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Using Dynamic Neural Networks for Battery State of Charge Estimation in Electric Vehicles

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Abstract

Due to urban pollution, transport electrification is being currently promoted in different countries. Electric Vehicles (EVs) sales are growing all over the world, but there are still some challenges to be solved before a mass adoption of this type of vehicles occurs. One of the main drawbacks of EVs are their limited range, for that reason an accurate estimation of the state-of-charge (SOC) is required. The main contribution of this work is the design of a Nonlinear Autoregressive with External Input (NARX) artificial neural network to estimate the SOC of an EV using real data extracted from the car during its daily trips. The network is trained using voltage, current and four different battery pack temperatures as input and SOC as output. This network has been tested using 54 different real driving cycles, obtaining highly accurate results, with a mean squared error lower than 1e-6 in all situations

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1. Introduction

Air pollution is currently one of the main causes of premature death in the world, particularly on urban population[1]. Air pollutants are responsible for the increment in cardiovascular and respiratory diseases that affect the human health and contributing to climate change by affecting the amount of sunlight that is reflected by the atmosphere.

Most of these pollutants are produced by the burning of fossil fuels in the transportation sector. For this reason, many governments are promoting the electrification of this sector, banning diesel and petrol cars in the city centers and providing financial incentives to boost the transition from conventional internal combustion engines (ICE) vehicles to electric ones[2-3].

One of the main challenges for the adoption of electric vehicles (EVs) is their limited range due to the lower energy density of batteries compared to fossil fuels[4]. A good and accurate estimation of the battery SOC is needed for an appropriate analysis and simulation of EVs behavior. It is also critical for current EV drivers and those fleet managers that are evaluating the possibility of changing their conventional ICE vehicles by EVs. SOC provides information regarding the remaining useful energy within the battery and its reliability and, therefore, for potential charging and discharging strategies.

Battery SOC estimation is a very difficult task because it has non-linear time-varying characteristic and it cannot be directly measured[5].

There are different SOC estimation methods such as equivalent circuit-based models, empirical models and electrochemical models. Circuit-based models are founded upon the electrical behavior of the battery, while electrochemical models are founded upon the equations of the battery chemistry, that have been used mainly for battery SOC estimation techniques[6].

Electrical circuit models are commonly used due to their simplicity, counting with three main approaches for SOC estimation. The first one uses the integration of the charging/discharging battery current over time, which evaluates the energy stored in the battery, as shown in Eq. (1):

$$SOC = 1 - \frac{1}{C_n} \int \eta i(t) dt \tag{1}$$

where i is the current, t is time, C_n is the nominal capacity and η, represents the coulomb efficiency (the ratio between the total charge extracted from the battery and the total charge put into the battery over a full cycle). The main drawback of this method is that the estimation is performed in an open loop and the errors (due to noisy measurements, temperature variation or other disturbances) accumulate over time, therefore, a recalibration is needed from time to time. There are also other problems caused by the difficulty of establishing the initial value of the SOC[7] and the need of a complete discharge of the cell and periodic capacity calibrations[8].

The second approach, and the most conventional electrical circuit-based method, is the Open Circuit Voltage (OCV) model. The estimation is built through an open circuit voltage after the battery remains in steady-state enough time to reach balance[9]. SOC and OCV show typically a linear relationship, which depends of the type of battery. OCV provides good accuracy on the SOC estimation but the method requires a long rest time to reach the equilibrium[10]. Thus, it is used only while vehicles stay at parking.

Finally, there is a third established method, the Internal Resistance method, that uses the current and the voltage of the battery to calculate the internal resistance of the battery but it is less accurate and increases the difficulty of the measure.

Traditionally, electrochemical models lead to large memory and computation requirements, so they are not desirable for current battery SOC estimation. A common electrochemical method is the Electrochemical Impedance Spectroscopy (EIS) that estimates the impedance of the battery using capacitances and inductances through a wide range of frequencies[11]. However, results coming from EIS are not easily reproducible.

Other models[12-14] combine elements of both electrochemical and circuit-based modelling techniques. In general, these models can estimate SOC levels directly or take advantage of supporting estimator algorithms as the Kalman filter (KF). KF has become a usual tool to estimate the dynamic state of the battery despite of its high computational cost. KF is able to predict and correct the new state of the batteries during the system operation, providing a recursive solution for estimating the SOC based on a linear model, which uses the earlier states and a measurement equation which updates the state aiming at getting a good approach to the real value[15].

Artificial Neural Networks (ANN) are computational models based on the structure and functions of biological neural networks used as intelligent machine-learning tools for a wide range of applications[16]. ANN are adaptive and are able to fit well non-linear systems as the battery behaviour. Different solutions for SOC estimation are based on ANN as supporting algorithm[16-20], but most of them use a conventional multilayer perceptron trained using backpropagation[17-20]. These authors have trained and validated their results with data provided by an electric circuit model[17] or a small battery cell18,20, but they have not used data extracted from a real electric vehicle, except[19].

