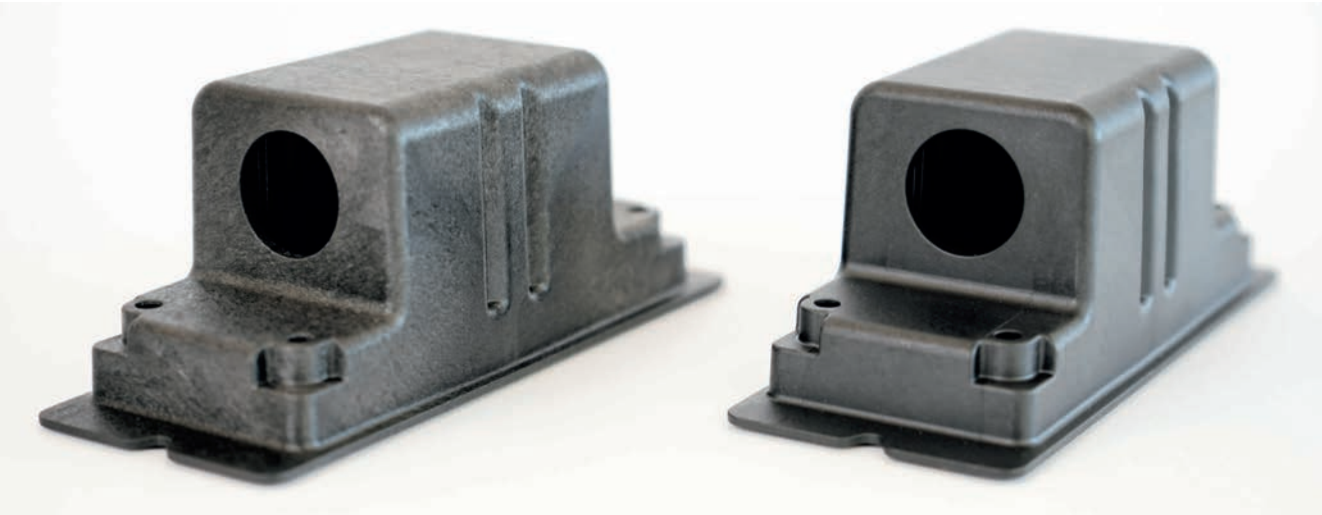
AI-Based Optimization of Injection Molding Machine Settings

Optimal Machine Settings in Just a Few Clicks

Determining suitable injection molding machine settings through trial-and-error or simulation software can often be very time-consuming. However, machine learning (ML) models can precisely capture even complex relationships between machine settings and product quality based on initial experimental results. Quality predictions utilizing these models enable the optimization of machine settings with significantly reduced experimentation.



Two injection-molded sensor housings from Sick: With surface defects (streaks, left) and after optimization of machine settings (right).
© Sick

Before starting mass production, appropriate process parameters, such as pressure, temperature, and cooling time, must be defined for each combination of mold and plastic type to ensure part quality. Quality is determined by measuring the deviation of actual part dimensions from those specified in technical drawings. Typically, suitable machine settings can only be accurately determined by experiments conducted on the injection molding machine or through simulation. Both methods are time-consuming: machine experiments require representative results obtained only after stabilization phases, while simulations demand significant computational resources and time.

Thus, machine operators often face the dilemma that larger experiments could yield better settings but involve longer setup times. To accurately capture the relationships between settings and part quality from experimental data, applying ML methods to these results is beneficial. These methods allow the interpolation of part quality for additional machine settings without further experimentation.

However, this approach usually requires the manual transfer of experimental results into statistical analysis software. Moreover, operators must be familiar with often complex software tools.

Multi-Objective Optimization of Machine Parameters as Motivation

The use of data-driven predictions enabling users to optimize product and process quality opens extensive potential [1]. Due to the complex and nonlinear relationships between input and output variables in the injection molding process, this process is particularly suitable for the application of ML methods.

