Design of a Dynamic Neural Network with Kalman Filter for the Identification of Nonlinear Systems. Application: prediction of the maximum power generated by a Photovoltaic module

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Abstract

In this paper, the design of dynamic neural networks with Kalman filter is proposed and applied to identify nonlinear dynamic systems. The optimal parameters of a dynamic neural network, which contains several autoregressive moving average (ARMA) sub models, weighs and biases, are obtained using the well known delta rule. Using the obtained parameters of the ARMA sub models, a new dynamic network based on Kalman filter is designed. The obtained system is able to filter noise, identify the complex parameters and predict one more step ahead comparing to the original dynamic network. Due to the existing denominators inside each sub model, the stability of the dynamic neural networks should be mentioned. A maximum power of the photovoltaic system was chosen as a realistic nonlinear system to demonstrate the identification performance. Several simulation results were carried throughout this paper.

Key words: Dynamic neural network, Kalman filter, Nonlinear identification, Photovoltaic system.

1. Introduction

In the last few decades, the neural network's application has found its place in the scientific and industrial world due to their abilities to identify, observe and control nonlinear systems [1]-[4]. In neural networks, the nonlinearities are approximated by superposition of nonlinear functions. These networks are universal approximations [5] and can be considered as general nonlinear filters [6]. A Neural cell does not only contain the nonlinearity aspect but, also contains dynamics in the form of feedbacks [2], [7]. Several approaches have been proposed to produce the dynamics into the neural cells [7]-[12]. For example, in [8] Back et al. proposed a new neural architecture based on the finite impulse response (FIR) and infinite impulse response (IIR) synapses and Ayoubi [11] introduced the IIR filter into the neuron to identify nonlinear dynamic systems. Hence, the dynamic neural units promise a good tool to identify and control nonlinear dynamic systems.

On the other hand, since its discovery in 1960, the Kalman filter is one of the greatest discoveries in the history of statistical estimation theory [13], and is one of the most popular state estimators for linear systems which are affected by noise [1]. The Kalman filter's applications are not just focused to the signal estimation, but they are also used to estimate the neural network parameters [14], [15].

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In this paper, the design and the development of a new dynamic neural unit scheme based on the Kalman filter is proposed. The proposed architecture can take into consideration at the same time four things: 1) the system's nonlinearity, 2) the dynamics into the system, 3) the filtering noise coming to the constructed model's input output and 4) the prediction of one step further using the power of the Kalman filter.

2. The Proposed Architecture Description

In the dynamical neural unit (DNU) approach, each neuron contains in addition to the nonlinear activation function a linear IIR filter [11] (see also [2, 7, 12]). After training the network, the optimal parameters for each neuron have been found. It should be mentioned that during the training procedure the model could be unstable due to the poles of each sub model. To ensure the stability it should be simply that all poles (poles are zeros of each denominator) of each sub model lie inside the unit circle. Using the obtained parameters, the state space systems are constructed for all neurons into the network. The unknown input-output noises (w_k and v_k are the input and the output noises, respectively) will be introduced to each neuron. Noises w_k and v_k will be added into each input output for all neurons. This procedure produces another neural output $\hat{y}_b^j(k)$ which is a noisy DNU output, where j is the j^{th} neurons into the network. The resulting network cannot reject theses noises without adaptation procedure (Figure 1 a).Therefore, the Kalman filter is introduced to each neuron according to a given noisy output $\hat{y}_b^j(k)$ of each neuron j (Figure 1 b).

The Kalman filters estimate the output for each neuron and filter noises without any adaptation procedure. Hence it produces a model taking into account the real functions done by human neuron which are: the nonlinearities, the dynamics and the filtering, which are provided by sigmoidal activation functions and Kalman filters inside each neuron respectively. The resulting Dynamic Neural Kalman Units (DNKUs) is shown in Figure 2 containing n inputs, M neurons in the hidden layer and one output. The implementation of the proposed DNKUs algorithm is given as follows:

DNKU algorithm:

1) Train the DNU [2, 7, 11, 12].
2) Construct the matrices A_i, B_i, C_i and D_i of the state space, based on the optimal parameters obtained in step 1, for each neuron.
3) Introduce the noisy input -output and construct the noisy space state [16].
4) Calculate the initial conditions of the Kalman filter [16].
5) Implement the m Kalman filters for each neuron.
6) End.

One can see in the above algorithm that there are no feedbacks or any other kind of adaptation algorithm after step 5. This means that the Kalman filters inside neurons present internal and implicit adaptations which filter noise from signals.

