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A class of Monotone Fuzzy rule-based Wiener systems with an application to Li-ion battery modelling

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ABSTRACT

A class of Fuzzy rule-based Monotone Wiener Models (FMWMs) is introduced. These are transformation models comprising a linear dynamical block and a memoryless nonlinearity. The smoothest dynamical block that has an output which is comonotonic with the training data is sought. The dependence between the output of the linear block and the output of the system is described via a set of fuzzy rules.

This paper considers systems with a sensitive dependence on the initial conditions and also with a moderate amount of uncertainty in the initial state. A new learning algorithm is proposed that makes use of recent statistical tests for assessing the comonotonicity of imprecisely perceived sequences of data.

The main aim of the proposed models is to estimate different health parameters of rechargeable batteries for automotive use. For this practical application, FMWMs are shown to improve a selection of models with a varying degree of embedded domain knowledge, ranging from first-principles models to universal approximators.

1. Introduction

The reliability of the electric vehicles depends critically on the design and management of battery packs (Garg et al., 2017). Unfortunately, accurate on-vehicle assessments of the health of Li-ion batteries would require of specialized laboratory equipment that is not compatible with the intended use of these vehicles (Gordon et al., 2017). Nevertheless, approximate electrochemical, intelligent, electrical and mathematical models exist that can be used on-board (Chaoui et al., 2017).

Electrochemical models are arguably the most precise, but depend on parameters that are either not provided by the manufacturer or change from battery to battery (Zhang et al., 2017). In contrast, intelligent and mathematical models and equivalent circuits do not suffer from this limitation because they do not attempt to model the electrochemical processes taking place in the electrodes. Their purpose is rather to predict the observable outputs of the battery (current, voltage and temperature). The ambiguities in a model arising from the presence of unobservable variables (state of charge, state of health) are mitigated by injecting prior knowledge about the problem domain and combining it with the knowledge that is revealed in the data. This domain knowledge can be explicit, taking the form of constraints on the values of the learned parameters, or be implicitly built into the structure of the model, as occurs, for instance, with grey boxes and semi-physical models (Lindskog and Ljung, 1995).

A balance must exist between those elements of the dynamic behaviour of the system that are taken for granted and those that are learned from data, as embodying domain knowledge in the learning task reduces the degree of uncertainty in the model while, at the same time, raising the degree of systematic error (Barlow, 2017). Thus, the first challenge for the problem being addressed in this paper is to ascertain the minimum amount of knowledge to be injected in the model. On the one hand, if too many assumptions are made, some of them will not hold and the systematic error will increase. On the other, if the dynamics of the model are left unrestricted, the amount of data that is needed to fit the model parameters will grow exponentially. In this paper it is proposed that the only knowledge embedded in the battery model consists in enforcing the monotonicity of certain nonlinear blocks in the transference function of the model. The rationale behind this premise arises from the observation that the voltage of a resting battery and its charge are also comonotonic. It has been stated that the most widely studied monotonic dynamical models are monotone Hammerstein or Wiener models, which consist in a composition of a linear system with a memoryless nonlinear monotone function (Schetzen, 2010). For instance, any digitally sampled system can be regarded as the composition of a continuous system and a staircase function. Saturations, dead zones, backlashes and different kinds of hysteresis also match this kind of

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prior information: monotonic dynamic models have a wide range of applicability.

To the best of our knowledge, all data-driven battery models to date have been learned through prediction error methods (PEMs) (Ungurean et al., 2017). PEMs depend on a parametric definition of the model; while the learning task consists in finding the values of the free parameters in the model that minimize the prediction error, given a training dataset comprising two temporal sequences: inputs to the system and measured outputs (Ljung, 2002). In contrast, Monotone Wiener (MW) models can be learned through transformation models (Belle et al., 2011) such as MINLIP (Pelckmans, 2011), which are less restrictive than PEMs in the parametric definition of the model. MINLIP does not aim to minimize the prediction error, but redefines the identification as the search for the simplest model that approximately interpolates the measured outputs. This search is performed in two stages: (i) a smooth dynamic linear model is found whose predictions are comonotonic with the observed outputs, without taking into account the prediction error, and (ii) a memoryless nonlinear mapping is defined from the predictions of the linear part to the output of the system. This last nonlinear mapping is a by-product of the learning and does not depend on a prior parametric definition. For this reason, MINLIP is potentially resilient to the epistemic uncertainty mentioned previously.

It will be shown in this paper that transformation models are meaningful for this research topic because the nonlinear mapping in the MW model carries information about the battery's health that may be more accurate than state-of-the-art approaches to this problem (Abu-Sharkh and Doerffel, 2004; Xu et al., 2014). However, it is not possible to apply the MINLIP algorithm to battery models, because these do not have a Finite Impulse Response (FIR) (Ljung, 1998) and the MINLIP algorithm depends on this property. The second challenge of this research study is to extend MINLIP to non-FIR data. Furthermore, a linguistic description of the nonlinearity is convenient for this problem, as the state of health can be retrieved from this description. Accordingly, this paper also aims to introduce a linguistically understandable definition of the nonlinearity through a new category of models that will be called Fuzzy rule-based Monotone Wiener Models (FMWM) in what follows.