Numerous studies in the literature compare various ML techniques for quality prediction or evaluate the prediction of different process and quality parameters [2–9]. Besides quality prediction, optimizing machine settings is another

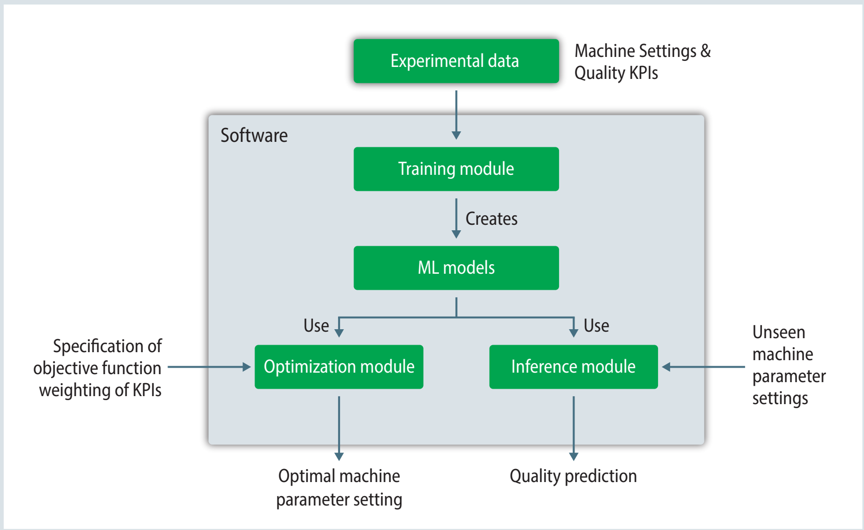


Fig. 1. "AI-driven Molding Assistant": Illustration and integration of the individual software modules. The optimization module adjusts the machine parameters to maximize component quality.

extensively researched and promising application. Given the sometimes conflicting influences of machine parameters, optimization typically involves multi-criteria objective functions (multi-objective optimization) using appropriate algorithms. Machine parameters can thus be optimized for product quality requirements while maintaining acceptable productivity and cost efficiency [10].

Further optimization goals include minimizing product defects [11] and reducing energy consumption [12]. However, generating the large amounts of data required for ML training poses a significant challenge. Typically, such data must be laboriously generated through simulations or experiments on actual machines. Methods like transfer learning address this problem by enabling models to efficiently handle smaller datasets [13].

The goal of this initiative is to implement ML applications in injection molding processes and transfer them into practical, user-friendly software. The newly developed software "AI-driven Molding Assistant" (AIMA) is specifically tailored to the user's existing process. During the setup process, the user is continuously supported by data-driven predictions to shorten process setup times.

From Experimentation to Setting Recommendations in One Tool

A consortium consisting of INC Innovation Center GmbH, the Hong Kong Industrial AI and Robotics Centre (FLAIR), and Sick AG has jointly developed the software solution AIMA for injection molding processes. This solution allows predicting quality KPIs and optimizing machine parameters using ML methods. It seamlessly builds upon initial experiments on the influence of machine settings, whose results can be imported directly into the tool.

Users, even without extensive data science knowledge, can train ML models on this data using an intuitive interface. The trained models can then generate quality predictions for alternative settings without additional experiments. Moreover, these ML models feed into an optimization module that determines machine parameters maximizing part quality (**Fig. 1**).

Quality Prediction as an Integral Component

With the prediction function, users can represent the relationship between machine settings and resulting part quality. First, users import tabular results from initial experiments, either directly from injection molding on real machines or from simulation software. Then, users define features (machine settings) and target variables (quality KPIs) and may exclude individual features from model building. Model fitting and selection occur automatically, requiring no further specifications or programming skills from the user.

The prediction module trains multiple univariate models for each target variable, including linear regression, decision trees, and random forests, listed here in ascending order of their complexity. Model suitability depends on factors like considered KPIs, mold type, plastic type, and available experimental results. For each quality KPI, the prediction module compares model prediction quality using the coefficient of determination, selecting the best-performing model. The outcomes, including model types, fitting quality, and influence of individual machine parameters on quality KPIs, are presented, visually. »

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Text

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Service

More information on the project partners:
www.innovation-center.com
www.sick.com
www.hkflair.org

