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NONLINEAR MODEL PREDICTIVE CONTROL

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Abstract

Nonlinear Model Predictive Control (NMPC) has been introduced in commercial applications. Since mid 1996 approximately 50 applications have been commissioned in polymers, chemicals, food, pulp and paper, and oil refining.

This industrial presentation provides a brief overview of the commercial NMPC package and moves quickly to a summary of a specific polymers application that was chosen to demonstrate the different nonlinear models that can be used in a NMPC application.

1. Introduction

The nonlinear features of NMPC are facilitated by neural networks. Inferred property models are obtained by training neural network models on process and lab data [1] These models are implemented on-line to provide feedback for the NMPC controlled variables.

The above is just feedback, however, and does not make the controller any more nonlinear that any other linear MPC with an inferred property as feedback. The true nonlinear structure of NMPC comes from another neural network model. This model is similar to the inferred property model but is usually more parsimonious and is purposely constructed to accurately represent the process sensitivities over the operating range of the controller.

The "control model" sensitivities are passed as gains to the NMPC internal models at each control interval. The otherwise linear difference equation internal models are thus made nonlinear by what some have called "continuous gain scheduling". Actually, since the gain updating also takes place during the manipulated variable move-controlled variable trajectory calculations, a description more fitting would be "predictive gain scheduling" [2].

2. The Models in NMPC

There are two models in NMPC. The first is the normal dynamic model that is implemented in different packages as a parametric difference equation, a non-parametric step response, or a non-parametric impulse response. The NMPC discussed here uses parametric difference equation models.

The second model is what makes NMPC nonlinear. It is a map of the process steady-state controlled variables surface in the space of the NMPC manipulated and disturbance variables. The NMPC discussed here uses neural networks to generate this map, usually from plant data. Since a neural network can be very efficiently trained on data from an equation-based model, sometimes a NMPC application uses a copy of a physical model instead of a model trained on plant data [3]. The application presented in Section 5 uses a hybrid model, i.e., a model trained on a combination of plant data and data generated from equations.

The second model is also used in the pre-control-move calculation optimization step, that is solved in this case by a nonlinear optimization algorithm. This is in contrast to the standard MPC optimization step which uses the static gains of the dynamic model as the basis for optimization decisions.

3. Field Installations

There are currently about 50 applications of this NMPC in the field. These include applications in polymers, chemicals, food, pulp and paper, and oil refining. Applications are listed by industry in the survey paper by Qin and Badgewell [4]. The majority of the applications of the NMPC package discussed here have been in polymers.

4. Polymers Applications

NMPC is particularly beneficial in process applications where grade changes are made. A polymers line, for example, can manufacture a dozen grades or more, and the difference between grades can be large in terms of the process sensitivities. In polypropylene it is not unusual to see gain change by a factor of fifteen between grades. A linear (fixed-gain) MPC application in this case must be drastically de-tuned. The result is good performance for the hi-gain grade, and sluggish performance for the low-gain grade. So sluggish, in fact, that the linear MPC application does not meet performance requirements for disturbance rejection and grade transition times.

Grade transitions also provide excellent data for training neural network models. The two models discussed in Section 2 are often quite accurate in polymers applications. This is in part due to the extensive data made available by a history of frequent, and significant, grade changes.

5. Polypropylene Example

This example documents one of the early applications of NMPC in the polymers industry: a Spheripol design polypropylene loop reactor at OPP Petroquimica's plant in Triunfo, Brazil. This application was chosen as an example for several reasons:

- The inferrred property model and the steady-state map model are the same model.
- The inferred properties are predicted very accurately by the model.
- The steady-state model is a hybrid model, trained on field data and data from equations.
- The process is highly nonlinear.
- The client has previously given permission to publish these results [5].
- This project has a very high return on investment.

The application is a 3 input – 3 output NMPC controller/optimizer with neural network inferred properties for the controlled variables. Trend plots that demonstrate grade change control performance are presented for:

- linear MPC, i.e., with the nonlinear capability of the NMPC package turned off – Figure 1.
- NMPC without optimization – Figure 2.
- NMPC with nonlinear optimization – Figure 3.

