Wavelet- Neural Network Approach for On-line Prediction of Time Series: Application on Power Demand Signal in a Fuel Cell Hybrid Vehicle (FCHV)

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ABSTRACT

In order to achieve an online optimization and an energy management for Hybrid Electric Vehicle (HEV) device, an adaptive Wavelet-Nonlinear Autoregressive Neural Network (WNARNN) approach is developed in this paper for time series prediction. The signal or time series used for such an application is the real power demand required by a HEV's driver.
Simulation results showed that this approach is a good tool for online energy management, and thus for increasing the power sources lifetime.

1. INTRODUCTION

In order to develop an adaptive model for time series prediction, which is useful for online energy management in a Hybrid Electric Vehicle (HEV) including a Fuel Cell (FC), a Wavelet-Nonlinear Autoregressive Neural Network (WNARNN) model is proposed in this paper.

Various strategies have already been applied in the field of energy management such as: Dynamic Programming (DP) [1], [2], Fuzzy Logic (FL) [3], Particle Swarm Optimization (PSO) [4], Neural Network (NN) [5], etc... But these techniques have difficulty to optimize the power sharing between each power source in HEV.

The proposed approach is first based on the classical decomposition by wavelet of a given signal or time series [6], in order to separate its high-frequency and low-frequency components. The study is then followed by a Nonlinear Autoregressive Neural Network (NAR-NN) [5],[7],[8] which uses time-lagged feed-forward network networks to achieve the prediction part for each of the obtained signals by the wavelet decomposition [7],[9].

The time series used for simulation in this study represents the actual demand in power of a HEV's driver, added by the value of the power demand coming from auxiliaries of the vehicle (the sampling time on this time series is equal to 10 ms, see figure 1).

Simulation results showed the efficiency of this approach in a real world application.

The paper is organized as follow:
Section 2 gives an overview of the considered HEV, the chosen architecture and the problematic statement. The wavelet-neural network approach is presented in section 3, while all the useful definitions, techniques and mathematical notions are detailed. The simulation results are presented in section 4, and a general conclusion ends the paper in section 5.

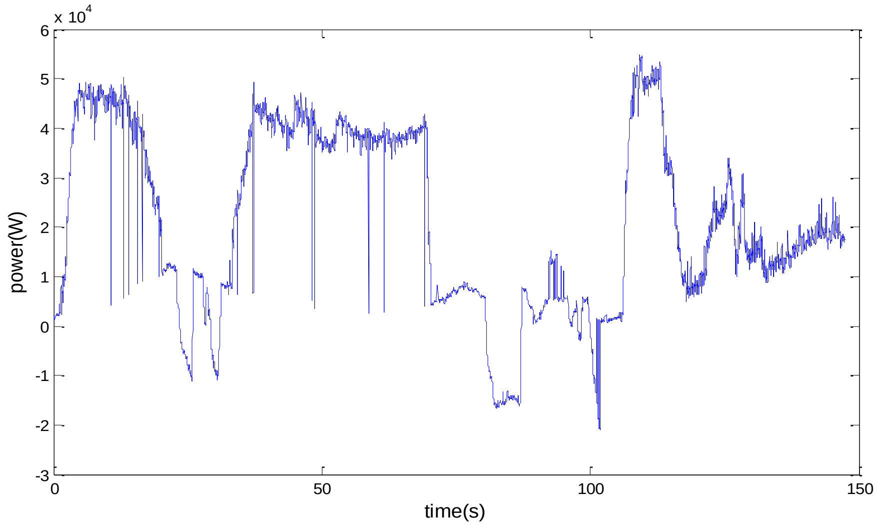

Figure 1. Power demand signal

2. HYBRID ELECTRIC VEHICLE AND ENERGY MANAGEMENT

2.1. HYBRID ELECTRIC VEHICLE

Atmosphere pollution caused by toxic gas rejected by conventional vehicles and fuel consumption continues to grow day by day [1].

