

Grey-box modelling for Online Monitoring of Dynamic Processes

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Resistance spot welding

- Major role in car and battery manufacturing
- The nugget size is directly proportional to the weld strength, however, too much molten material can lead to expulsion.

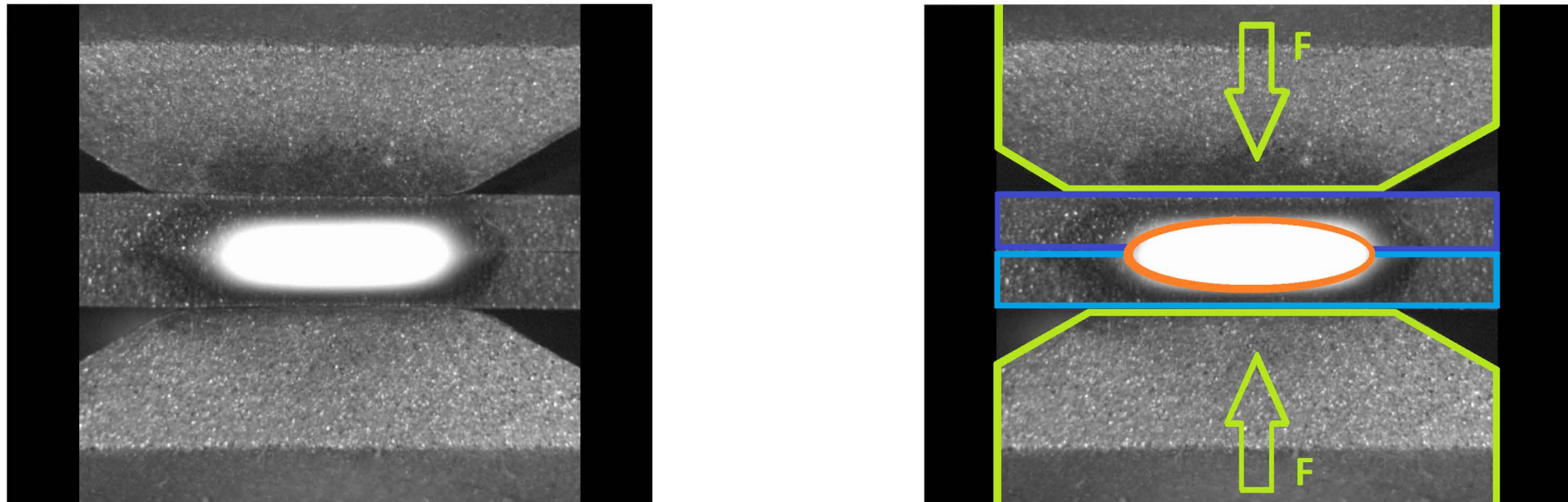


Fig. 1 Cross-section of a welding nugget. Right: annotated cross-section with the electrodes (green) pressing the two metal sheets (blue) together. Electric flow generates heat, which melts the sheets. The welding nugget (orange) is formed.

Challenge

Goal

Performing active process control for resistance spot welding

Main challenges

- Discrepancy between process (~70ms) and simulation time (~2h)
 - Very fast, highly non-linear process
 - Complex multi-physics simulation
- Process drift: uncontrolled and difficult to predict variation of the model parameters in time
- Multiple sources of uncertainty

Proposed approach

- Development of a “grey-box” digital twin
- White-box physical model e.g. FE → accurate but slow
- Black-box Kriging surrogate model → fast but varying accuracy, introduces additional error
- Develop an adaptive calibration scheme for the surrogate model
 - Active refinement considering process drift
 - Avoid operating in areas of low surrogate accuracy

