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Continuous-Time Block-Oriented Adaptive on-Line Modeling for Time Varying Systems

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Abstract
The development and maintenance of accurate predictive models for dynamic systems are highly challenged by system complexity, limited information (i.e., data), changing cross and time correlation structures and changing model parameters. Thus, for a model or modeling method to achieve long term success in implementation into a real system, it must be phenomenologically sound and adaptive, as well as being capable of immediate update from recently obtained process data (i.e., plant data). A model is phenomenologically sound when its structure accurately captures physical input and output relationships, and the stochastic behavior of process and measurement noise. On-line adaptive methods are critical to success because process variations that cause changes to noise correlation structures and model coefficients are frequent in real systems. A common occurrence in non-adaptive, off-line, model identification is the requirement of a new model by the time the model is ready for implementation due to significant process variations. For a method to have on-line adaptive abilities, it must be capable of using process data (which have a low signal to noise ratio, and limited range over the operating space) to update its fitting performance.

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Comments
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The development and maintenance of accurate predictive models for dynamic systems are highly challenged by system complexity, limited information (i.e., data), changing cross and time correlation structures and changing model parameters. Thus, for a model or modeling method to achieve long term success in implementation into a real system, it must be phenomenologically sound and adaptive, as well as being capable of immediate update from recently obtained process data (i.e., plant data). A model is phenomenologically sound when its structure accurately captures physical input and output relationships, and the stochastic behavior of process and measurement noise. On-line adaptive methods are critical to success because process variations that cause changes to noise correlation structures and model coefficients are frequent in real systems. A common occurrence in non-adaptive, off-line, model identification is the requirement of a new model by the time the model is ready for implementation due to significant process variations. For a method to have on-line adaptive abilities, it must be capable of using process data (which have a low signal to noise ratio, and limited range over the operating space) to update its fitting performance.

Most approaches in the systems engineering literature are discrete-time (DT) methods that take a state space approach. Model building typically estimates exogenous (physical) structure, stochastic structure, and model coefficients simultaneously under some optimization criterion, such as minimum SSE. However, the approach of this work is a continuous-time (CT), closed form one, which separately builds and updates exogenous and stochastic model structures using expert knowledge off-line (a human) and on-line (an algorithm). A critical advantage of a CT approach over a DT approach is that it is able to make effective and immediate use of data that are taken infrequently and at different sampling times. This may not be a critical advantage, say in a chemical process, where all variables are sampled often and at the same time, but it can be in an application like blood glucose modeling when inputs such as food intake occur infrequently and out of sequence with glucose measurements. Our block-oriented, gray box approach determines all model structures off-line in separate stages using, preferably, statistically designed data [1, 2], but can also use plant data [3] for this step. This step also produces estimates of all model coefficients based on the process conditions contained in the off-line data set. Note that, we obtain the stochastic model structure using results from autocorrelation and partial autocorrelation analysis. In the on-line mode, model accuracy is tested frequently, and the model is updated using a knowledge driven algorithm and recent plant data.

This talk will present results from two studies. In the first study, a real distillation process, a series of daily tests will be run, where the model from the previous day is no longer valid at the start of the day due to a change in an unmeasured disturbance variable (such as feed composition). During the first part of each day, data will be collected under limited changes in input variables and used to automatically update the model. The output data in the second part of the day will be compared predicted values from the updated model. We will evaluate both simulation predictions from the model and one-step-ahead (OSA) predictions.

The second study will involve modeling the state variables blood glucose and insulin in men and women and comparing the results with those in [4]. The study in [4] involved using a coupled prediction model. Thus, we will evaluate our ability to extend block-oriented modeling to multiple-input and multiple-out (MIMO) systems with couple state variables. We have developed a block-oriented, decomposed, multiple-input, single-output (MISO) method [1, 2, 5] but we have not found a true MIMO Hammerstein or Wiener method in the literature. Since chemical processes are often coupled, this approach will be useful when coupled, block-oriented modeling can lead to significant improvements in accuracy.

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