In order to limit fuel consumption and then atmosphere pollution, an alternative solution is to consider a hybrid electric vehicle. The HEV combines two or more power sources; at least one of them is electric. Among these sources; one can consider: Internal Combustion Engine (ICE), battery, UltraCapacitor (UC), Fuel Cell (FC), etc. [1], [10]. An example of a real HEV is the ECCE project (or Electrical Chain Components Evaluation). ECCE is an HEV (in fact a heavy-duty mobile testbench) designed for the evaluation of actual electric components [10]. This is an experimental Hybrid Vehicle developed at FCLAB Laboratory in Belfort, with support of the French DGA, see figure 2.

This type of vehicles can be considered as a compromise between a conventional vehicle, where the ICE provides all the vehicle propulsion power, and the electric vehicle which contains energy storage system, such as battery and ultracapacitor in order to be propelled by electricity [1], [10].

Therefore, multiple power sources are available in the HEV, which requires control strategies (called energy management strategies) to optimize the power split between them in order to recover the power needed by the driver. Moreover, reducing fuel consumption and extension of devices lifetime can also be treated.

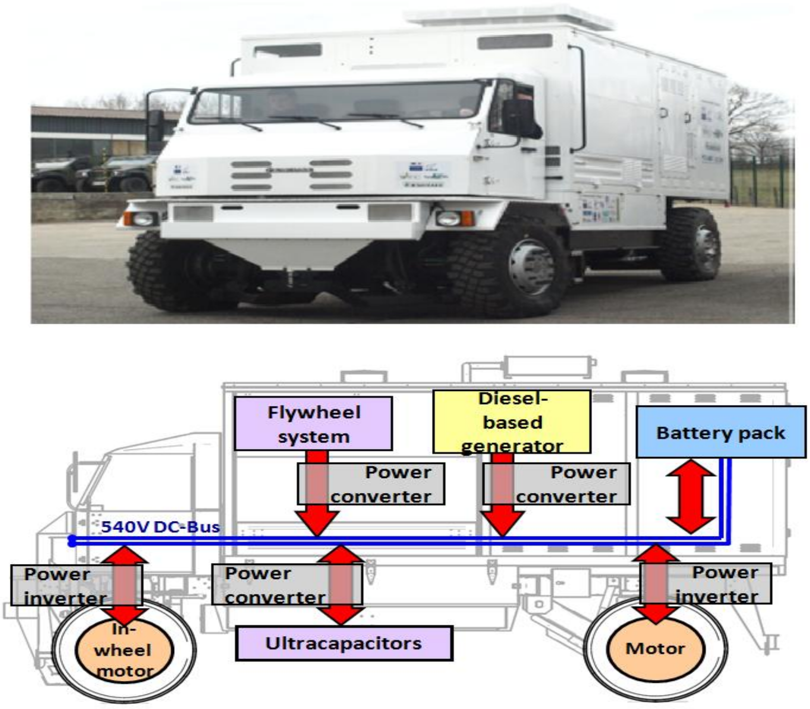

Figure 2. The ECCE hybrid vehicle

2.2. ENERGY MANAGEMENT STRATEGY

The energy management strategy for a HEV is based on mathematical algorithms, which are supposed to be embedded on board in the HEV.

Each component of the HEV has different characteristics that have to be considered in the management strategy.

Therefore, the HEV power management is a mutli-objective optimization problem [1], [2], [10], [11], [12].

In this paper, a fuel cell-battery-ultracapacitor power supply system, and a fuel cell-ultracapacitor power supply system are considered for the HEV. Thus, one has to describe the characteristics of these devices.

Fuel Cell: Such a source is developed to provide energy over a long period of time. However, the fuel cell does not allow energy recovering and has limitations to manage high electrical dynamics [1], [10].

Battery: The battery is also a specific device that can store and deliver power over a long period of time. The frequency load, and the temperature related to this load, can affect dramatically the performances of the battery and decrease its lifetime. Thus, the battery cannot be used for high frequency parts of the power request, and can only cover the low frequency part [13], [14].

