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Time domain identification of a simplified model of So–Nick BESS: A methodology validated with field experiments

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ABSTRACT

The aim of this paper is to derive an accurate input/output dynamic equivalent model of a So–Nick Battery Energy Storage System (BESS). For this purpose, an on-line identification methodology has been applied. By this methodology, unknown model parameters are identified in the continuous time domain by solving an optimization problem aimed at minimizing the error between output trajectories of the physical system and its dynamic equivalent model. The methodology is based on the Sensitivity theory involving the Lyapunov function, ensuring the stability of the algorithm.

Experimental results are used to validate the proposed approach by adopting the Sodium–Nickel Battery Energy Storage System (BESS) embedded into the experimental Prince Lab of the Polytechnic University of Bari, Italy.

1. Introduction

Battery Energy Storage Systems (BESSs) are attracting growing attention as a viable solution to the increasing penetration of Distributed Generators (DGs) and, more properly, of non-programmable Renewable Energy Sources (RESs). In fact, thanks to their fast response time and their control flexibility, BESSs are capable to balance short-term power fluctuations of non-programmable RESs circumventing thus the problems associated with the inherent intermittence of such resources [1]. At the same time, the energy storage can contribute to alleviate grid congestions caused by a high share of DGs. Due to the potential benefits offered by BESSs, there is a continued interest in providing incentives and other economic support for increasing the adoption of such systems [2]. As result, many types of BESSs have been installed into distribution networks or are in the planning stage. Anyway, the issue on how to control such devices in order to maximize advantages deriving from their adoption is still pending, even if a lot of approaches have been developed during the last years [3–7]. In particular, in Ref. [4] a predictive control has been suggested for optimizing resources of residential prosumers in a demand response framework. In Ref. [5] a recurrent neural network control strategy has been developed. In Ref. [7] the authors developed an optimal management strategy for the hot-temperature sodium nickel chloride battery system. The optimal control actions are evaluated by adopting a discrete-time model for the given BESS technology.

Although, these control strategies have proven to be effective for the optimal BESS management, they are highly sensitive to both steady-state and dynamic behavior of the BESS which, in turn, are greatly dependent on several factors such as the size and location of the BESS, the type of the adopted battery, the working temperature, the state of charge, and the charge and discharge rates.

In order to obtain stable performances under several operating conditions, both steady-state and dynamic behavior of BESSs need to be investigated. Such studies are usually made through static and dynamic simulations performed by means of mathematical simulation models implemented into commercially available software tools. Therefore, the correctness of results obtainable with these simulations strongly depends on the adopted BESS model. For this reason, several types of models with different degree of complexity have been recently developed.

The technical literature extensively investigated on the battery model, ignoring the effects of interfacing converters on performances of the overall BESSs. In this sense, full order models able to keep all possible battery dynamics in every operating condition have been derived [8–10]. In these works, experimental investigations have been adopted to derive the dynamic models of the batteries. In particular, referred papers adopt dynamic battery responses following to current pulses under several operating conditions in terms of battery temperature and state of charge (SOC). Anyway, resulting tests can be numerous thus, papers [11–13] developed methods based on electric

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circuit models ignoring thermal and chemical effects. If more accurate estimations are required, detailed battery models should be adopted. In this sense, the simultaneous estimation of the SOC and electric parameters can be done by adopting a temperature-based model combined to an Unscented Kalman Filter (UKF) [14,15], or an adaptive UKF [16], or an extended Kalman Filter (EKF) [17,18].

However, the computational effort required by the identification problem can be reduced by decoupling slow and fast dynamics in the time domain as suggested in Refs. [19,20]. If a high accuracy level is required, models need to be more sophisticated, as in Refs. [21,22]. An alternative approach in deriving fruitful battery models has been provided by data-driven methods. The basic idea is to derive a simple empirical model able to correlate the battery inputs with the outputs by adopting nonparametric approaches such as Recursive Last Squares (RLS) [23], Adaptive Genetic Algorithm (AGA) [24], and dynamic Markov machine model [25]. However, as outlined in Ref. [26] the accuracy of these methods is largely dependent on the amount and quality of training data available. For this reason, many researchers focused on reduced order models whose parameters are continuously updated as the system operating conditions change, giving rise to on-line auto adaptive parameter identification algorithms. They are based on the Extended Kalman Filter [27], the Least-Squares (LS) [28], the Recursive Least-Squares (RLS) [29–31], the, Genetic Algorithm (GA) [32], and the Lyapunov direct method [33,34].

Anyway, if dynamic studies of AC networks embedding BESSs must be performed, these battery models must be integrated with those of AC/DC interfacing converters, as in the case of the papers [35,36]. Derived high order models would be fruitfully adopted for small signal stability analysis in microgrids embedding fast-acting power electronic converters as in Ref. [37]. In Refs. [38,39] an incremental BESS model for load frequency control has been developed. In order to enhance the performances of these models, in Ref. [40] an incremental BESS model operating at constant power has been suggested.