Some authors[16] have pointed out the limitations of this type of networks in the approximation of time series, and they propose to use other types or ANN (like Radial Basis Function Neural Networks, Elman Neural Networks and other types of unsupervised neural networks like self-organizing maps), although again, it is usual to validate these networks with data obtained from other simulated models.

The main contribution of this paper is to develop a NARX artificial neural network to estimate the SOC of an electric vehicle using real data extracted from the car during 54 different daily trips, which presents a greater challenge, as the vehicle (and its traction battery) is not operating in a controlled environment.

The reminder of this paper is organized as follows. Section 2 describes the origin of the experimental data. Section 3 defines the NARX ANN model used to estimate the SOC. In Section 4, results are described, and finally, the main conclusions are provided in section 5.

Nomenclature

ANN	Artificial Neural Network
BMS	Battery Management System
EIS	Electrochemical Impedance Spectroscopy
ICE	Internal Combustion Engine Vehicle
KF	Kalman Filter
Li-ion	Lithium ion technology
MSE	Mean Squared Error
NARX	Nonlinear Autoregressive model process with eXogeneus input
OCV	Open Circuit Voltage
RNN	Recurrent Neural Network
SOC	State of Charge of Electric Vehicle
VE	Electric Vehicle

2. Experimental data

In order to train the proposed neural network to model the battery pack SOC behavior, more than 800 km trips during 3 weeks were registered using a 2016 Nissan Leaf (Fig. 1.(a)). This vehicle has a 30 kWh lithium-ion battery pack that contains 192 laminated prismatic cells for a total rated battery voltage of 360V. This pack is made up of a string of 4 modules (15V nominal voltage-83 Ah rated capacity), each containing eight cells per module in a 2P 4S arrangement (2 in parallel, 4 in series).

A Bluetooth OBDII (On-Board Diagnosis II) scanner was plugged into the vehicle's OBD port to register several information available from the CAR-CAN bus. The installation of this device is shown in Fig. 1.(b) and (c).

(a) (b) (c)

Fig. 1. (a) 2016 Nissan Leaf. (b) Location of the OBD port (c) Installation of the Bluetooth OBDII scanner

An app named LeafSpy Pro was installed in a smartphone. This app registers data read from the vehicle and stores it in a .CSV file. Data registered in these files have two different sources, one from the smartphone:

- A timestamp, saved in the format HH:MM:SS.
- Geographic coordinates, defined by latitude and longitude in the format ddd mm.mmmmm (degrees and minutes with 5 precision digits).
- Altitude in meters.
- Speed in km/h.

And the other data is directly obtained from the CAR-CAN bus:

- State of Charge, SOC, of the traction battery.
- Battery capacity in Ah.
- Pack Volts, which is the average voltage of the 192 cells.
- Pack Amps, which represents the battery amperage.
- Pack Temperature, T1-T4 C, which represents the battery temperature sensors located in different parts of the battery pack (in the center of the rear battery block (T1), front right hand battery block (T2), etc.), as it is shown in Fig. 2.

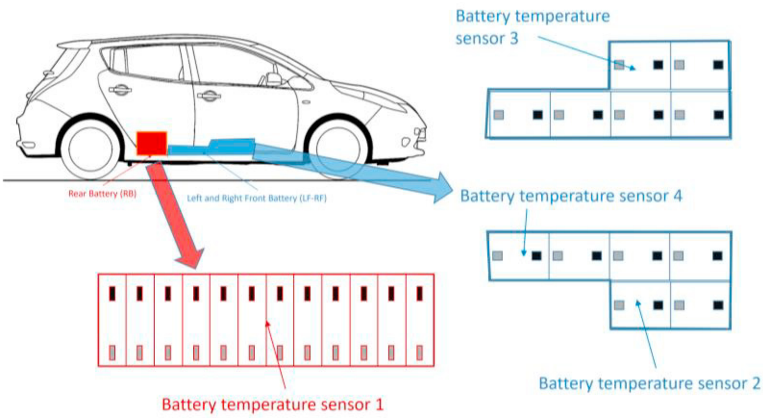

Fig. 2. Battery modules layout and temperature sensors location

A graphic example of a specific driving trip used to generate data for the neural network training is shown in Fig. 3. The 24 km circuit combines a mix of city paths and roadways in order to test the vehicles under different driving situations.