Ultracapacitor: The ultracapacitor can generate and deliver power very quickly, so it is suitable to cover regenerative braking power, since it can be charged and recharged very quickly. Thus this device could cover the high frequency part of the power demand.

Moreover, it has to be noticed that ultracapacitor is cheaper than a battery and a fuel cell system [13], [14].

Taking into account all these characteristics, as well as the high prices of the fuel cell and batteries, it seems important to work on their lifetime extension.

2.3. PROBLEM STATEMENT

In this work, our objective is to maintain a long lifetime for the fuel cell and the battery. To achieve this purpose, the energy part to be provided by these two devices must not contain sharp variations. The remaining part of power request will thus be is addressed to the ultracapacitor, since it is less influenced by the rapid dynamic load.

For instance, let's consider the power demand as a signal, as shown in figure (1). This signal contains different frequency bands. According to their specific characteristics; the strategy will be the following: low frequency part of the power demand will be addressed to the battery and the fuel cell in order to avoid a damage of their performance. The high frequency part will be addressed to the ultracapacitor taking advantage of its ability to recover rapid and unexpected breakings.

To do so, the Wavelet Transform (WT) is used in this work as a mathematical tool that separate the frequency bands in a time signal.

3. WAVELET-NEURAL NETWORK BASED APPROACH

3.1. WAVELET TRANSFORM

Wavelet Transform is a method which can extract characteristics of sharp variations in a given signal, non stationary and transient parts [6], [11], [15]. The continuous wavelet transform is defined as follows:

$$W_{a,b}(t) = \int_{-\infty}^{+\infty} x(t)\varphi_{a,b}^{*}(t)dt \qquad a \in \mathbb{R}^{*+}\ b \in \mathbb{R} \tag{1}$$

where * is the complex conjugate, *a* and *b* are respectively the scale and position parameters, x (t) is the signal to be transformed and

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{a}}\varphi\left(\frac{t-b}{a}\right) \tag{2}$$

φ beeing a zero-mean pass band function, called mother wavelet.

The WT decomposes *x (t)* into multiple components at different time and frequency bands.

3.2. DISCRETE WAVELET TRANSFORM

If *a* and *b* are defined by $a = 2^j$ and $b = k\,2^j$ where *j* and *k* are both relative numbers [6], thus the discrete wavelet transform is defined as follow:

$$W_{j,k}(t) = \int_{-\infty}^{+\infty} x(t)\varphi_{j,k}^{*}(t)dt \tag{3}$$

where

$$\varphi_{i,j}(t) = 2^{-\frac{j}{2}}\varphi(2^{-j}t - k) \tag{4}$$

The Discrete Wavelet Transform (DWT) is equivalent to a filtering operation. The signal *x (t)* is decomposed into two signals: a high frequency, and a low frequency signal.

The discrete decomposition operation runs as follows:

The filter bank is composed of four filters: two for analysis (decomposition phase) and two for synthesis (reconstruction phase), see figure 2.
The analysis filters are: h_0 *(z)* which represents the high-pass filter and h_1 *(z)* which represents the low pass-filter.
The two filters are following by down-sampling operations where the resulted output data size is equal to half the original input data size.
As for the reconstruction part, an inverse process is considered. The synthesis filter bank involves a low-pass synthesis filter l_0 *(z)* and a high pass synthesis filter l_1 *(z)* combined with up-sampling operation, see figure 3.

