Educational Simulator for Frequency Estimation using ANN

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Abstract

The parameter estimation of signals is one of important topics in electrical and electronics engineering area. For the estimation of main/fundamental parameters (amplitude, frequency and phase) of signals, many methods and techniques proposed. In this study, educational simulator for frequency estimation of signals is realized with artificial neural networks. Artificial neural networks are used for training Prony coefficients. Designed simulator is written in MATLAB and effects of neural net parameters (cost function, activation function, neuron size, etc.) on learning ability can be compared. Besides educational purposes, developed simulator can be used by engineers in order to create frequency estimators in practical studies.

Key words: Frequency estimation, Prony method, neural networks

1. Introduction

Signal parameter estimation is an important topic in the power electronics field. Especially, frequency estimation has crucial role in detecting signal quality. The frequency spectrum or harmonic spectrum of signals contains information of its total harmonic distortion [1]. For this reason, analysis of harmonic spectrum of signals is remarkable topic since early stages in power electronics [2-3]. Classical techniques of revealing harmonic content in signals are capable of only uncovering integer multiples of main harmonic [4–6]. If signal contains an inter-harmonic which is non-integer multiple of main harmonic, it couldn't be detected properly. In early stages of power electronics, there are no inter-harmonic sources in grids. But, after invention and usage of semiconductor devices, inter-harmonic concept is introduced in terminology. Therefore, many techniques are proposed recent years for detecting inter-harmonics [7–11]. One of important works for revealing inter-harmonic spectrum of signals dates back to XIX. century [12]. In this work, valuable signal parameter extraction technique was derived by Prony. This technique produces polynomial coefficients which are related with amplitude, phase and frequency information of signal. Based on these techniques, many hybrid methods are proposed in literature. Adaptive Linear Neuron (ADALINE) method is one of them [8]. Prony and ADALINE methods are discussed in section 2 in this paper.

In this study, Prony coefficients are tried to be estimated with ADALINE and non-linear artificial neural networks (ANN). Aim of this work, designing a simulator, which gives opportunity to student designing different ANN topologies in order to understand and comprehend how ANN could be used in frequency estimation. Signal model is derived from Photovoltaic systems (PV) which are run with Perturb and Observe Maximum Power Point Algorithm (P&O MPPT) [13].

2. Materials and Method

2.1. Data model

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Data model which is used in this study is based on P&O MPPT algorithm [13]. Proposed mathematical model is implemented in simulator which is created in MATLAB [14] and test data are produced. Mathematical expression is showed in Eq. (1). In this equation, i_g is generated current by MPPT algorithm, f_g is fundamental frequency, f_n is harmonic frequency which is affected by MPPT frequency, A_n and $Ø_n$ amplitude and phase values which are created by step voltage.

$$
\left.
\begin{aligned}
i_g(t) &= \sum_{n=1}^{\infty} \frac{A_n}{2} \left[cos\big(2\pi t(f_g - f_n) + Ø_n\big) - cos\big(2\pi t(f_g + f_n) + Ø_n\big) \right] \\
a_n &= \frac{2V_{step}}{\pi n} sin\left(\frac{\pi n}{2}\right) \;,\; b_n = \frac{2V_{step}}{\pi n} cos(\pi n - 1) \\
A_n &= \sqrt{a_n^2 + b_n^2} \;,\; Ø_n = tan^{-1}\left(\frac{b_n}{a_n}\right) \\
f_n &= \frac{(2n-1)f_{MPPT}}{4}
\end{aligned}
\right\}
\tag{1}
$$

2.2. Prony method

Fourier analysis can be extended as Eq. (2). In this equation, damping factor 'σ' is added to classical Fourier analysis. Solving technique of this eqsuation is called as Prony Method with respected to his work. Steps in Prony method can be divided in three steps [15-18].

$$
\hat{y}(t) = \sum_{i=1}^{\infty} A_i e^{\sigma_i t} Cos(2\omega f_i t + \varphi_i)
\tag{2}
$$

- *Step 1*: Linear prediction model (LPM) is constructed based on observed data.

$$
y_N = a_1 y_{N-1} + a_1 y_{N-1} + \cdots + a_M y_{N-M}
$$

$$
\underbrace{\begin{bmatrix} y_M \\ y_{M+1} \\ \vdots \\ y_{N-1} \end{bmatrix}}_{S} = \underbrace{\begin{bmatrix} y_{M-1} & y_{M-2} & \cdots & y_0 \\ y_M & y_{M-1} & \cdots & y_1 \\ \vdots & \vdots & \ddots & \vdots \\ y_{N-2} & y_{N-3} & \cdots & y_{N-M-1} \end{bmatrix}}_{R} \underbrace{\begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_M \end{bmatrix}}_{a}
\tag{3}
$$

- *Step 2*: Calculate roots of characteristic polynomial (Prony polynomial) which are obtained from LPM.

$$
\mu^M - a_1 \mu^{M-1} - \cdots - a_{M-1}\mu - a_M = 0
\tag{4}
$$

- *Step 3*: Find complex amplitude, phase and frequency values with using roots which are calculated from Step 2.

$$\begin{bmatrix} y_0 \\ y_1 \\ \vdots \\ y_{N-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \mu_1 & \mu_2 & \cdots & \mu_M \\ \vdots & \vdots & \ddots & \vdots \\ \mu_1^{N-1} & \mu_2^{N-1} & \cdots & \mu_M^{N-1} \end{bmatrix} \begin{bmatrix} d_1 \\ d_2 \\ \vdots \\ d_M \end{bmatrix} \tag{5}$$