NMPC decreases transition time by a factor of four over linear MPC. NMPC with optimization further decreases transition time about 35% over NMPC alone. There are several paths which can be used to complete a transition; the NMPC optimizer selects the "right" path based on economics, not purely on the controlled variable predictions.

This NMPC application has been in closed-loop since mid 1996. Polymer grade transition time has been reduced by two thirds. Production rate has been increased dramatically. This unit currently holds the world record for Spheripol unit production.

5. References

1. Martin, G. "Soft Sensors", presented at the ISA/96 Conference, Chicago, Illinois, October 7-10, 1996, included in *Advances in Instrumentation and Control*, Vol 51, Part 1, pp. 245-257.

2. Martin, G. D., Boe, E., Piche, S., Keeler, J. D., Timmer, D., Gerules, M, and J. P. Havener, "Method and Apparatus for Modeling Dynamic and Steady-State Processes for Prediction, Control, and Optimization. Patent allowed but not issued yet.

3. Thompson, W., Martin, G., and N. Bhat, "How Neural Network Modeling Methods Complement Those of Physical Modeling", presented at the 1996 NPRA Computer Conference, Atlanta, Georgia, November 11-13, 1996.

4. Qin, S. J., And Badgewell, T. A., "An Overview of Nonlinear Model Predictive Control Applications", presented at the NMPC Workshop in Ascona, Switzerland, June, 1998.

5. Demoro, E., Axelrud, C., Johnson, D., and G. Martin, "Neural Network Modeling and Control of Polypropylene Process", presented at the Society of Plastics Engineers Conference, Houston, Texas, February 24, 25, 1997.

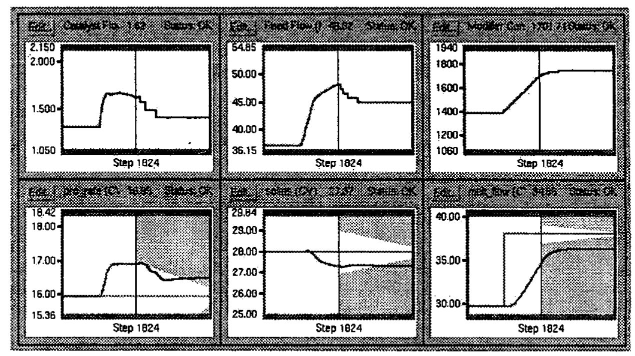

Figure 1. Linear MPC, Step Change in Melt Flow Setpoint.

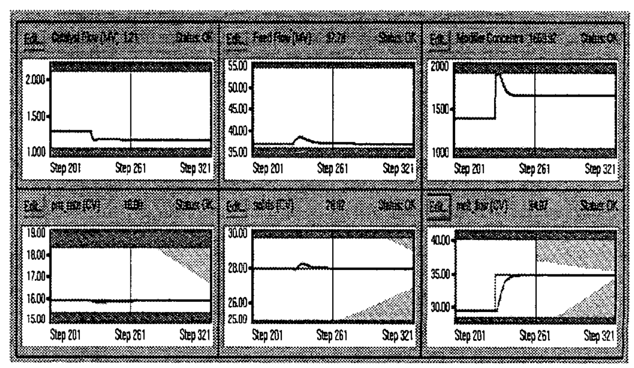

Figure 2. NMPC, Step Change in Melt Flow Setpoint.

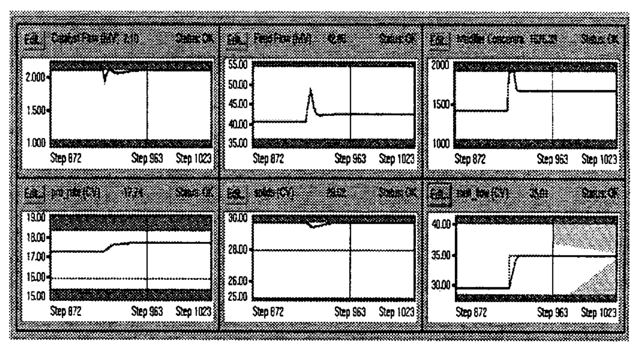

Figure 3. NMPC With Optimization, Step Change in Melt Flow Setpoint.