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Practice Article

Demonstration of leapfrogging for implementing nonlinear model predictive control on a heat exchanger

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ABSTRACT

This work reveals the applicability of a relatively new optimization technique, Leapfrogging, for both nonlinear regression modeling and a methodology for nonlinear model-predictive control. Both are relatively simple, yet effective. The application on a nonlinear, pilot-scale, shell-and-tube heat exchanger reveals practicability of the techniques.

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1. Introduction

Model Predictive Control is well established and accepted within the process industries [1]. Further, it has been demonstrated that nonlinear models provide control advantages when the process is nonlinear, and when the model-based controller appropriately compensates for changes in process gain and dynamics that arise with changes in operating conditions [2–5]. Such studies reveal that once tuned, controllers with nonlinear models remain tuned throughout the entire operating range. Further, they indicate that the modeling environment (neural network, fuzzy logic, gain scheduling linear models, first-principles, etc.) is irrelevant to the control benefits. Although modeling approach is irrelevant to control, the choice of a first-principles nonlinear model preserves process knowledge; and, once developed for control, the nonlinear models provide additional benefits in optimization, constraint forecasting, design, and diagnosis. This work continues the investigation and demonstration record toward the practicability of using first-principles modeling for model predictive control.

The literature also indicates that computational issues associated with the horizon-predictive optimizer limit the application of nonlinear models, especially when implemented in standard control devices [6]. Accordingly, MPC models are usually linear, and often solved with optimizers that seek on-constraint (exterior) solutions. By contrast, this work reveals that Leapfrogging as a nonlinear, constraint-handling, global optimization technique is efficient enough to be implemented in conventional devices; and can find an interior optimum. This application provides a credible implementation in pilot-scale equipment, and a methodology that can guide others to implement nonlinear, horizon-predictive, constraint-handling control using an engineer's process models.

This work uses the ISA nomenclature for MV and CV. The manipulated variable (MV) is the output of the controller, the signal to the process. The controlled variable (CV) is the process variable desired to be kept at a set point (SP). In model predictive control (MPC) the controller employs an optimizer to find the sequence of present and future MV actions that best shape the model-predicted (time-forecast) CV trend.

1.1. Leapfrogging

Leapfrogging is a recently developed population-based direct-search optimization technique based on a set of heuristic rules [7–9]. This optimization technique is initiated by computing the objective function (OF) value at random spots within the feasible decision variable (DV) space. The random points are called the players (alternate

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conventions might refer to trial solutions as particles or individuals). The worst player (when seeking a minimum, the worst has the highest OF value) leaps over the best player (with the lowest OF value) to a random location within the reflection of the DV hyper-volume connecting the worst and the best player. The leap-over might determine a new best, or might not. The process of leaping worst over best continues until all the players converge at a point, the optimal solution.

Leapfrogging has been revealed as having distinct advantages over several other optimization techniques, and also has been demonstrated on several applications [7,10–12]. In order to establish credibility and applicability of the Leapfrogging optimization technique to an advanced process control environment, this work focuses on demonstrating its application in implementing nonlinear regression modeling and nonlinear model predictive control (NMPC) on a pilot-scale heat exchanger (HX).

1.2. Nonlinear regression modeling

Developing a dynamic model of the process is a first step for the implementation of MPC. The model is regarded as the proxy for the process, and is used to forecast the future behavior of the process. In this application the process is nonlinear, and the model will be developed from first-principles. However, exact values of the model coefficients cannot be known *a priori*, so nonlinear regression will be used to adjust nonlinear model coefficient values to make the dynamic model best match process response.

Nonlinear regression is an optimization that seeks to make the model best match the process. In this case the optimizer decision variables (DVs) are the model coefficient values, and the objective is to minimize the sum of squared deviations between model and actual:

$$\min_{\{p_1,p_2,p_3,p_4\}} \sum (\mathrm{CV}_{p,i}-\mathrm{CV}_{m,i})^2 \tag{1}$$

where CV represents the process controlled variable, the subscripts m and p indicate model and process, i is the data index, and p_1–p_4 represent the model coefficients.

1.3. Model predictive control

Model predictive control (MPC), alternately termed horizon predictive control or advanced process control was independently developed by several groups in the 1970s and is associated with several landmark publications [13,14]. Since then, many variations have arisen in the search for a full-featured, simple, robust controller. The objective of MPC chosen for this work is to predict the sequence of future control actions (MV moves) that should be implemented to make the process reach the set point, along a desired path, avoiding constraints. The desired path is often termed the reference trajectory. At each sampling, MPC chooses a set of possible future MV values and uses a dynamic model of the process to forecast the CV values over a future time horizon. It iteratively improves (optimizes) the MV sequence to find the set that best leads the CV in the proximity of the reference trajectory, avoiding constraints. Once an MV sequence has been optimized, only the first step is implemented. At the next sampling, the entire procedure is reevaluated.

In optimization the set of MV moves is termed the trial solution (TS), and an individual MV would be a decision variable (DV). The "cost" to be minimized (deviations from the model-forecast CV from the reference trajectory, and penalties for state variable violations) is termed the objective function (OF).

Since the model is not exactly the same as the process, there is a process model mismatch (pmm) (often termed the residual) between the process response and the model values. In this MPC application the pmm is used to bias the set point of the process to provide a biased SP for the model. The reference trajectory is a transient path from the current modeled value to the biased set point. The controller aims at moving the model towards the biased SP, which in turn means that the process will be moved towards the SP.

Basically, the objective function for the optimization technique is represented in Eq. (2).

$$\min_{\{\mathrm{MV}_1,\mathrm{MV}_2,\mathrm{MV}_3\}} \sum_{t=1}^{H} (r_t-\mathrm{CV}_{m,t})^2 \tag{2}$$

The optimizer seeks to minimize the sum of squared deviations between the reference trajectory and model forecast across a future horizon. Here the subscript t represents the integer count for future time intervals. In this work at every sampling time, the optimizer computes three future MV moves, the decision variables that would make the process move towards the SP, after which, only the first MV value is implemented. As will be developed, the OF will include penalties for constraint violations.

2. Methodology

2.1. Experimental

A heat exchanger (HX) network in the Unit Operations Laboratory (UOL) at Oklahoma State University is used for this study. The HX is a 4-pass shell-and-tube HX of 1 meter long and 0.2 m diameter. It is one of the five heat exchanger units in a pilot scale network shown in Fig. 1.

For this study, the shell-side fluid is steam which condenses, transferring heat to the tube-side fluid water. The outlet water temperature is considered as the CV for this study and the controller signal to the steam valve is considered as the MV. The CV is measured in a thermowell about one meter downstream of the HX tube fluid exit. Piping is either 3/4 or 1 in. in diameter. Orifice flow meters and thermocouple transducers transmit 4–20 mA signals to a National Instruments Compact Field Point data acquisition and control system (DACS). The controller is implemented in LabView, compiled in a standard personal computer, downloaded to the DACS for local execution, which eventually sends signals to devices that operate the air-actuated modified-equal-percentage flow control valves.

2.2. HX modeling

A first-principles process model is first developed. Assuming that there are no ambient loses, a simple steady state energy

Fig. 1. HX Network.

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