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A Data-Driven Reduced Order Modeling Approach Applied in Context of Numerical Analysis and Optimization of Plastic Profile Extrusion

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In order to be competitive in modern industry, processes are highly optimized and need to be operated as cost-effectively as possible. In order to enable this, a deep knowledge of the process and its sensitivity towards perturbations is required. One important tool to acquire this knowledge is numerical modeling and analysis. Although, the numerical analysis results in good predictions about the actual process, often it is computationally intensive in terms of resources and time. Since optimization and in process evaluation, however, demands computational cheap and fast models,the demand for reduced order models (ROM) increased over the last decades [1, 3].

In course of this work, we examine the process of plastic profile extrusion, where a polymer melt is shaped inside the so-called extrusion die and fixed in its shape by solidification in the downstream calibration unit. In this context we will present a data-driven ROM approach that considers the characteristic flow behavior of polymers and their temperature sensitivity[2].

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