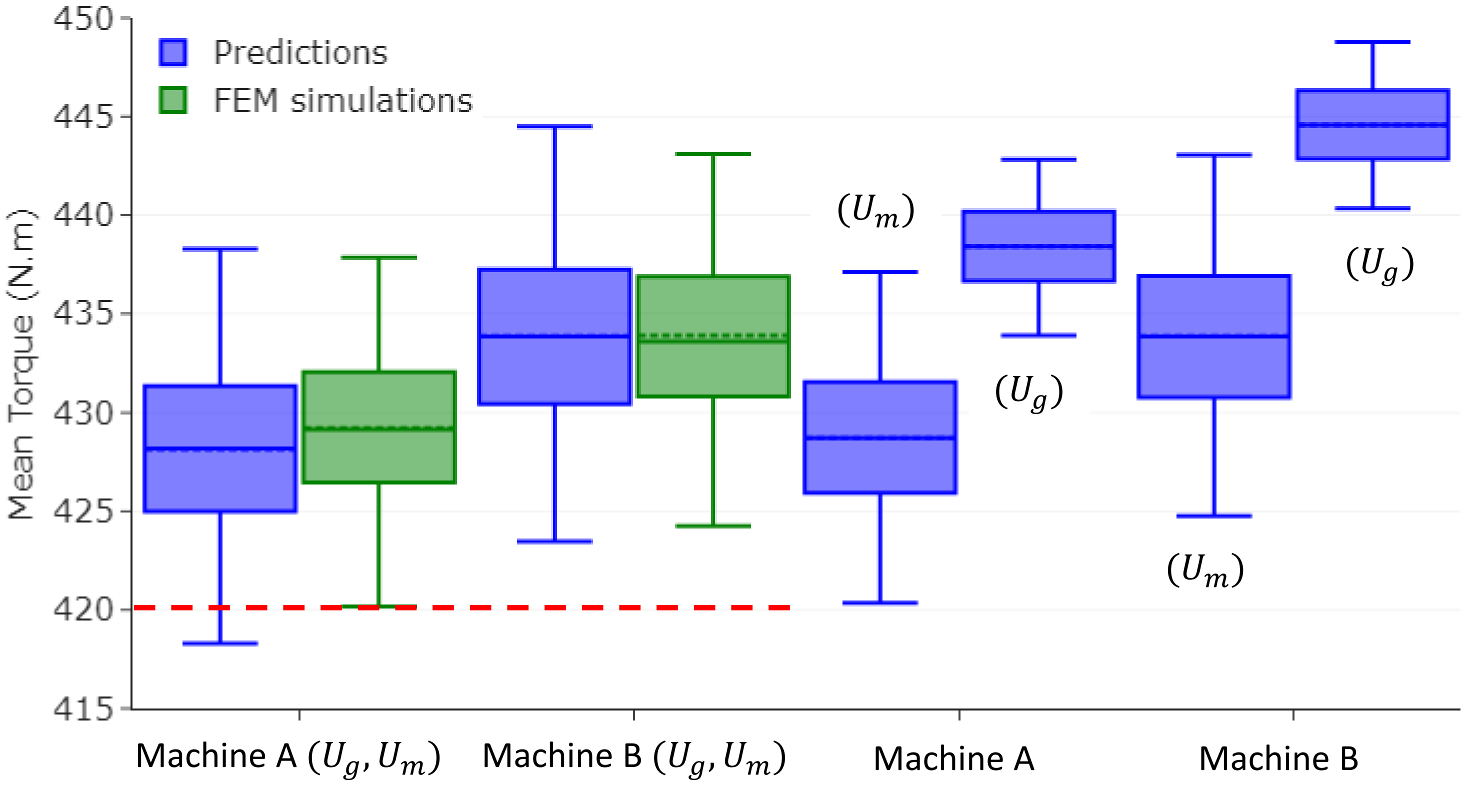
Results verification



- Finite element simulations were performed to build the boxplots of two machines (green). These boxplots were compared with the values predicted by the metamodels (blue).

Prediction errors (Mean Torque GPs):
- Number of U (at x fixed x_A^*, x_B^*) points: 200
- RMSE machine A : 1.9 N.m
- RMSE machine B : 1.24 N.m
- Good $\hat{f}$ accuracy around (x_A^*, x_B^*)

- As we can see, the mean torque values are more sensitive to materials' properties (U_m).

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Conclusions and Perspectives (1)