Finally, it should be noted that algorithms for learning monotone dynamical models are related to other machine learning problems different from system identification. Isotonic regression or classification is a well known problem (Ben-David, 1995; Gutiérrez and Garcia, 2016) and soft computing-based techniques exist that search for a set of linguistic rules that obey monotonicity assumptions (Fernández et al., 2015). To the extent of our knowledge, however, the isotonic assumption has not yet been fully developed for fuzzy Wiener or Hammerstein models (Abonyi et al., 2000).

This paper is organized as follows. Section 2 reviews monotone Wiener models and the MINLIP algorithm. Section 3 introduces FMWMs and an extension of the MINLIP algorithm for non-FIR systems. Numerical results are discussed in Section 4: an illustrative example is worked first, followed by the description of a practical application in which the state of health of a battery is measured using the proposed algorithm. The results thus obtained are compared with those of a selection of algorithms. The conclusions of the paper are presented in Section 5.

2. Monotone Wiener models and the MINLIP algorithm

As already stated, Wiener models are block-oriented models in which a linear dynamical subsystem is followed by a static nonlinear function. Formally, a Wiener model (f,θ) comprises a linear dynamical model defined by the parameter θ, applied to an input variable $\{u_t\}_t$, $u_t \in \mathbb{R}^m$, and a nonlinear function $f : \mathbb{R} \to \mathbb{R}$ applied to the output of the linear model. The static nonlinearity $f(\cdot)$ has variously been represented by polynomials (Bai, 2002), piecewise linear maps (Wigren, 1993), splines (Zhu, 2002), neural networks (Al-Duwaish et al., 1996), support vector machines (Goethals et al., 2005), local linear models (Kozek and Sinanović, 2008), and kernel regression (Greblicki, 1992). Fuzzy Wiener Models (FWMs) make use of a Fuzzy Rule-Based System (FRBS) to model the function f (Abonyi et al., 2000; Tang and Li, 2013).

Let the output of the linear subsystem be $\{z_t\}_t$, $z_t \in \mathbb{R}$. Thus, the output of the Wiener model is the sequence $\{\hat{y}_t\}_t$, where $\hat{y}_t(f,\theta) = f(z_t)$. This sequence depends on the input sequence $\{u_t\}_t$, the parameter θ and the nonlinear function f. In the particular case of the system being FIR, there is a value d such that $\{\hat{y}_t\}_{t>d}$ is independent of the initial conditions of the system. This point is emphasized, as it will be subsequently shown later that this hypothesis does not hold for the problems addressed in this paper.

Given a pair of sequences $\{y_t\}_t$ and $\{u_t\}_t$, the purpose of the learning algorithm for FIR systems is to find the value of θ and the function f for which the sequence $\{\hat{y}_t\}_t$ best approximates the true output of the system $\{y_t\}_t$. PEMs aim to minimize the following risk:

$$\mathrm{risk}(f,\theta) = \sum_{t=d}^{T} (\hat{y}_t(f,\theta) - y_t)^2. \tag{1}$$

As f is monotone, a constraint is added. Thus, learning a model consists in solving the following optimization problem:

$$\begin{aligned} &\min \mathrm{risk}(f,\theta) \\ &\text{s.t. } x \le y \text{ implies } f(x) \le f(y). \end{aligned} \tag{2}$$

The MINLIP algorithm (Belle et al., 2011; Pelckmans, 2011) is a recent alternative to constrained PEMs in which the purpose of the learning is redefined so as to find the simplest function that interpolates the data. The noiseless problem can be formulated as follows:

$$\begin{aligned} &\min \mathrm{complexity}(f) \\ &\text{s.t. } \hat{y}_t(f,\theta) = y_t, \quad \text{for all } t = d+1,\dots,T. \end{aligned} \tag{3}$$

The set of assumptions on which this algorithm depends and the definition of this algorithm when the data is noisy are described in Appendix A.

3. Extended MINLIP for MISO and non-FIR systems

It is safe for damped systems to assume independence between the output of the system and its initial conditions, as wrong estimations of the initial state influence only the initial predictions $t = 1 \dots d$, and these periods have been ignored in the definition of the previously seen optimization problems (see Eq. (3)).

However, this assumption is problematic for lightly damped systems (Juang, 1994). For instance, batteries, which have prompted this study, have a strong dependence on their initial conditions. When a battery is being discharged, neither the initial value of the state variables (e.g. the charge of the battery) nor the influence of the inputs (e.g. charging current) can be neglected at any point in the future. Although strictly speaking battery models are stable, d is larger than the simulation horizon; thus inaccurate measurements of the initial state invalidate the predictions of the model. Dropping the FIR assumption requires introducing a full state-space model in the MINLIP framework. Details of the proposed definition of a State-Space Wiener Model (SSWM) are given in Section 3.1.

Note that this formulation is also valid for Multiple Input, Single Output (MISO) FIR systems, as explained in the following subsections. However, non-FIR systems or non MISO FIR systems are not addressed by this method. An extended algorithm is proposed in the following subsection that solves those cases where the aforementioned conditions are not met.

3.1. State space Wiener models

Let a linear subsystem be defined by the following state-space equations:

$$x_{t+1} = Ax_t + Bu_t \tag{4}$$

$$z_t = Cx_t + Du_t \tag{5}$$