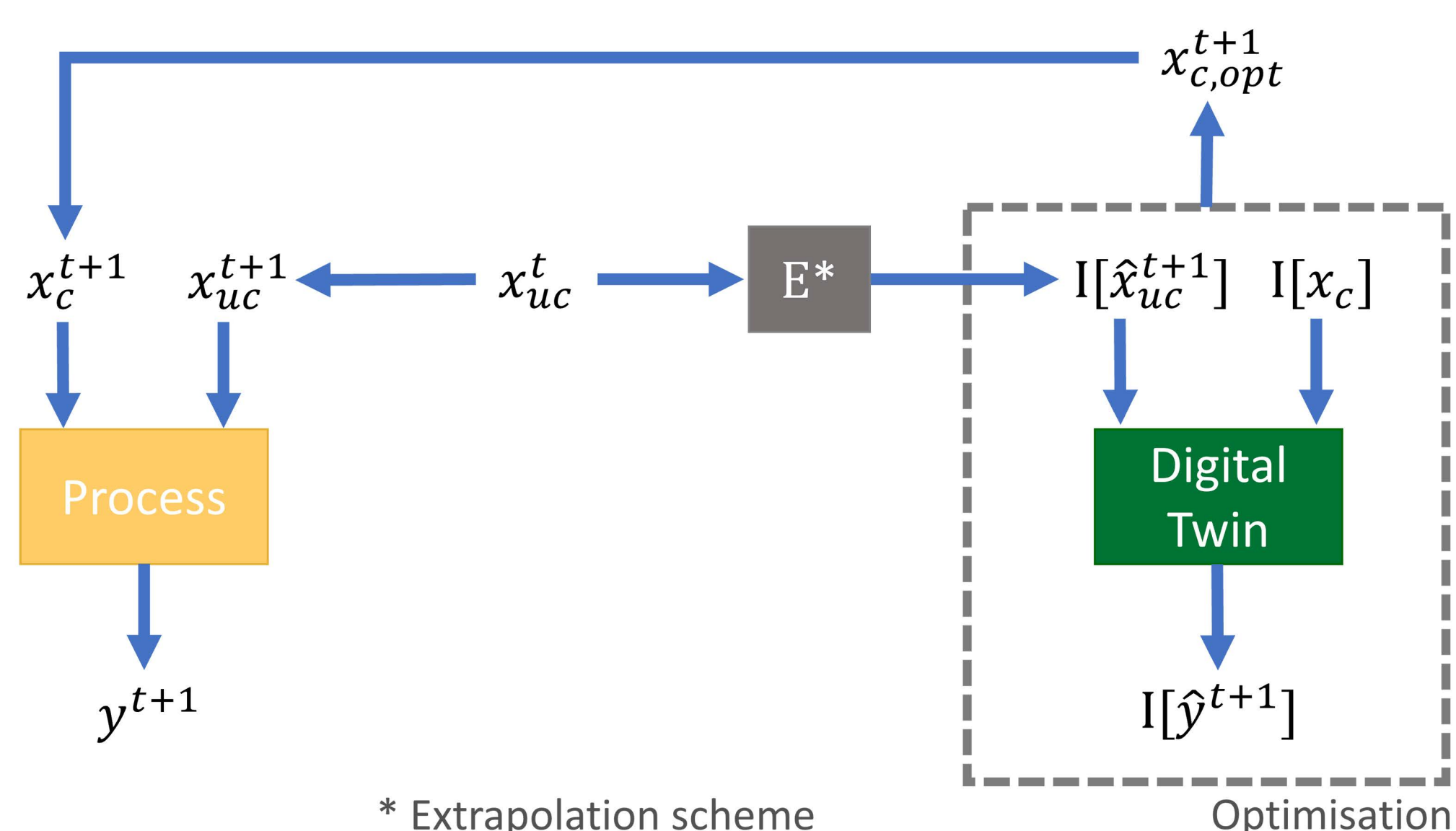


Fig. 2 Schematic of the proposed approach.

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References

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First implementation

Main features

- Analytical performance function in 2D
- One dimension: x_c represents controllable input parameters
- One dimension: x_{uc} represents state parameters, uncontrollably affected by the time-dependent process drift
- Process control over multiple processes
- Time evolution of x_{uc} unknown → extrapolation, given as an interval

Goal

Avoid that the next instance of the process lies in the failure domain

Method

Two parts are running in parallel

• Process control

1. Build initial Kriging meta model of limit state function $g(x)$
2. Estimate $I[\hat{x}_{uc}^{t+1}]$
3. Calculate the worst estimate for current x_c and ideal x_c

$$\hat{P}_{f,w} = \min_{x_c \in I_c} \left(\max_{x_{uc} \in I[\hat{x}_{uc}^{t+1}]} \left(\hat{P}_f(y(x_c, x_{uc}) \notin [y_{lim}]) \right) \right)$$
4. If $\hat{P}_{f,w} \geq P_{f,max}$
 - If estimation error small stop process
 - Else stop process until meta model is refined
5. Adjust x_c^{t+1} if necessary