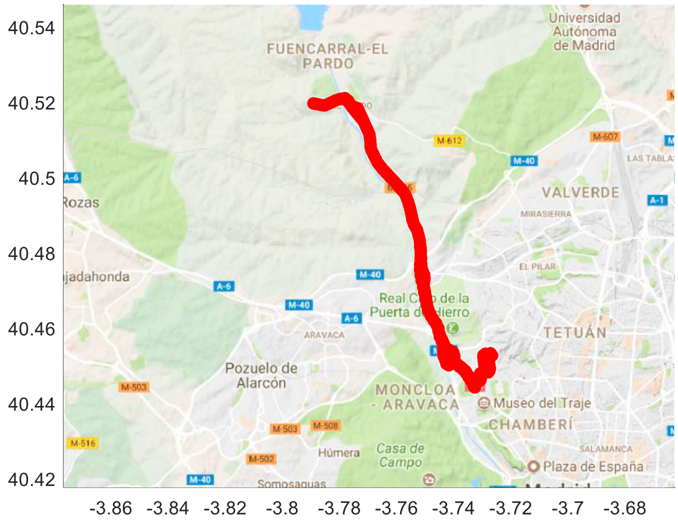

Fig. 3. Registered trip used to generate data for neural network training.

Fig 4.(a) shows the relationship between the vehicle speed and the current flowing in/out the battery vs. time in this specific trip. The current is positive when the motor is driving the vehicle and it is negative during the regenerative period, when the behavior of the electrical machine is reversed, acting as a generator. Fig 3.(b) presents the measurements from the different temperature sensors installed inside the battery pack during the same period of time.

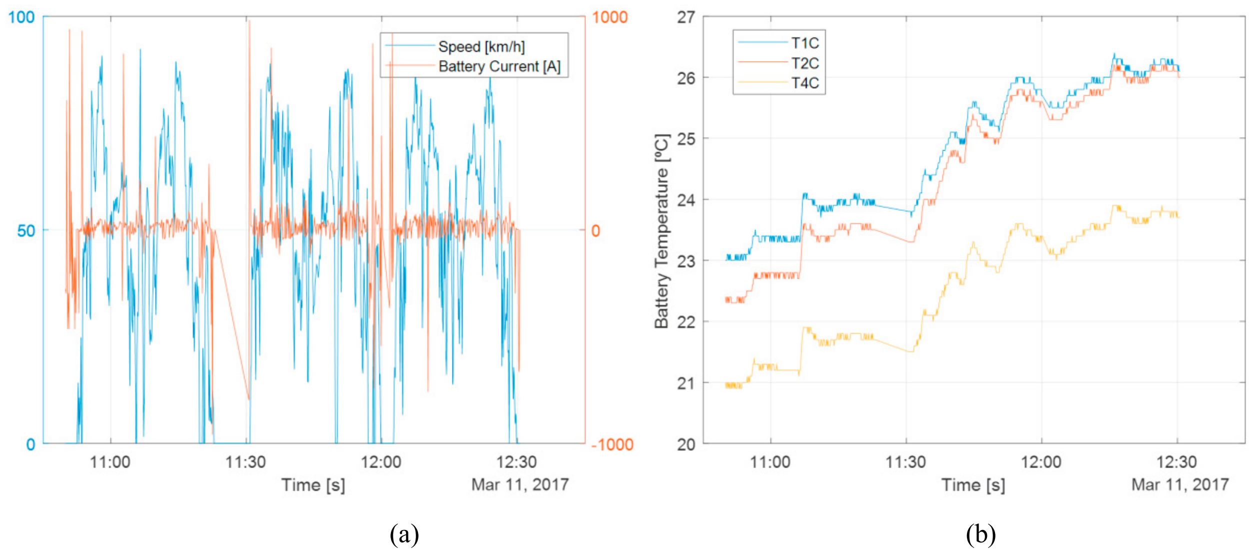

Fig. 4. (a) Vehicle speed and battery current; (b) Temperature battery sensors.

3. Artificial neural networks

The proposed NARX model uses a feedforward neural network with first tapped delay lines as it is shown in Fig. 5. The next value of the estimated output, SOC[k+1], is regressed on previous values of the output signal (SOC[k], SOC[k-1], SOC[k-2]) and previous values of independent (exogenous) input signals (voltage, V, current, I and the four temperatures, T_{1C}, T_{2C}, T_{3C} and T_{4C}.