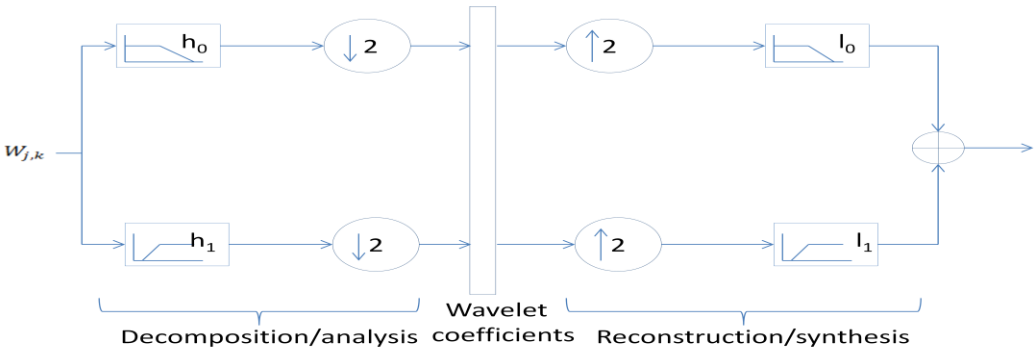

Figure 3. Wavelet filter bank

3.3. CHOICE OF THE WAVELET

Thanks to their implementation simplicity and to their finite length, Daubechie's wavelets have been chosen in this study [6].
The Daubechie's family of wavelets, noted '*dbN*' are wavelets which have the shortest filters. For this study, '*db4*' is the wavelet that will be used and 4 as decomposition level.

4. NEURAL NETWORK

The neural network is a set of formal neurons which are connected all together.
A formal neuron is an algebraic, parametric and bounded function. It is a real function; the variables are the inputs, called x_j (figure 4), multiplied by weights w'_{ij}, and the product $x_j\, w'_{ij}$ being the input of an activation function *g* which produces the output:

$$y_i = g\left(\sum_{j=1}^{n} x_j\ w'_{ij} + b'_i\right) \tag{5}$$

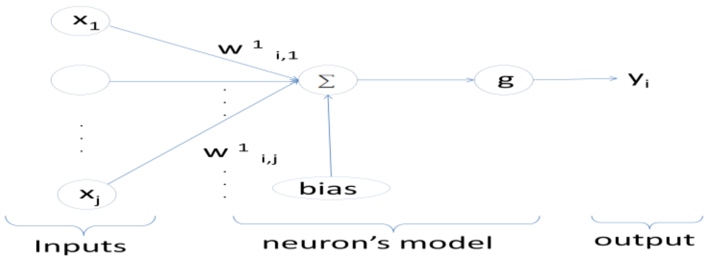

Figure 4. Formal neuron

A neural network is able to solve many problems such as: classification, shape recognition, modeling, time series prediction, etc.
In this work, a specific neural network developed to time series prediction, is used. In the next paragraph, a brief explanation of such networks will be given.

The most current network generally used is the multi-layer perception (MLP). The MLP is composed by multiple layers of formal neurons, as shown in figure 5.
The information moves from the input layer to the output one. Each layer is composed by several neurons, and the output layer's neurons correspond to the output of the system.

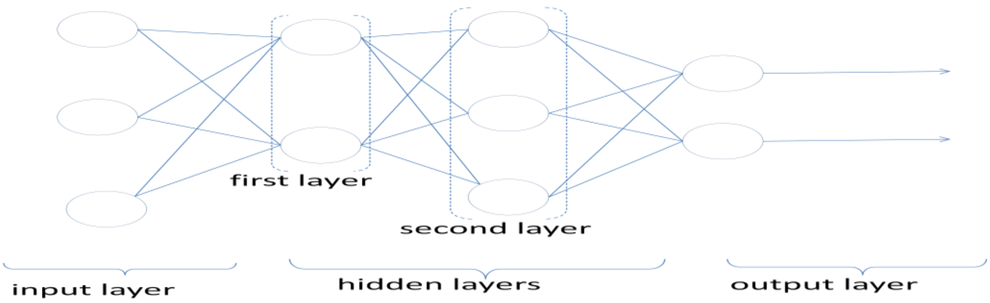

Figure 5. Multi-layer perceptron MLP

In the specific MLP used for time series prediction, the output of the system corresponds to the prediction of the time series at time t ($\hat{x}_t$).
This MLP's structure can be described as in figure 6.

