SMART FILTER ELEMENT DEVELOPMENT – APPLIED MACHINE LEARNING FOR OPTIMIZED ELEMENT LAYOUTS

Thomas Gose (*) [1)], Christoph Schulz [1)],
Florian Keller [1)], Julian Ziegler [1)], Christoph Hitzke [2)] , Sonja Zöllner [2)]

1) MANN+HUMMEL GmbH, 71636 Ludwigsburg, Germany
2) MANN+HUMMEL Innenraumfilter GmbH & Co. KG , 95502 Himmelkron, Germany

(*) Contact details: thomas.gose@mann-hummel.com
Phone +49 7141 984211

ABSTRACT

In recent years the importance of data and its' interpretation has been grown significantly in development processes. Modern methods of Data Sciences enable developers to discover hidden insights in existing datasets or to create new datasets well suited for machine learning. Emerging "data lake" structures can consist of measurement data as well as simulation data or even mixed data from various sources as long as it adds up to the overall knowledge.[1]

The presented work will discuss challenges in the application of machine learning for optimized filter element layouts.[2,3] The goal is to enable developers to find optimal filter designs within seconds instead of hours or days. The optimal filter element design needs to consider the design space and customer specifications, amongst others. Looking on the workflow, the seamless integration of this novel design approach into the whole development process as depicted in Figure 1 is a core requirement.

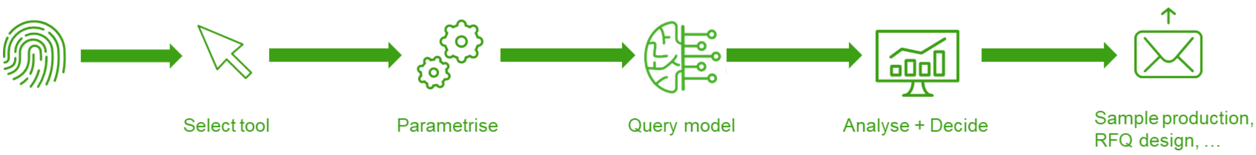

Figure 1: Scheme of the user workflow

The goal of the approach is to maximize the use of the results of a multi-parameter optimization by providing these in an easy and explorative way to the developer being the domain expert.[4] This combines challenges of different disciplines as besides model quality also user experience and conformity to the matured automotive development processes need to be satisfied.[5] From a technical point of view the mentioned multi-parameter optimization is the backbone of the tool shown. The optimization parameter can vary and e.g. be pressure drop, dust holding capacity or media area, amongst others.

Model quality strongly depends on the input data quality and the covered parameter range. "Much data" does not necessarily mean sufficient data for machine learning. An example is shown how to deal with this challenge using a hybrid dataset. Moreover, one key factor to user acceptance besides reliability is the user interface. This is particularly true when multi-layered data needs to be presented in a concise way to drive a tangible element design decision.

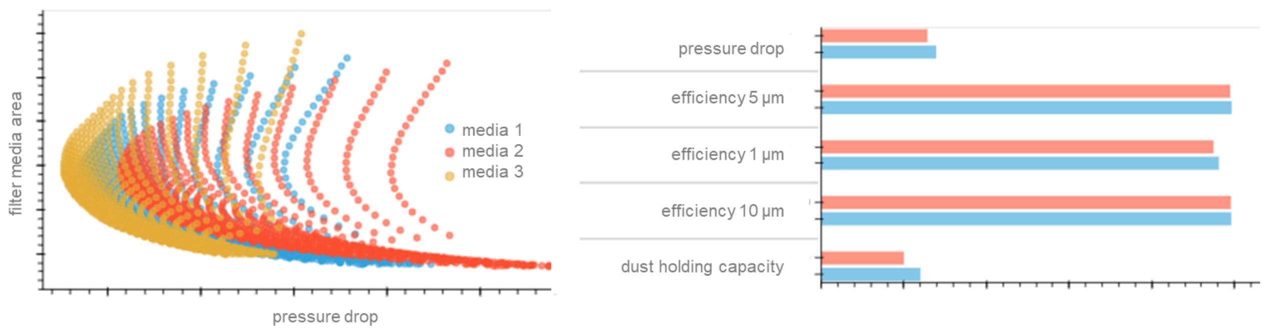

Figure 2: Interactive plot showing all possible design options (left) and comparison of selected designs for chosen parameters in more detail (right)

A way to realize this is presented, illustrating how machine learning based data analytics in the field of filter element development can turn out to economic benefits e.g. by reducing the material usage and the product carbon footprint.

REFERENCES

1) Schulz C., Gose Th., *Smart Filter Element Development - Creating ML & optimization. based tools provided as webservices*, WOST 2022 Conference, 24.06.2022, Weimar.
2) Ziegler J., et al. *A Graph-based Approach to Manage CAE Data in a Data Lake.* Procedia CIRP, 2020, 93. Jg., S. 496-501.
3) Ziegler, J., et al.: *A Metadata Model to Connect Isolated Data Silos and Activities of the CAE Domain.* In: La Rosa, M., Sadiq, S., and Teniente, E. (eds.) Advanced Information Systems Engineering (CAiSE). pp. 213--228. Springer International Publishing, Cham (2021). https://doi.org/10.1007/978-3-030-79382-1_13.
4) Viaene, S.: *Data Scientists Aren't Domain Experts*. IT Professional 15(6), 12-17 (2013), doi: 10.1109/MITP.2013.93
5) Gray, J., et al.: *Scientific Data Management in the Coming Decade.* SIGMOD Record 34(4), 34-41 (2005), doi: 10.1145/1107499.1107503

KEYWORDS

digitalization, filter element development, filter element optimization, machine learning, virtual prototypes