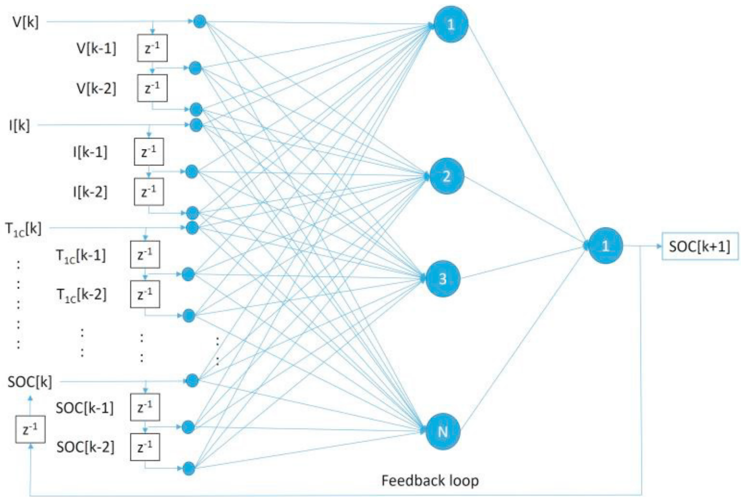

Fig. 5. NARX with two tapped delay lines for five input time series (voltage, V, current, I and four temperatures, T_{1C}, T_{2C}, T_{3C} and T_{4C} and the output (SOC).

Training is performed in a series-parallel scheme, since the true output (SOC) is available during this period, allowing using a static backpropagation algorithm and improving the final accuracy.

During the validation and test stages, a parallel scheme (shown in Fig.5) is used, where the estimation of SOC is fed back to the network.

4. Results

It is very important to provide significant data to the ANN in order to estimate the SOC accurately. In this work more than 50 different trips during three consecutive weeks were registered, by means of driving more than 800 km with different initial SOCs (from fully charged to discharged situations), allowing describing all battery dynamics under real situations.

Fig. 6(a) presents the main result of this work, by comparing the real SOC with the estimated by the proposed NARX ANN method. It is observed that the output SOC from the model is very close to the real SOC with a mean squared error (MSE) of 9.2727e-07.

Fig. 6(b) shows the MSE for the whole trips set (54 different trips). It can be concluded that the precision of the proposed model is very high, with an error less than 1e-6 in all situations.

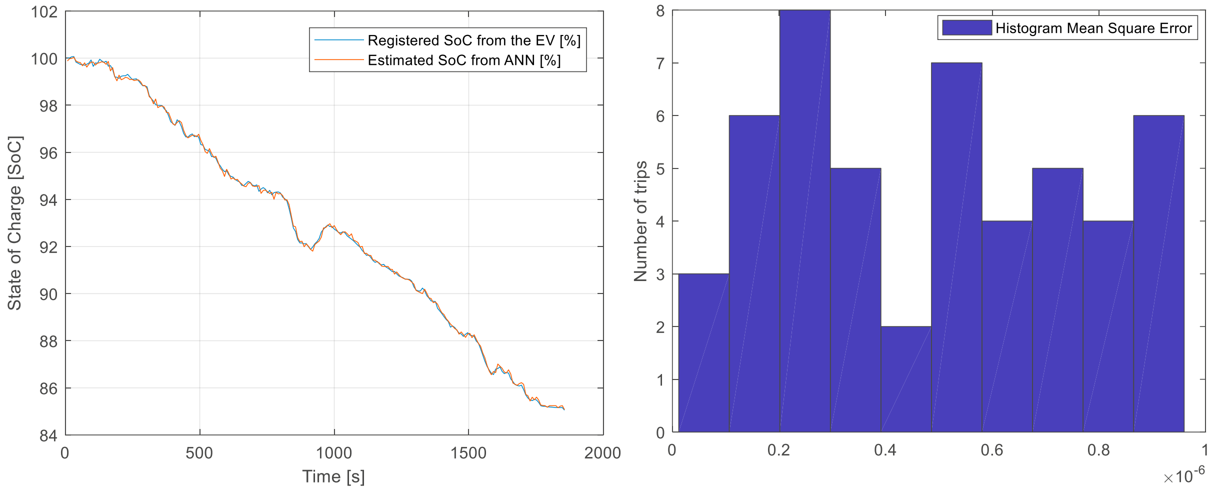

Fig. 6(a). Real SOC evolution vs Estimated SOC from the dynamic NARX ANN. 6. (b) Histogram of the Mean Squared Error from the 54 different trips

5. Conclusions

An accurate estimation of the battery SOC of electric vehicles is critical to avoid range anxiety in the drivers, facilitating the mass deployment of this type of traction technologies in polluted urban areas. There are several ways to estimate SOC but most of them have been developed in a controlled environment (small laboratory facilities or under standard driving cycles).

This paper presents a dynamic recurrent artificial neural network, based on a Nonlinear Autoregressive with External Input (NARX) scheme, to estimate the SOC of a battery pack of a Nissan Leaf electric vehicle.

The ANN is trained using real world data, obtained from 54 different daily trips. This data was provided by the installation of an OBD scanner in the CANbus port of the vehicle, obtaining information about voltage, current, temperature and SOC of the battery pack during more than 437 km. With this information, the NARX-ANN was trained off-line and then it was tested with new data trips, achieving a mean squared error lower than 1e-6 in all situations.

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