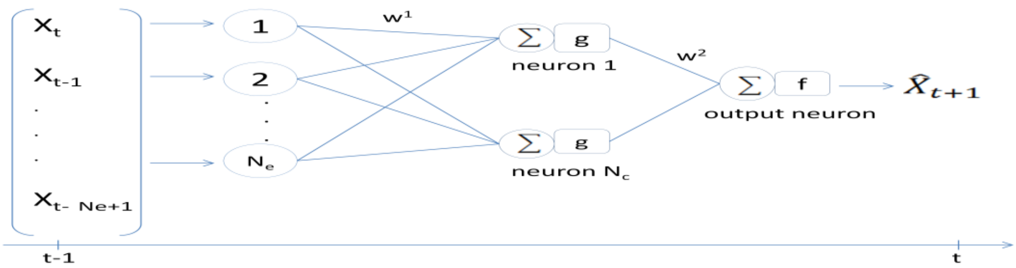

Figure 6. MLP for time series prediction

From an analytic point of view, this network expressed as follows:

$$\hat{X}_{t+1} = f\left(\sum_{i=1}^{N_c} y_i\, w_i^2 + b^2 \right) \tag{6}$$

Where $y_i = g\left(\sum_{j=1}^{N_e} X_{t-j+1}\, w'_{ij} + b'_i \right)$, N_e is the number of input neurons, N_c is the number of hidden neurons, and g is the activation function (sigmoid). In this type of MLP, the function f is linear function $y = x$, thus eq. 6 becomes:

$$\hat{X}_{t+1} = \sum_{i=1}^{N_c} g\left(\sum_{j=1}^{N_e} X_{t-j+1}\, w'_{ij} + b'_i \right) w_i^2 + b^2 \tag{7}$$

The number N_e is determined by the number of significant values in the Partial AutoCorrelation Function (PACF) [8], [9], [16].
The learning operation is based on the Levenberg-Marquard algorithm (LM) [9].

In the next section, some details will be given for the proposed method, as well as the simulation results.

5. WARNA BASED ENERGY MANAGEMENT STRATEGY

5.1. THE PROPOSED ALGORITHM

The time series of figure 1 represents the power demand, required by an Electrical Chain Components Evaluation ECCE's powertrain (figure 2).

In this work, an adaptive wavelet autoregressive neural network for online energy management in HEV is developed. With this objective, a part of the time series (namely the first 700 points) is considered for the simulation purpose.
First, wavelet transform is applied on the signal S ('db4' as wavelet, and 4 as decomposition level). Five signals are obtained, as shown in figure 7: a low frequency signal (or approximation signal) A4, and high frequency signals (or detail signals) D4, D3, D2 and D1.
As mentioned before (in section 2), the fuel cell and the battery cannot deal with rapid variations. Therefore, they will cover the low frequency part, so the signal A4 will be attributed to these two devices.
Moreover, since the fuel cell cannot accept the negative part of A4, this part will be addressed to the battery, together with 40% of the positive part. The fuel cell will thus provide the remaining part (proportion of 60%) of the positive part of A4. These proportions are based on the results obtained in [11].

