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Nonlinear autoregressive neural network in an energy management strategy for battery/ultra-capacitor hybrid electrical vehicles

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ABSTRACT

Hybrid electric vehicles are one of the most promising solutions for reducing pollution and fuel consumption. However, their propulsion system comprises a number of different onboard power sources with different dynamic characteristics, meaning that some strategy is required for sharing power between them that takes their characteristics into account.

In this paper, a new real time energy management strategy for battery/ultra-capacitor hybrid vehicles is proposed. This strategy is based on sharing the total power between the onboard power systems, namely the battery and the ultra-capacitors, using a Nonlinear Auto-Regressive Neural Network (NARNN) as a time series prediction model, and Discrete Wavelet Transform (DWT) as a time-frequency filter. The objective of this strategy is to lengthen the life of the battery. We simulated this new strategy using actual data from a military hybrid vehicle. The results were found to be promising and show the robustness of the proposed method.

1. Introduction

Electrical Vehicles (EV) [1], Hybrid Electrical Vehicles (HEV) [2] and Fuel Cell Electrical Vehicles (FCEV) [3] have become important topics for researchers, in view of a number of environmental and energy issues [4]. Compared to conventional vehicles they have substantial advantages: by combining different power sources, output power can be greater and more efficient [5] and the braking energy can be recovered [6]. However, the widespread development and adoption of these vehicles has been held back by issues relating in particular to lifetime, energy density and cost of purchase [7]. HEVs can incorporate multiple power sources including fuel cells, electric motors, batteries, and ultra-capacitors. Each type of onboard power source has its own particular dynamics. For instance, batteries and fuel cells are suitable for low, continuous dynamic loads, while ultra-capacitors can tolerate rapid transients. Longer lifetimes and higher energy densities of the sources may be obtained through the use of an Energy Management Strategy (EMS). An EMS is a mathematical algorithm, implemented in the vehicle, and designed to share the requested power between different onboard power sources, taking into account their different dynamic characteristics.

A number of EMSs have been developed in the literature. Among these EMSs, Artificial Neural Networks (ANNs) have proved to be accurate methods adapted to real applications in energy management for hybrid electrical vehicles.

Since 1982, ANNs have been applied successfully to a variety of electric power systems.

An energy management strategy using wavelet-neural network combination was proposed in [8]; the purpose in this study was to control power distribution in a hybrid Fuel Cell/Ultra-Capacitor (FC/UC) vehicular system. The role of the ANN was to perform the charge sustaining of the UC, leading to a reduction in fuel consumption.

An adaptive intelligent energy management for plug-in hybrid electric vehicles, based on a neuro-fuzzy inference system, was proposed in [9]. This method enables real time adjustments of power for different onboard power sources, taking into account different road geometries, wind and environmental thermal conditions.

In [10], a Radial Basis Functional Neural Network (RBFNN) model was used to eliminate the effect of battery degradation on its State-Of-Charge (SOC). A 6 Ah Lithium Ion battery was used for this study, and the RBFNN gave a more accurate SOC estimation, as well as robustness in relation to aging cycles, temperature and loading profiles.

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In [11], ANNs were used to predict the SOC of batteries and battery/super-capacitor hybrids. The method was proved to be robust, and its performance had a correlation coefficient greater than 0.95.

A recurrent neural network was developed in [12] for performing energy management in hybrid electric vehicles that feature ultra-capacitors. The improvement in fuel consumption was better than that obtained using a dynamic programming method.

In [13], a neural network combined with dynamic programming was used for real time energy management in a power-split Plug-in Hybrid Electric Vehicle (PHEV), leading to an optimised battery current and improved fuel economy.

Neural networks were also used in [14] to provide a control strategy for a hybrid power system in a fuel-cell electric vehicle. For this purpose, a three-layer neural network was developed, that gave a better improvement in performance than a fuzzy control strategy.

An independent Radial Basis Function (RBF) network was used in [15] to develop intelligent model-based fault detection for a Proton Exchange Membrane Fuel Cell (PEMFC) dynamic system. The algorithm can detect different types of faults and classify them, meaning that appropriate action can be taken to rectify these faults.

ANNs were also employed for fault diagnosis and fault tolerance for PEMFCs in [16,17].

One of the remaining problems in energy management strategies proposed in the literature is that the energy management strategy fails to take into account the dynamic characteristics of the power sources, which can lead to damage in these sources and reduce their lifespan and their efficiency. This can occur in the case of a battery, for example, since the battery cannot tolerate rapid variations in the power load, and can suffer damage when it is required to respond to such fast dynamics.