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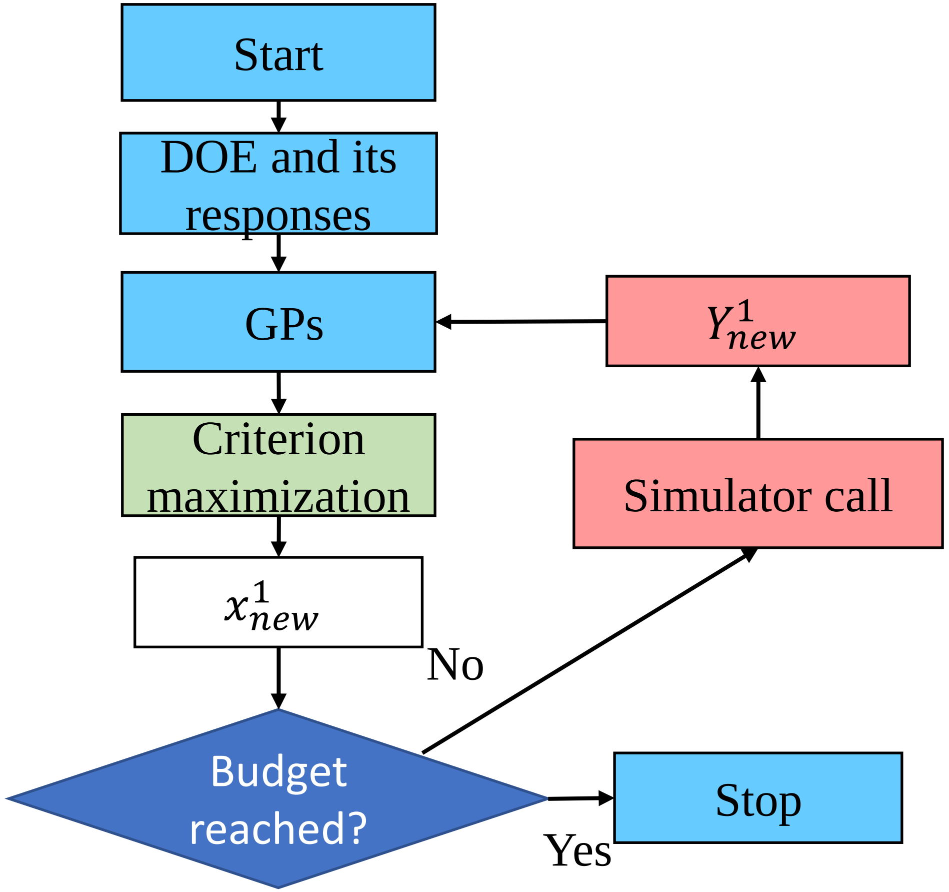
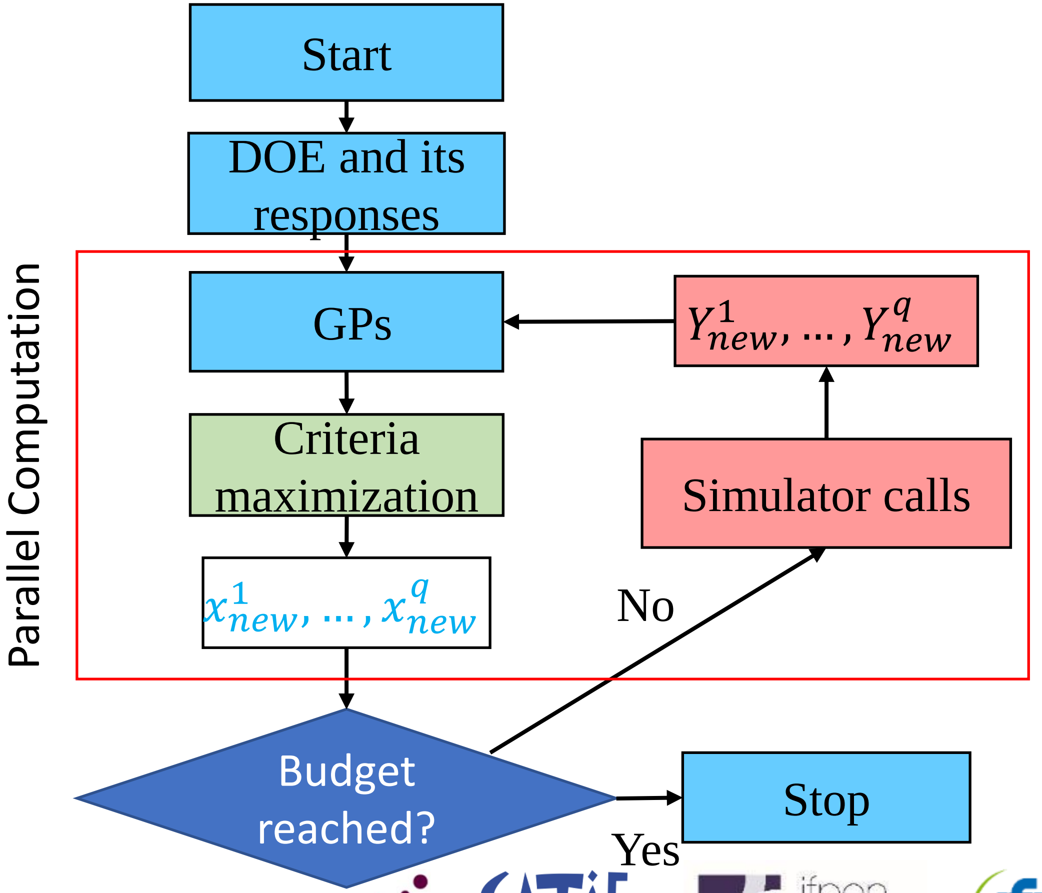
EFISUR

$$\min_{\boldsymbol{x}\in D_x} \mathbb{E}_{\boldsymbol{U}}[f(\boldsymbol{x},\boldsymbol{U})]$$
$$s.t.\ \mathbb{P}_{\boldsymbol{U}}(g_i(\boldsymbol{x},\boldsymbol{U}) \le 0, i = 1, \dots, l) \ge 1-\alpha$$



Modified EFISUR

$$\min_{\mathbf{x}\in D_x} \mathbb{E}_{\mathbf{U}}\left[\sum_{j=1}^{k} w_j f_j(\mathbf{x}+\mathbf{U})\right]$$
$$s.t.\ \mathbb{P}_{\boldsymbol{U}}(g_i(\boldsymbol{x}+\boldsymbol{U}) \le 0) \ge 1-\alpha_i, i = 1, \dots, l$$



Conclusions and Perspectives (2)

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- The modified EFISUR algorithm has successfully solved a constrained multi-objective electrical machine optimization problem taking into account uncertainties

- After validating this algorithm on a simplified application, ongoing work on a more realistic problem with all the constraints related to electrical vehicle applications:
  - 2 objectives : efficiency and permanent magnets overall weight expectations
  - 7 probability constraints (mean torque, power, torque ripple,….)

- Future work on Multifidelity Optimization since several simulators (with different accuracy) are available

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