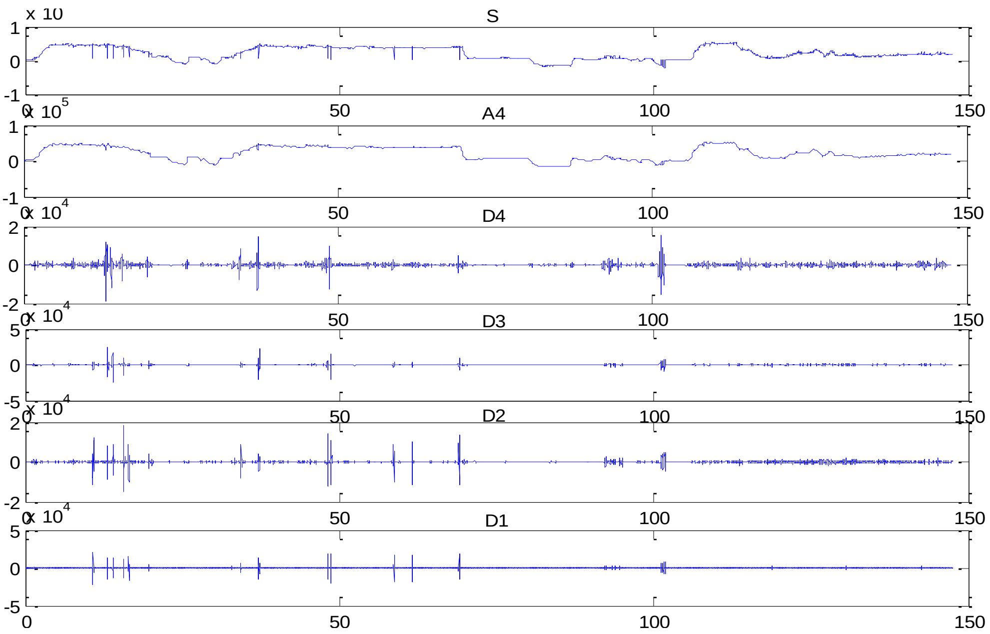

Figure 7. Wavelet decomposition

The high-frequency signals are considered as the power split of the ultracapacitor bank.

Now, the online part of the energy management is beginning. Time series prediction based on autoregressive neural network is considering to rich this aim.
A MLP with 5 points as time window's size and one hidden layer with 5 neurons are considered. The learning operation begins over the first 500 point of A4. These points enter to the MLP and the output of the network is the prediction value of the 501th point.
The data are not available a priori in the future (after 500^{th} point) for the real time application. The network will continue the prediction for the next steps. At each time step, the network developed in this study, instead of taking the predicted value and set it as the last point in the

sliding window; takes the real value of the instantaneous power request, and set it as the last point in the sliding window to predict the next point, and so on. This algorithm is simulated on 200 points and gives the results shown in the figure 8.

5.2. SIMULATION RESULTS AND ANALYSIS

For the signal which will be afterwards shared between the battery and the fuel cell, as mentioned above, the results are good since the percentage of maximal value of the prediction error is equal to 0.22 % (see table 1), which shows the performance of this method, and encourages its application.

Since the wavelet filter is a perfect reconstruction filter [6], thus the signal of power demand S is equal to the sum of all the resulted signals from the wavelet decomposition, then:

$$S = A4 + D4 + D3 + D2 + D1 \quad (7)$$

Let's suppose:

P: the signal of prediction in figure 8, form point 501 to 700

x: $S - P$

y: the sum of the detail signals obtained by the wavelet transform, form steps : 501 to 700

z: the signal of the error, this is the difference the two signals x and y.

$$z = x - y \quad (8)$$

The plot of the prediction result for the signal y is presented in the figure 9, with a zoom over the error prediction, on the right of the figure. The percentage of the maximal error is equal to 11.39 % (table 1) which can be considered as a small percentage. Finally, this signal will be addressed to the ultracapacitor.

Table 1: means square error and percentages

Signals	mse	Percentage of the maximal error value
A4	982.8	0.22 %
y	1724.5	11.39 %

In case of a fuel cell vehicle, where no battery and only ultracapacitors, the fuel cell takes all the positive part of the low-frequency signal, the negative part and the high-frequency signal are added and attributed to the ultracapacitor bank.