• Active refinement of the Kriging model considering

- Local quality of calibration and limit state function
- Process drift
- Necessary evaluation time of the white-box model

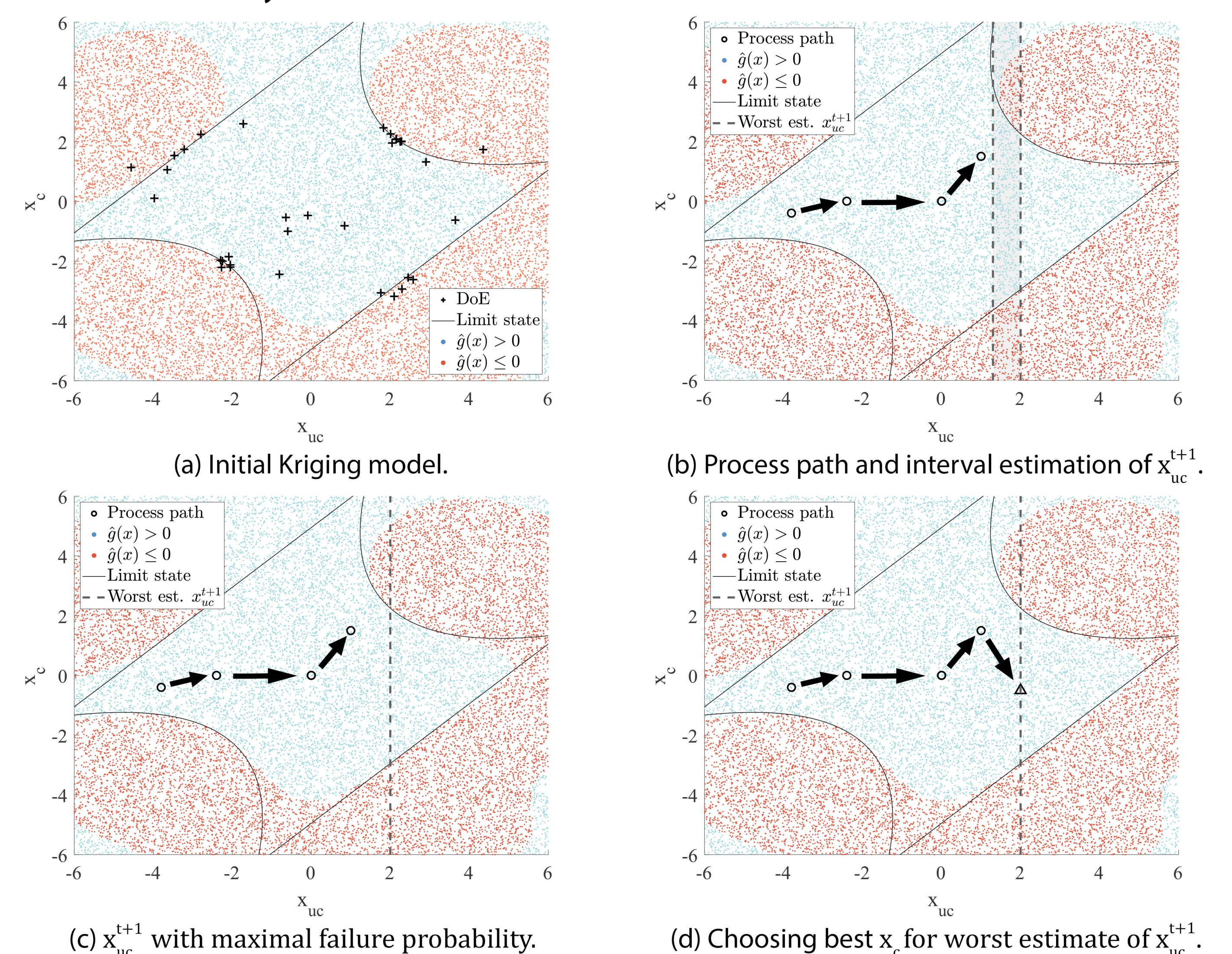


Fig. 3 Visual representation of estimating the worst x_{uc} and the according best x_c . Subfigure (a) shows the initially trained kriging model based on 33 model evaluations and the true limit state function.

Future development

- Employ multifidelity adaptive Kriging meta modelling
- Consider aleatory and epistemic uncertainties
- Use a significantly more complex and exact model

Contact

Feel free to contact me for discussion and any questions that may arise at miriam.dodt@kuleuven.be.