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Using uncertain prior knowledge to improve identified nonlinear dynamic models

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ABSTRACT

This paper addresses the parameter-estimation problem for linear-in-the-parameter nonlinear models for the case in which uncertain prior knowledge is available in the form of noisy steady-state data. An *uncertainty-weighted least-squares* (UWLS) algorithm is developed which takes into account not only the dynamical and the steady-state data but also a measure of relative uncertainty of both data sets. Also, it is shown that a previously developed bi-objective optimization estimator is a special case of UWLS. A consequence of this is that UWLS can take advantage of tools developed in the context of multiobjective optimization to automatically determine an adequate relative uncertainty measure for dynamical and steady-state data sets. The developed algorithm and related ideas are investigated and illustrated by means of examples that use simulated and measured data.

1. Introduction

Black-box identification stands for a set of techniques which aim at building dynamical models from dynamical data without resorting to any other source of information besides the data [17]. This type of modeling came as an alternative to describing the process based on first principles. A commonly used midway solution is to take the model structure from a first-principles model and to estimate parameters from a set of dynamical data using statistical estimators. This procedure is referred to as semiphysical modeling [16] and is one of the many methods that compose the universe of gray-box modeling techniques.

In gray-box modeling it is generally assumed that, in addition to the set of dynamical data, there exists some additional information about the system. Then, the challenge is to take into account such information *in addition* to the dynamical data in building the final model. In semiphysical techniques the auxiliary information is the model structure and the remainder of the model (the parameters) are obtained from the identification data. The term *a priori* information is often used in this context of Bayesian techniques when usually such information comes in the form of a probability density function (PDF) of the noise, for instance [21]. In this paper the *a priori* information is relaxed to be another set data, which is assumed to be steady-state data. Such data convey information about the process static function, and it is generally referred to as auxiliary information [10].

The static nonlinearity or some aspects of it, e.g. monotonicity, is often used as auxiliary information. The need for models with good performance in both steady-state and transient regimes is acknowledged by various authors [10,13] in that models with such feature can be used, for instance, in control problems [5]. It is often necessary to take additional steps in order to guarantee that the identified model has acceptable steady-state performance [13]. *This is especially true in the cases where the steady-state information is not well represented in the dynamical test data.* Nevertheless, very few methods are able to impose a given (*a priori*) static nonlinearity function onto a dynamical model. To be able to do this, the model must be nonlinear and how to code a given static function into a dynamical model must be known. For nonlinear discrete-time polynomial models, this is described in [3].

Gray-box identification is only a reasonable option when black-box techniques failed *for lack of information in the (dynamical) identification data set*. The best scenario is achieved whenever all the desired information about the process is clearly present in the training data set. Whenever this fails, *then* gray-box methods can be tried. In such methods the lack of information in the dynamical data is balanced by the use of auxiliary information which “must find a way into the model”. Therefore, there is an important assumption made, very often implicitly, in gray-box techniques, namely, that the auxiliary information is precisely known. As pointed out by Johansen: “If the prior knowledge is correct, this will in general lead

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