Active Learning with HilomotDoE

The Design of Experiments (DoE) is used in the development and optimization of many products and processes. The experiments are used to model a functional relationship between design parameters (inputs) and the corresponding qualities (outputs) given by the process (see Fig. 1). Because of resource intensive experiments, a trade-off between accuracy and number of experiments has to be made. The objective of the DoE is to estimate an accurate functional relationship between design parameters and the corresponding qualities of the process/product with as few experiments as possible. The DoE can be distinguished in two different types:

1. Unsupervised DoE – Offline, the design parameter combinations are determined prior to the experiments.
2. Supervised DoE/active learning – Online, the next design parameter combination (query) is optimized after carrying out one or a couple of experiment(s).

In general, an active learning strategy depends on a model of the unknown process. Thus, usually, an unsupervised DoE has to be done a priori.

A supervised DoE optimizes the next query point with respect to a given objective. Typical objectives in an active learning context are: (i) Finding the optimum of the process with respect to the design parameters using the identified model; (ii) exploration of the process boundaries. Both objectives are subject of our work. In this project we are focusing on increasing the model accuracy utilizing a novel active learning strategy.

The process is modeled using an artificial neural network. Through a so-called training algorithm, the model is able to learn the relationship between the design parameters and the corresponding quality. Here the model is trained using the Hierarchical Local Model Tree (Hilomot) – algorithm. This algorithm finds regions of similar (linear) relationship between inputs to outputs.

The extension to an active learning strategy is the HilomotDoE algorithm. The next design parameter combination (query) is placed in a region, where the model is not able to represent the process appropriately. In other words: The query is set to that location, where the gained information out of the process is supposed to be maximal. After a new training of the model, this procedure is repeated until a certain termination criterion is met (see Fig. 2). With this approach, the test bench time/ the number of required experiments of a combustion engine, were decreased by a factor of 2, while achieving the same model accuracy as with an unsupervised DoE.

Figure 1: Block diagram of a general process with design parameters as inputs and a quality as output

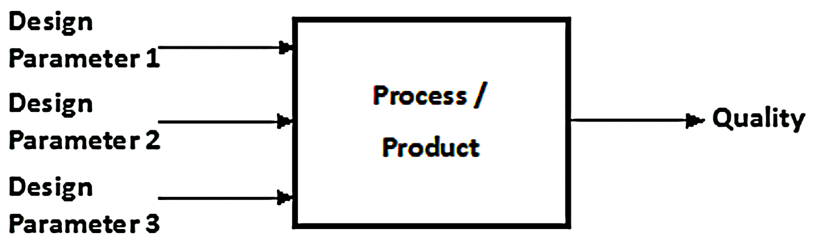
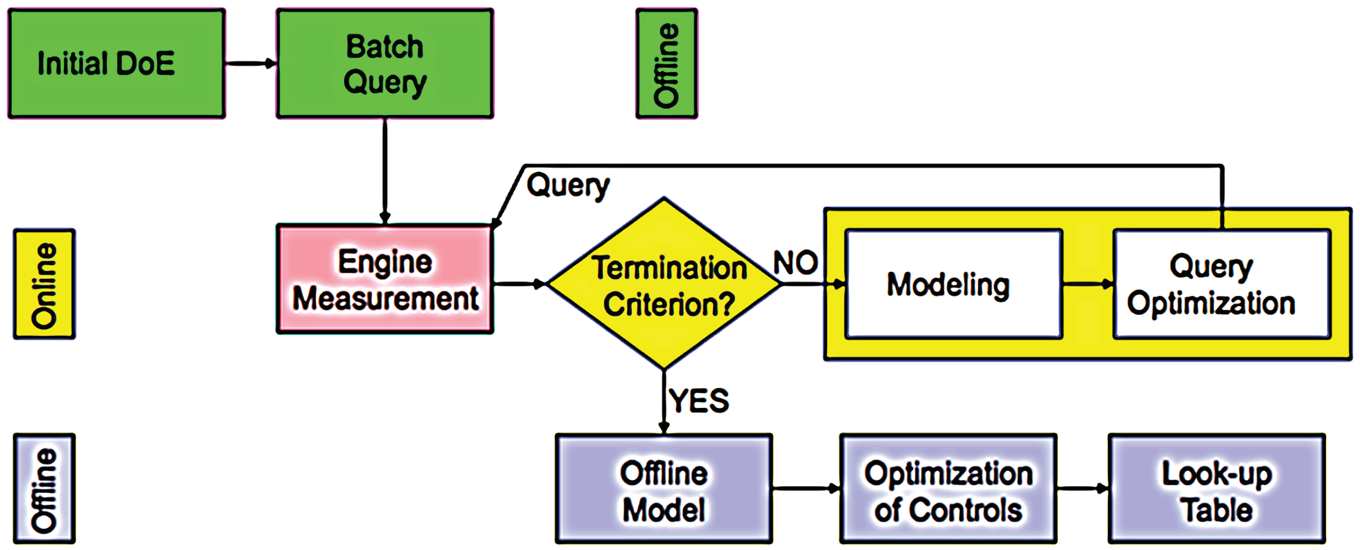


Figure 2: Active Learning strategy with the engine measurement as an example.



I Project Management and Execution

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