References

You can find the list of references at ***www.plasticsinsights.com/archive***

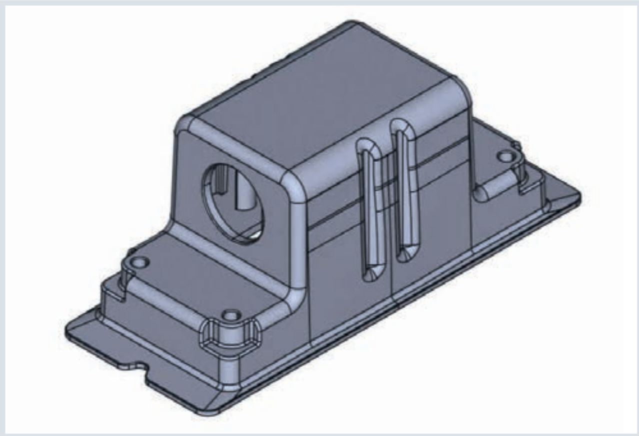

Fig. 2. One of Sick's sensor housings (CAD illustration) evaluated using the AIMA software solution. © Sick

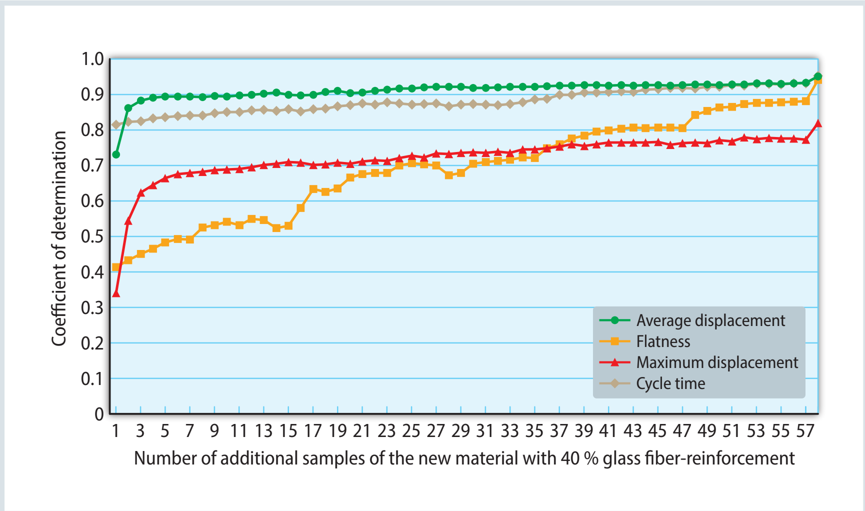

Fig. 3. Illustrated is the incremental expansion of a dataset (initially containing samples of materials with 20 % and 50 % glass fiber-reinforcement) by additional samples of a material with 40 % glass fiber-reinforcement. Even with only a few additional samples of the 40 % reinforced material, a reliable model predicting the quality of injection molding processes for this material can be created. Source: INC Innovation Center; graphic: © Hanser

Optimization of Machine Settings – for Beginners and Experts

Using models trained with the prediction module, users can optimize machine parameters with the optimization module. This module lets users individually weigh various workpiece KPIs to create an objective function and set machine parameter boundaries reflecting permissible machine ranges. These barriers reflect the permissible setting range of the injection molding machine.

The optimization module's user interface provides two modes: a quick setup mode enabling rapid optimization with minimal settings and an expert mode for advanced fine-tuning. This dual-mode system makes the software appealing to beginners and data-driven optimization experts alike.

The application described was developed and evaluated using data from Sick.

Insights from Development and Evaluation

Sick needs optimal machine settings for the injection molding of sensor housings. Sick conducts molding simulations and interpolates results to find suitable settings. The AIMA software simplifies and standardizes this process, offering a broader model selection in the prediction step. Evaluations used different Sick housings (**Fig. 2**), involving glass fiber-reinforced polyamides with varying fiber percentages.

Examined machine parameters included injection speed, material and mold temperature, holding pressure and the duration it got applied, and cooling time. Workpiece quality was measured through maximum and average distortion, average surface distortion, and distortion at specific points. Models in the prediction module showed strong conformity with simulated molding results, achieving coefficients of determination exceeding 80 %. The best model choice varied depending on the KPI considered. Additionally, we observed diminishing marginal utilities for additional experimental samples once a suitable initial simulation was performed.

A similar effect occurs when simulation samples for a known plastic material are supplemented with a few new experimental samples for similar, but related materials. For instance, adding limited new data for a 40 % glass fiber material to simulation data for 20 % and 50 % glass fiber-reinforced materials led to reliable predictions for the new material (**Fig. 3**).

Conclusion

In collaboration with Sick, a streamlined tool supporting process optimization workflows while improving process modeling was developed. According to a Sick development engineer, AIMA expands the use of statistically sound optimization methods within the company by lowering the barriers in comparison to existing solutions. ■