Although these models can achieve good performances, their application is limited to the specific BESS technology and conditions for which they have been developed. To overcome this issue, a generalized energy storage system model has been proposed in Ref. [41]. It is mainly adopted for voltage and angle stability analysis even if, as shown in Ref. [42], it can be also coupled with a wide range of control strategies.

Even if attractive for their accuracy, these models seem to be very expensive from a computational point of view, giving rise to unpractical real-time controllers. To overcome this problem, it may be advisable to adopt reduced order models of BESSs. These models are usually obtained by neglecting dynamics that do not significantly affect the dynamic phenomenon of interest [43–45]. However, these methods require a thorough knowledge of physical laws characterizing all BESS dynamics like full order models. In addition, the resulting simplified model cannot be generalized to other BESS dynamics. This occurs because the derived reduced order model is rigidly bounded to the initial assumptions made to handle only selected dynamics. For these reasons, it is advisable to consider input–output models that usually treat the physical system to be modeled as a gray-box model. In the attempt to exploit this unexplored methodology on BESSs, in this paper a simplified model which is flexible enough to capture all dynamic features of a BESS has been derived. In particular, this paper has been focused on the Sodium–Nickel Chloride batteries since they have not received sufficient attention from the scientific community over the last decade. In order to take advantages in terms of the computational burden in treating low order models in stability studies, parameters to be identified refer to a second-order dynamic equivalent model. As in classical input–output model identification, the derived model is not supported by physical laws and thus, it could not have physical meaningful and correspondence with the physical system. Model parameters must be adjusted so that the assumed second-order model reflects the same dynamic behavior of the given system following the same input.

The identification problem can be treated as an optimization problem aimed at minimizing the error between output trajectories of the BESS and its dynamic equivalent model. In this paper, the solution of this problem is evaluated by adopting a non-linear parameter identification process involving the Sensitivity theory applied to the Lyapunov method. The application of this methodology ensures an always stable algorithm that can be applied in the continuous time domain.

Experimental results are used to validate the proposed approach by adopting the Sodium–Nickel Battery Energy Storage System (BESS) embedded into the experimental Prince Lab microgrid at the Polytechnic University of Bari, Italy.

2. Mathematical formulations of the on-line parameter estimation method

The aim of this section is to develop a methodology for the on-line parameter identification of a simplified model of a generic dynamic system by means of input/output measurements. The essential idea is to excite the physical system and its simplified model with the same input, and to compare their corresponding outputs. As first step, the methodology requires the definition of an adequate order of the model able to give a “good” fit of the system output. In this sense, the model order will be chosen as compromise between the accuracy and the derived computational effort. Once the appropriate model has been selected, the on-line identification process takes place, updating model parameters until steady state values are reached. Note that, the adoption of a dynamic equivalent model instead of the full dimensional system will produce a structural fitting error that will be recovered by time-varying parameters. In particular, after a first transient characterized by large oscillations, parameters will reach steady-state values fluctuating around an average value, which will be taken as “true” values.

The identification of unknown parameters adopted in this paper, is based on the Lyapunov method involving the Sensitivity theory [46].

Let the given system be represented by the following differential equation:

$$y^n(t) + \alpha_{n-1}y^{n-1}(t) + \ldots + \alpha_0 y(t) = \beta_m u^m(t) + \ldots + \beta_0 u(t) \tag{1}$$

where n and m are positive-integer constants representing the order of the plant, such that $n > m$; $u(t)$ and $y(t)$ are, respectively, input and output trajectories in the time domain; α_i (for $i = 0, \ldots, n-1$) and β_j (for $j = 0, \ldots, m$) are time-constant parameters of the dynamic system.

It is assumed to approximate the dynamic behavior of the system under investigation (1) with the following dynamic equivalent model:

$$\hat{y}^h(t) + \hat{a}_{h-1}(t)\hat{y}^{h-1}(t) + \ldots + \hat{a}_0(t)\hat{y}(t) = \hat{b}_p(t)u^p(t) + \ldots + \hat{b}_0(t)u(t) \tag{2}$$

where h is the order of the assumed fitting model, such that $h \le n$ and $h > p$.

Let define the $[h + (p + 1)]$-dimensional vector of unknown parameters as:

$$\hat{\boldsymbol{\Phi}}(t) = [\hat{a}_{h-1}(t)\hat{a}_{h-2}(t)\ldots\hat{a}_0(t)\hat{b}_p(t)\ldots\hat{b}_0(t)]^T \tag{3}$$

Define the h-dimensional fitting error vector $\boldsymbol{e}(t)$ as:

$$\boldsymbol{e}(t, \hat{\boldsymbol{\Phi}}(t)) = [\,y - \hat{y} \quad y^{(1)} - \hat{y}^{(1)} \quad y^{(2)} - \hat{y}^{(2)} \quad \ldots \quad y^{(h-1)} - \hat{y}^{(h-1)}\,]^T \tag{4}$$

The aim of the identification procedure is to adjust the set of unknown parameters such that the fitting error vector is null or with a