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Use of Nonlinear and Machine Learning Techniques for Improved APC Modeling

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Abstract Text:
Objectives

Model identification for advanced process control (APC) applications including model predictive control (MPC) and soft-sensor (or inferential) is one of the most time-consuming steps which requires dedicated plant tests and the skills of a highly experienced chemical engineering control engineer. The empirical models (such as first-order plus dead time, or FOPDT) need to be validated by judging the model attributes such as the gain value or sign, the dead time, and the shape of the step response based on prior process knowledge [1]. Plant tests must be repeated when the model identification does not match with the prior process knowledge.

To reduce the effort and cost of the model identification, this study proposes a simultaneous model fitting method which incorporates a priori information as constraints of the optimization problem. This approach can be applied to both linear empirical models and non-linear first principles models using the GEKKO optimization suite which specializes in dynamic optimization problems including nonlinear programming (NLP), differential algebraic equations (DAE), and artificial neural networks (ANN) [2].

Case studies and discussions

Two model identification examples are considered in this study. One is developing the inferential model for a soft-sensor in a distillation column. The other is a horizontal tank with a level control loop. Soft sensors play a critical role in estimating product quality (i.e. composition) in a real-time manner, especially in the chemical processing industry. They infer the product quality in the distillation column based on measurable column operating variables, such as tray temperature and pressure. The low frequency and time delay of on-line analyzers and lab sample results are not suitable for the real-time control applications. In the inferential fitting case, the industrial distillation column operation data is used to estimate the model parameters of the inferential model. The model is structured with three different blocks in series: the pressure compensated temperature (PCT) block, the FOPDT block, and the static nonlinearity block. For the nonlinearity block, a piecewise linear (PWL) function and an ANN are used and compared with a real-world result that uses a simple log transformation. Introducing the PWL and ANN as a nonlinear static gain block describes the nonlinearity of the process more accurately in an extended range of operation, which is difficult to achieve with a simple logarithm transformation.

In the tank example, instead of having a chain of model blocks, a nonlinear physics-based model is considered. The model is designed to accurately describe the nonlinear character of a horizontal tank with spherical caps. It has an inlet and an outlet flow with a PID level control loop configured on the outlet flow. The physics-based model consists of material balance equations combined with the tank geometry. The unknown parameters (such as the tank geometry) in the nonlinear model are estimated using the closed-loop operation data with the level controller.

Conclusions

In the inferential model fitting example, we investigate the hybrid approaches including piecewise linear and artificial neural net embedded into the simultaneous model fitting platform. The simultaneous model fitting by specifying constraints in a single optimization running reduces the extra effort to validate the model manually with a priori information and to manually sort out the appropriate segment of the historical operation data for each block. In the tank model example, the physics-based model is used to identify the unknown parameters using the available operation data. The identified physics-based model can then be used as a priori constraint in the simultaneous dynamic estimation problems in an empirical model fitting which is the most common type of advanced process control system. The benefit of this example is to improve the accuracy of the empirical linear model fitting and reduce the amount of time and effort by imposing the nonlinear constraint from the physics-based model as a priori information.

References

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