Our aim in this paper is to propose a new energy management strategy for hybrid vehicles powered by batteries and ultra-capacitors. The strategy is designed to attribute a suitable amount of power to be supplied by the battery and the ultra-capacitors respectively, taking into account their dynamic characteristics, and sufficiently fast to be potentially included in a real-time application. We use a Nonlinear Autoregressive Neural Network (NARNN), Wavelet De-noising (WD) and Discrete Wavelet Transform (DWT) to achieve modeling and prediction of the time series. The strategy is similar to the one developed in [18], the difference between the current work and the work done in [18] is that the strategy of energy management proposed in [18] can be applied only offline, that means when the whole load profile is already known before the vehicle runs (the case of trains, metro, etc.). In the present work, we apply this strategy online (in real time), when the load profile is not known a priori, therefore, the DWT in this case cannot be used alone since a time series prediction is necessary. Thus, we use an adequate time series prediction technique, which is accurate and fast, such as NARNN, to achieve the online part of the strategy. The NARNN is seen to be quite a fast prediction model, which makes it suitable for the real-time applications. Moreover, time-frequency filtering is necessary to separate the power between the battery and the ultra-capacitors, taking their frequency characteristics (dynamic characteristics) into account, which is possible using the DWT. With our proposed strategy, the battery has a longer lifespan and higher performance, since it is protected from high variations and transients in the power signal.

The paper is organised as follows: Section 2 gives a general introduction of the NARNN with some analytical formulations. Section 3 describes the experimental data used in this work. The proposed energy management strategy is detailed in Section 4, followed by the numerical application and the results that are detailed in Section 5; and finally Section 6 is a general conclusion of the present work.

2. The nonlinear auto-regressive neural network

Classical time series models, such as ARIMA (Auto-Regressive Integrated Moving Average), are linear models. However, in all applications subject to high variations and rapid transients, the time series cannot be modeled by a linear model, and so a nonlinear model should be proposed for time series.

With this objective, a generalization of the ARIMA models for nonlinear cases can be used. Such a model is expressed as follows [19]:

$$\Delta_{y-1}^{d} = h\left(\Delta_{y-1}^{d}, \Delta_{y-2}^{d}, \ldots, \Delta_{y-p}^{d}, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q}\right) + \varepsilon_t \tag{1}$$

where $\Delta_y^d = \left(1 - B^d\right) y_t = y_t - y_{t-d}$ is the differentiation operator, B^d the delay operator and h an approximation nonlinear function.

In [20], it was proved that time series can always be modeled by the following nonlinear, autoregressive (NAR: Nonlinear Auto-Regressive) model that is formulated as

$$y(t) = h(y(t-1), y(t-2), \ldots, y(t-p)) + \varepsilon(t) \tag{2}$$

A Nonlinear Auto-Regressive Neural Network NARNN is a recurrent neural network [21,22]. It forms a discrete, nonlinear, autoregressive system with endogenous inputs, and can be written in the following form [23]

$$\hat{y}(t) = h(y(t-1), y(t-2), \ldots, y(t-p)) + \varepsilon(t) \tag{3}$$

This is a multilayer, recurrent, dynamic network, with feedback connections [24], as illustrated in Fig. 1.

The learning rule is based on the gradient descent of the propagation algorithm.

The choice of the NARNN can be explained by the following arguments: The classical recurrent network (Elman, Jordan, etc. [25]) encounters some difficulties when faced with problems with long period dependence (the case for time series). These difficulties originate in the gradient descent problem [26]. It was proved in [26] that, given a cost function E at time t, by: $E_t = 1/2(\hat{y}(t) - y(t))^2$, the gradient descent relative to weight w is defined by

$$\frac{\partial E_t}{\partial w} = \left(\widehat{y}(t) - y(t)\right)\frac{\partial \widehat{y}(t)}{\partial w} = \left(\widehat{y}(t) - y(t)\right)\sum_{k<t} \frac{\partial \widehat{y}(t)}{\partial \widehat{y}(k)} \cdot \frac{\partial \widehat{y}(k)}{\partial w} \tag{4}$$

To store information for a long period, when noise exists, the following condition should be established: $k \ll t \left|\partial\widehat{y}(t)/\partial\widehat{y}(k)\right| \to 0$.

In [27] it was shown that, in this case the gradient decreases exponentially, which means, for the values that are far from t, the weight values do not change, and consequently the network fails to perform. This is the case for all recurrent networks other than NARN, which makes NARNN very suitable for use in modeling and predicting time series.

NARNN is the network of choice in the present study, since, the vehicle's power demand (a time series: see next paragraph) needs

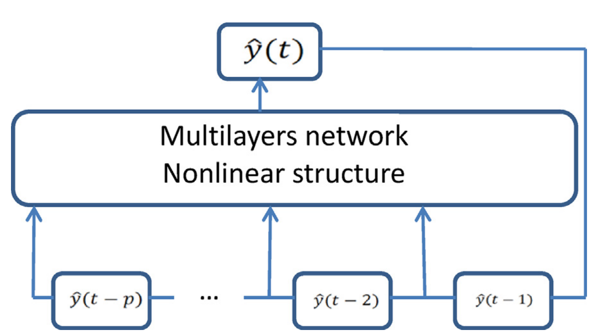

Fig. 1. The NARNN network.