Improving parameter identification of an austenite decomposition model using sensitivtiy analysis and experimental design

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Precise temperature control is critical in steel strip processing to achieve the desired quality and material properties. Achieving smart, efficient and precise production requires the implementation of advanced process control strategies based on a reliable thermal model of the plant. In [1], a thermal model was developed coupled with a low-dimensional phase transformation model to account for the release of latent heat during phase transformations in the annealing section of a continuous steel strip processing line. This phase transformation model is a non-linear, phenomenological kinetic model describing austenite decomposition, and is well-suited for model-based control applications.

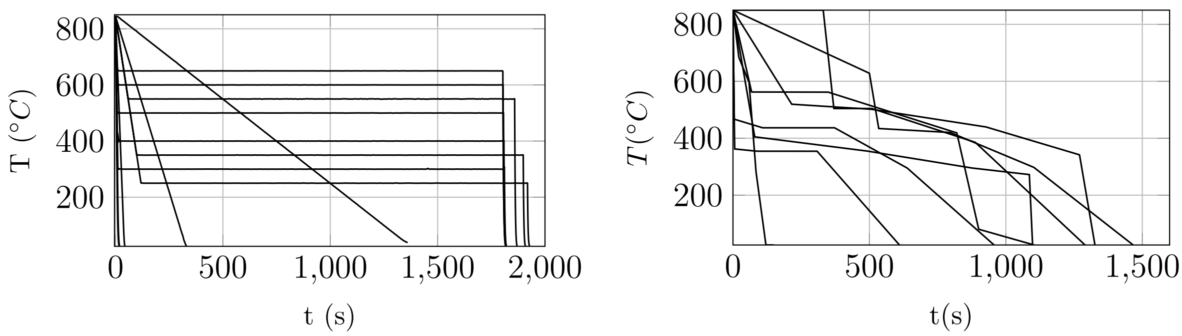
After developing a dynamical model such as the phase model, the issue of identifiability of unknown model parameters should be addressed. The central question is: Can the unknown or uncertain parameters $\boldsymbol{\theta}$ of our model be uniquely identified? Given that the developed model should adequately describe the input-output behavior of the system, parameter estimation can be performed by fitting the model to observed data through solving an optimization problem. However, this process is not always straightforward. The problem might be ill conditioned such that it does not easily converge or give unreliable parameter estimations which can lead to unsatisfactory model predictions.

A way to address these issues is through a parameter identifiability analysis by estimating the sensitivity of the model output $\mathbf{y}$ with respect to the model parameters $\boldsymbol{\theta}$ [2]. This can be used to calculate the collinearity index, which is a commonly used diagnostic tool that indicates the degree of linear dependency between parameters. A high collinearity index means that an output change due to modifying one parameter can be compensated by a specific change of other parameters. In this case, the parameters are not uniquely defined and the equality $\mathbf{y}(\boldsymbol{\theta}_1)=\mathbf{y}(\boldsymbol{\theta}_2)$ may hold true for specific parameter values $\boldsymbol{\theta}_1 \neq \boldsymbol{\theta}_2$.

A high collinearity index can arise from two main causes:

1. Some model parameters are inherently non-identifiable, or
2. the data used for parameterization does not sufficiently excite the system.

Cause 1 can be addressed by identifying poorly identifiable parameters via a sensitivity analysis and subsequently fixing their values, e.g. based on data from the literature. Various approaches exist to find poorly identifiable parameters such as orthogonalization methods, the eigenvalue method, and combinatorial methods [2, 3]. **Cause 2** can be addressed by producing training data that covers the necessary excitations of the system needed to identify the model parameters. A Design of Experiment strategy can achieve this in a systematic and efficient way. By using the existing dynamic model, the excitations



(a) Collinearity index: 18.49

(b) Collinearity index: 18.14

Figure 1: (a) 14 state-of-the-art, and (b) 8 optimized temperature trajectories.

of the system needed for unique and robust parameter identification can be determined [4]. The strategy allows for efficient experiment planning, because it reduces the number of required experiments and achieves better or similar estimations of the parameters.

For the considered phase transformation model, experimental measurements with temperature trajectories shown in Figure 1a are the industry standard. They include periods with constant cooling rates and temperature holds. During these experiments, the expansion (dilation) of the material is measured, which allows for back-calculation of the phase evolutions in the material, and thus parameterization of the phase transformation model. Alternatively, by using a Design of Experiment strategy, temperature trajectories can be optimized (Figure 1b) in favor of efficient and robust parameter identification. As indicated in Figure 1, this improves the collinearity index while needing fewer experiments.

In this talk, the topics sensitivity analysis and Design of Experiments will be explored to show how they can improve parameter identification. A demonstration of these concepts will be presented through their application to the phase transformation model.

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