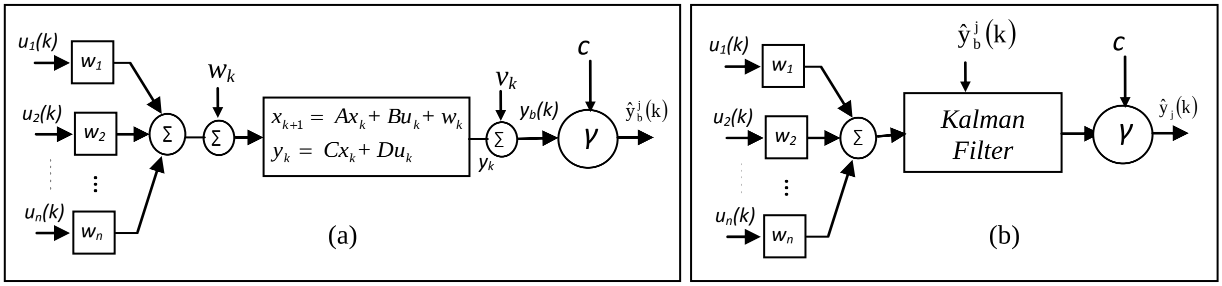

Figure 1. (a) A single neuron contains output plus noise,
(b) A single dynamic neural Kalman unit with n inputs and one output.

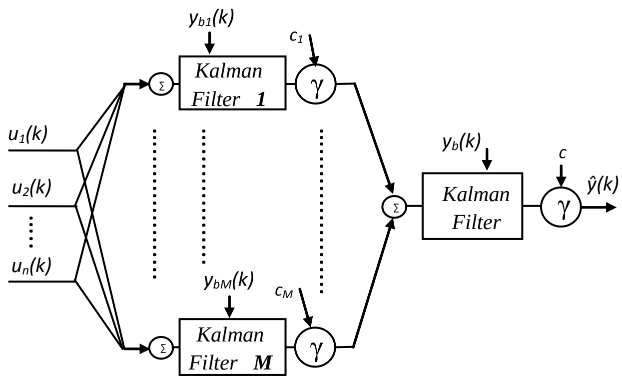

Figure 2. A dynamic neural Kalman units with n inputs M neurons in the hidden layer and one output.

3. Simulation Results

Due to its pollution-free and inexhaustible nature, the solar energy becomes one of the promising important renewable energy sources. There are many models in the literature which represent the current voltage characteristics of solar cells [18] and several algorithms focus on the maximum point tracking [19]. In this later, Florencia Almonacid et al. [19] have given a good comparison between several existing algorithms to estimate the energy produced by the photovoltaic (PV) generators and they have shown that the power generated by a photovoltaic generator using the diode model and the Araujo-Green’s model give almost the same results. In this paper, the Araujo-Green’s method is used to generate the maximum power.

In order to train the network input output pairs are need. Therefore, and as mentioned in [22] the daily irradiance and ambient temperature could be generated using very simple procedure. According to these inputs (the daily irradiance and ambient temperature) the maximum power of the photovoltaic system can be obtained.
To demonstrate this approach, Boumerdès city (Boumerdès is a seaside city located in the north of Algeria about 50 km east of the capital: Algiers) has been chosen as an example. To obtain the daily irradiance and ambient temperature, the geographical parameters (longitude and latitude) for one given place should be identified. Therefore, data given in [23] over almost 22 years have been analyzed for Boumerdès city (latitude: 36.7667 and longitude: 3.47722) and it concluded

that daily irradiance and ambient temperature during one year are generally between 0.1 and 0.9 kWh/m2 and between 2 and 32.5 °C, respectively.
The shift values of the irradiance and the temperature could be calculated as follows:

$$G_{shift/mean} = mean(G/year) + \min(G/year) = 0.5\,kWh/m^2 \tag{1}$$

$$T_{shift/mean} = mean(T/year) + \min(T/year) = 17.25°C \tag{2}$$

Now the sinusoidal signal, according to the fact that both temperature and irradiance have naturally the highest values in summer and the lowest ones in winter which produces a shift time into the sinusoidal function (-π/2), and it can be written as follows :

$$G_{filtred} = G_{shift/mean} + \frac{G_{shift/mean}}{2}\sin\left(\frac{2\pi}{366}d - \frac{\pi}{2}\right) \tag{3}$$

$$T_{a\_filtred} = T_{shift/mean} + \frac{T_{shift/mean}}{2}\sin\left(\frac{2\pi}{366}d - \frac{\pi}{2}\right) \tag{4}$$

Where d is the day's number.
Random signals will be added to the above filtered irradiance and temperature. To generate the random signal to be added to the irradiance, the Generalized Multiple-level Noise (GMN) signal [24] is used. The generated irradiance, temperature and the resulting maximum power, according to the manufacturer's constants (in this paper MSX-60 photovoltaic module is used) [25], during five years.
At the beginning of the training procedure, all filter coefficients are initialized to zero, weights are initialized randomly smaller. For the identification procedure, a sequence of 1464 samples (Four years) was used as training set and the rest 366 samples (one year) as validation set. The delta rule was used as a learning method in which a constraint inequality (all the poles lie into the circle unit) should be introduced. Figure 3 presents the modeled maximum power versus the response of the validated network, which contains two inputs (Temperature and irradiance), five neurons in the hidden layer and one output (5.1-DNU). The error which is also shown is defined as:

$$e = P_m - \hat{P}_m \tag{5}$$

It should be mentioned that the elements of matrices D_i on the state space model are of significant values representing the feed-through effect of the inputs to the P_m output, which mean that the resulting neurons contain internal feed-forwards.
To test the proposed architecture, equations (3) and (4) are used to generate average irradiance and temperature of Boumerdès city and Araujo-Green's model is used to obtain the corresponding maximum power.
We introduce the noises w_k and v_k (according to Figures 1 and 2). Figure 4 presents the obtained maximum power model, the noised model, and the DNKU responses, respectively. As remarked in Figure 4, the dynamic neural Kalman units approach filter noises (in dashed black color) comparing to the output signal plus noise (in dashed red color) from each neuron which produced a global model that can estimate the average maximum power (signal in blue color) with accepted accuracy. It should be noticed that the model plus noise has a lot of peaks that can destroy all instruments related to the maximum power. In addition, it is well known that the Kalman filter can predict one step ahead which gives another advantage to the proposed architecture.
To generalize the obtained DNKU model, we keep the neural architecture constant (i.e. two inputs, five neurons in the hidden layer and one output) and we introduce input output noises

with different levels (from 0% to 200% of the significant signal). The signal-to-noise ratios are shown in Table 1. We note that the above obtained results have been found using noises with 100%.
One can see from Table 1 that even though the introduced noises are twice times greater than the significant signal, the DNKU network could filter partially these noises. Therefore, the DNKU network has another propriety which is filtering noises.

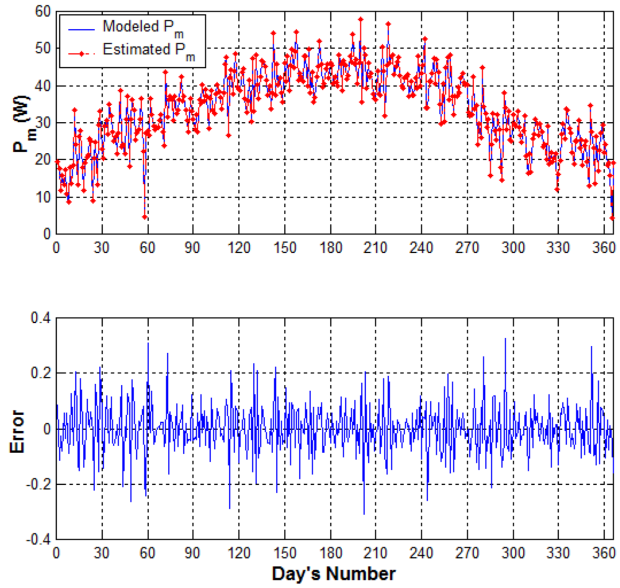

Figure 3. The modeled maximum power versus the response of the validated DNUs with five neurons in the hidden layer and one output.

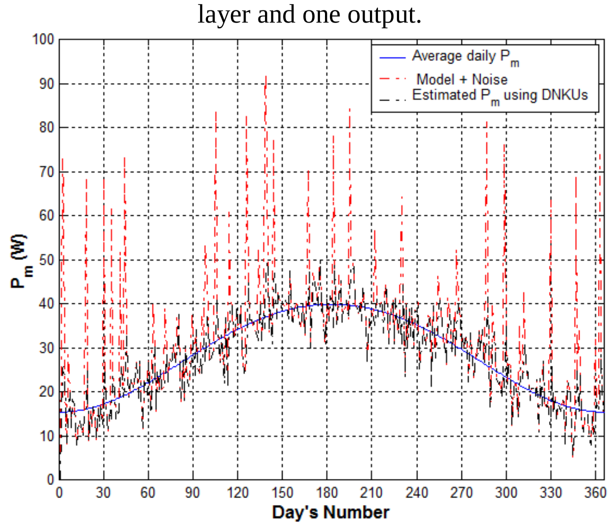

Figure 4. The modeled versus the estimated maximum powers using the DNKU approach.

Conclusions

In this paper, the design of the dynamic neural network with the Kalman filter is proposed and applied to identify the nonlinear dynamic systems. The proposed algorithm was implemented and

tested upon the maximum power generated from the photovoltaic system.
The performance of this algorithm was compared to that of the noised DNU model. According to these results, it could be seen that the identification approach based on the dynamic neural Kalman units model is suitable for the identification of nonlinear dynamic systems for three main reasons: a) the resulting network can identify nonlinear black box models, b) it deals with external and internal dynamics and c) it can filter noises. Hence, it can be concluded that dynamic neural Kalman units are very suitable to model and identify the nonlinear dynamic systems.

Table 1. Signal-to-noise ratios for different percentages of noises

Percentage of noises	Signal-To-Noise ratio (SNR) in dB
10%	32.442
30%	25.598
50%	20.495
75%	17.823
100%	14.688
150%	11.301
200%	7.5936

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