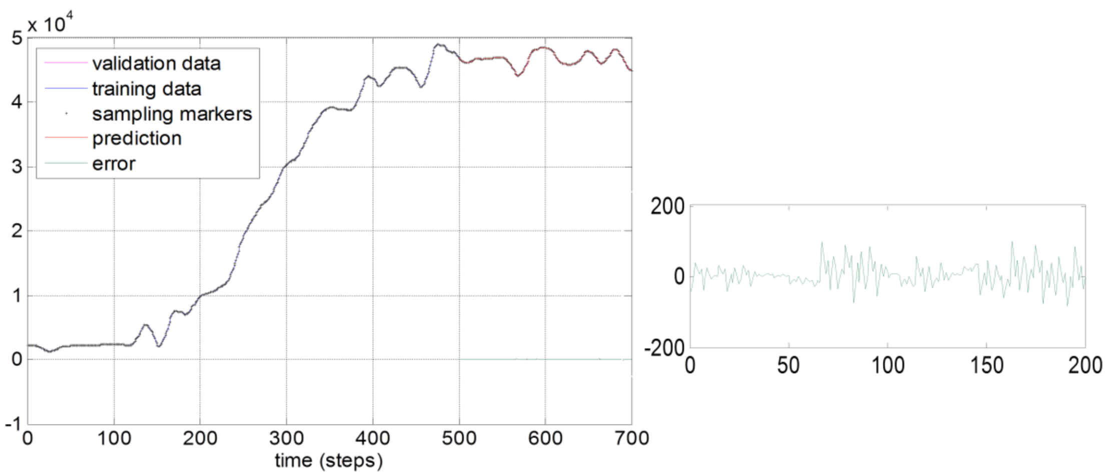

Figure 8. Results for the low frequency signal, the signal attributed to the fuel cell and the battery. On the right, a zoom over the prediction error.

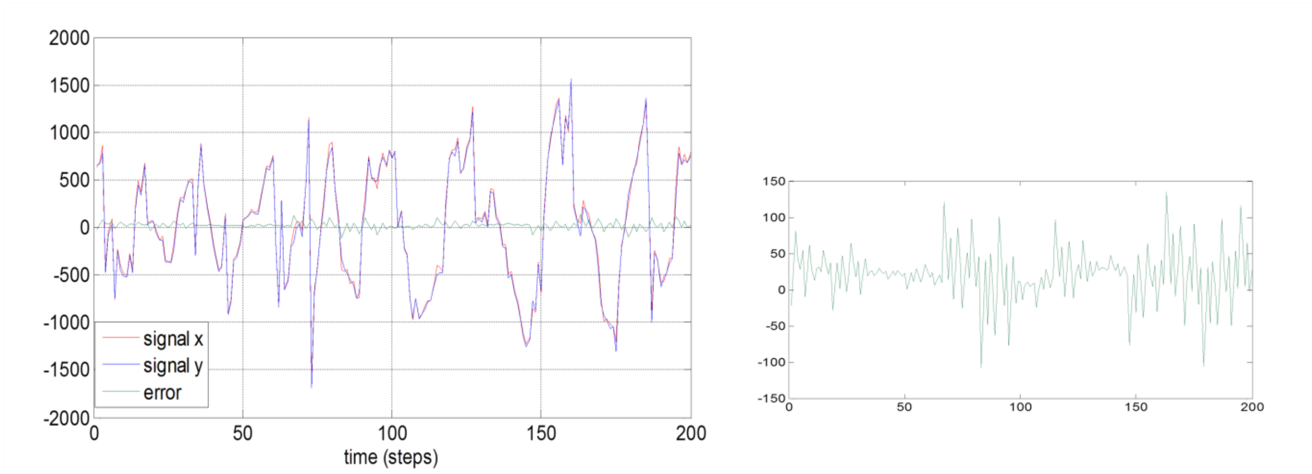

Figure 9. Results for the high frequency signal, the signal attributed to the ultracapacitor. On the right, a zoom over the prediction error.

6. CONCLUSION

In this work, a wavelet non linear autoregressive neural network WNARNN based model was developed, in the objective of realizing a real time energy management in a hybrid electric vehicle. Wavelet transform was applied first in order to separate high and low frequency components from a real power demand signal. The obtained signals are distributed between the power sources (fuel cell, battery and ultracapacitor) the low frequency signal was attributed to the fuel cell and the battery, and the high frequency signal was attributed to the ultracapacitor bank. This distribution was followed by an adaptive non linear autoregressive neural network to predict future values of the time series (in this case only one point in the future-at a sampling rate of 10 ms). The prediction errors were small; this encourages the application of this method in real world domain, and the implementation in the real HEV. This will be done in further works. Another interesting research topic could be to evaluate the algorithm prediction ability not only for one point in the future, but for larger time series in the future.

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