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Grey-box modelling for near-real time Online Monitoring of Dynamic Processes

M. B. Dodt
KU Leuven

Supervisor(s): D. Moens (KU Leuven), M. Faes (TU Dortmund)

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Address: KU Leuven, Dept. of Mechanical Engineering, LMSD Division, Jan Pieter de Nayerlaan 5, 2860 St.-Katelijne-Waver, Belgium

E-mail: miriam.dodt[at]kuleuven.be

Abstract:

A digital twin is a virtual representation of a physical process and can be seen as an expansion of the concept of numerical models including forward and backward communication between the model and the process. Following Kritzinger et al. [3] this concept can be divided in three stages depending, on the level of automation in model updating and process control [5]. Theses stages are called digital model, digital shadow and digital twin, with the last involving complete automation of both. Digital twins could have applications on all processes which behavior can unpredictably vary with time. Good examples are structural health monitoring or production process subjected to process drift. In this context a digital twin would help identifying process drift, estimating its influence and predicting possible future drift, making it a very useful tool for decision making, process optimization and control.

Although, a lot of research has already been conducted in that area, the current literature mainly consists of concept papers about digital twins, actual implementations are scarce and usually cover lower capability levels [3]. High-speed processes ($<$ 1 second) represent a highly challenging application of this framework since the the model evaluation is orders of magnitude slower than the process. This limitation makes active process control impossible on the scale of a single realization, process control is however possible over the span of a few process realizations in a production line. One notable example of this is resistance spot welding, which is essential for the manufacturing of cars or batteries [6]. In this application the challenge is further increased by the fact that the phenomenon to model is complex, time-dependent and highly non-linear. Under these limitations it becomes necessary to have a faster alternative to the physical model, called a surrogate.

The so called "grey-box" modeling approach is very well suited for this context. A grey-box is a combination of a white-box physical model with a black-box data driven surrogate. The white-box model provides an accurate estimation of the output and is capable of extrapolation but its evaluation is very time consuming. A black-box is very fast to evaluate but induces modeling error and cannot be relied on for extrapolation.
In summary, process monitoring data are recorded in real time. From these measurement the goal is to asses the current state of the process and estimate the corresponding quality fast enough to be able to take corrective action before quality becomes unacceptable. A black-box model can provide a fast estimation but has a limited domain of applicability and induces a significant error. A white-box model can provide a precise estimation that can be used to improve the calibration of the black-box but has a high computation time. Ultimately the measurement data from the monitoring will also be used for the calibration of both models through model updating. To solve this problem, it is proposed to investigate the use of multi-fidelity approaches coupled with a Kriging surrogate.

The Kriging approach is one of many methods to reduce computational cost by performing surrogate modelling. Kriging refers to a surrogate based on a Gaussian process which associates a set of inputs with correlated output Gaussian random variables [1]. The popularity of these models can be attributed to their ability of estimating their own localized accuracy represented by the posterior standard deviation of the

outputs. This information allowed the development of adaptive calibration schemes, aiming at iteratively selecting the calibration samples that minimize the error associated with a quantity of interest [1][2]. The choice of the calibration sample is done through a so-called learning function that allows for an efficient allocation of computation resources, only refining the calibration in areas that have significant influence of the desired output. The combination of Kriging surrogate with multi-fidelity approaches is an active research topic. The principle is to take advantage of white-box models with varying levels of complexity. Complex models have a high fidelity while simpler models have a low fidelity but can be evaluated much quicker (e.g. only considering first order principles, or using a coarse finite element mesh). The multi-fidelity Kriging approach aims at taking advantage of these models to efficiently calibrate a Kriging surrogate. As proposed by Mell et al. [4] this approach can be coupled with adaptive calibration schemes to further improve the efficiency.

Our goal is to develop an active calibration and control scheme conditioned by the respective computation time and accuracy of the different models as well as the current evolution of the process drift. This scheme has to be able to efficiently decide between estimating quality with the surrogate or refining the surrogate by running a white-box evaluation, with which level of fidelity and for which coordinates on the input space. In addition, based on the results, the decision must be made between letting the process proceed, correcting the process parameters to counter deviation from the optimum or stopping it until a computation has finished because of uncertainty in the quality. As a first approach this work is focused on proposing an efficient active learning scheme on a toy example with two levels of white-box fidelity and conditioned by a controllable time-dependent process drift.

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Short biography – Miriam Dodt graduated from the Leibniz University Hannover with a civil engineering background, focusing on computational methods in engineering. Her PhD, conducted in close exchange with the company Kapernikov, concerns the area of grey-box modelling applied to resistance spot welding.
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