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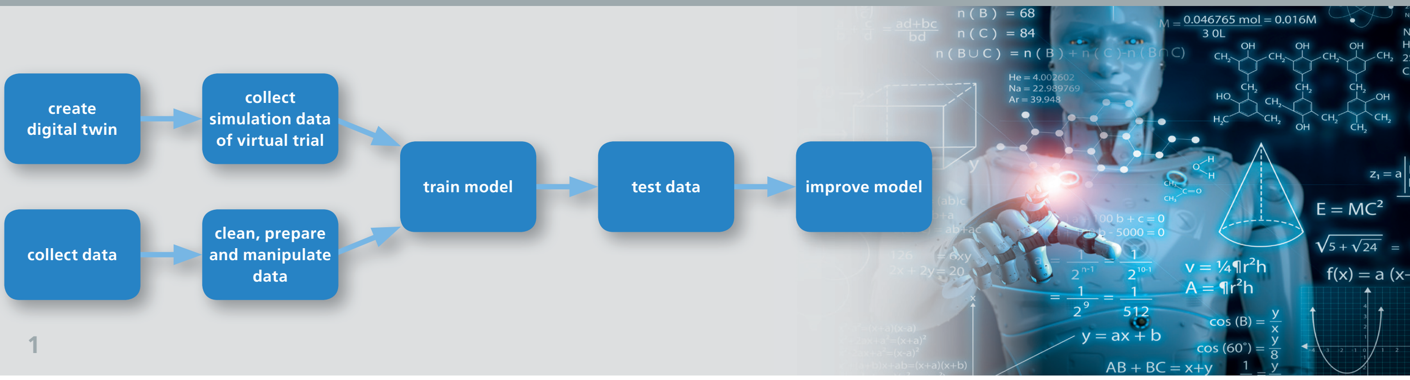

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1 *Hybrid machine learning workflow: experimental data is augmented with simulation-based data*

HYBRID MACHINE LEARNING FOR TEXTILE INDUSTRY

Today, we see dramatic changes in the demands being made of the textile industry. The trend in many areas is towards customization, similar, for example, to buying a new car. Consumers increasingly demand tailor made products. This shift in consumer behavior is lucrative for European textile companies as production of customer-specific products in small lot sizes results in the return of manufacturing to Europe. However, this requires the digital transformation of production, which we support with our hybrid simulation-based machine learning (ML) methods.

Data-based machine learning by itself is not sufficient

In data-based machine learning, we develop statistical learning algorithms that recognize patterns and laws in given data. The benefits of ML algorithms depend to a great extent on the quality and quantity of the available data. As a rule, enough measurement data is collected for the purpose of quality assurance in the textile industry. However, only in the rarest of cases is sufficient data available to make a connection between the process parameters and the product quality. Consequently, we are not able to use pure, data-driven machine learning – especially for plant and process optimization for today's customized production processes.

Hybrid simulation-based machine learning

To design and optimize production processes in the textile branch with machine learning methods, we develop and apply a hybrid approach.

Fraunhofer-Institut für Techno- und Wirtschaftsmathematik ITWM

Fraunhofer-Platz 1
67663 Kaiserslautern
Germany

Contact
Dr. Simone Gramsch
Phone +49 631 31600-4427
simone.gramsch@itwm.fraunhofer.de

www.itwm.fraunhofer.de

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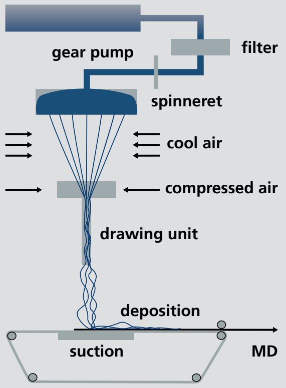

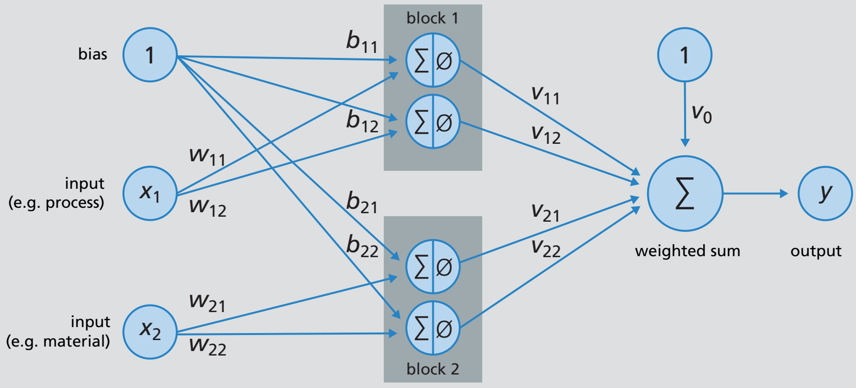

2 *Sketch of the working principle of a spunbond process*

3 *Sketch of a blocked neural network used to analyze the cause-and-effect relations in a spunbond process*

Extensive experience is available for process and product design in textile industry. We formalize this expert know-how by building a physical model to describe the process and, subsequently, implement a computer based simulation. Models provide the missing data for the development of suitable ML algorithms and linking with available measurements. In this concept, ML closes the gap between physical based simulation of production processes and the level of quality of the end products – which, in many cases, is not accessible to physical models.

Example – spunbond processes analyzed by blocked neural networks

In order to analyze the cause-and-effect relations of the influencing parameters in a spunbond process, we use the digital twin FIDYST (Fiber Dynamics Simulation Tool by Fraunhofer ITWM) in combination with the CFD solver ANSYS Fluent. We set up a design of experiments with varying process and material parameters. Then, we simulate the turbulent air flow in the spunbond process due to these varying process parameters. Finally, we simulate the fiber dynamics in the turbulent flow as well as the fiber laydown on a conveyor belt due to the varying material parameters.

The analyzed input parameters encompass the inlet air speed and suction pressure, as well as the material input parameters E modulus, density and line density (titer) of the filaments. The fiber laydown produced by the virtual experiments is statistically quantified. For example, we use the standard deviation of the throwing ranges in machine and cross machine direction as output parameters. Additionally, we compute a stochasticity parameter that describes the stochasticity of the fiber deposition. Small values of this stochasticity parameter (near zero) correspond to a deterministic deposition and large values to a completely stochastic process.

After we have generated a database of input/output data for the spunbond process, we split the data into a training and a validation set. We decide to use a blocked neural network as model. The block-structure matches the different nature of the process and material input parameters. Additionally, the trained blocked neural network forms not only the basis for the prediction of the fiber laydown characteristics, but also enables a quick ranking of the significance of the influencing effects.

We conclude our research by an analysis of the nonlinear cause-and-effect relations. Compared to the material parameters, suction pressure and inlet air speed have a negligible effect on the fiber mass distribution in (cross) machine direction. Changes in the line density of the filament have a ten times stronger effect than changes in E modulus or density. The effect of the E modulus on the throwing range in machine direction is of particular note, as it reverses from increasing to decreasing in the examined parameter regime.