2.3. Usage of ANN in frequency and complex amplitude estimation

Solving technique of Eq. (2) is called as Prony Method with Adaptive Linear Neuron (ADALINE) algorithm is proposed for finding signal parameters [8, 16]. ADALINE algorithm firstly calculates Prony polynomial coefficients based on Eq. (3). Frequency information is obtained from Prony polynomial coefficients. Then, second ADALINE network, which is fed by found frequency, is constructed. Using second ADALINE, amplitude and phase information is obtained. This procedure is shown in Fig. 1 and Fig. 2 [8].

$$\hat{y} = \sum_{m=1}^{M} A_m^* \sin(2\pi f_m^* k\Delta t + \phi_m^*) \tag{6}$$

$$\hat{y} = \sum_{m=1}^{M} (A_m^* \cos \phi_m^* \sin 2\pi f_m^* k\Delta t + A_m^* \sin \phi_m^* \cos 2\pi f_m^* k\Delta t) \tag{7}$$

$$\hat{y} = \sum_{m=1}^{M} (\omega_{2m-1}^* \sin \theta_m^* + \omega_{2m}^* \cos \theta_m^*) \tag{8}$$

$$\left. \begin{aligned} \omega_{2m-1}^* &= A_m^* \cos \phi_m^* \\ \omega_{2m}^* &= A_m^* \sin \phi_m^* \\ \theta_m^* &= 2\pi f_m^* k\Delta t \\ \mathbf{w}^*(k) &= [\omega_1^* \omega_2^* \dots \omega_{2M-1}^* \omega_{2M}^*] \\ \mathbf{x}^*(k) &= [\sin \theta_1^* \cos \theta_1^* \dots \sin \theta_M^* \cos \theta_M^*] \end{aligned} \right\} \Rightarrow \hat{y} = \mathbf{w}^*(k)\mathbf{x}^*(k) \tag{9}$$

In back-propagation network, calculation of Prony polynomial coefficients has a nuance. Since every input has relations with each neuron, sums of weights of neural nets should be considered. If it is assumed that one hidden layer exists, calculation of Prony polynomial coefficients is given in Equation (10). In Equation (10), a_k is Prony polynomial coefficient, k is coefficient number, $I_{k,p}$ is coefficient of neural net, which corresponds to kth coefficient of neural net and pth neuron, p is neuron number.

$$a_k = \sum_{k=1}^{n} I_{k,p} \tag{10}$$

In this study, based on schematic which is depicted in Fig. 1 and Fig. 2, back-propagation neural network simulator is designed in MATLAB. In back-propagation, every input has relation with every neuron, thus, LPM matrix is calculated with contribution of more neurons than ADALINE.
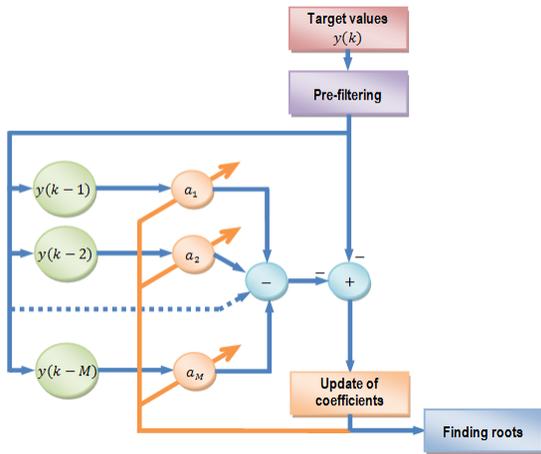
Figure 1. Frequency estimation state of ADALINE (Stage-1) [8]
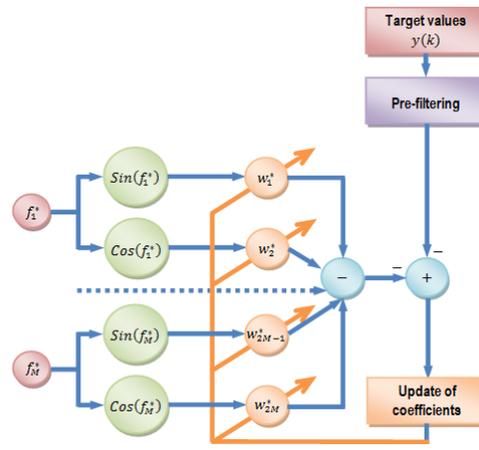
Figure 2. Amplitude and phase estimation state of ADALINE (Stage-2) [8]

Start of Stage-1

% P is Prony polynomial , $Q1$ is ADALINE network, a is weights of $Q1$ and coefficient of P, n is length of a S is output of $Q1$, R is input of $Q1$, z is roots of P, Δt is sampling time

1. Specify n
2. Train $Q1$ with outputs P and inputs R
3. Find a coefficients (weights)
4. If error is not acceptable go to 2
5. Construct Prony polynomial with a
6. Find z
7. Frequencies = $imag(ln(z)/2\pi\Delta t)$

End of Stage-1

Start of Stage-2

% $Q2$ is ADALINE network, $\mathbf{w}^*(k)$ is coefficient vector of $Q2$ network, w_k is element of $\mathbf{w}^*$ vector, y is analyzed signal and output of $Q2$, $\mathbf{x}^*(k)$ is input vector

1. Calculate $\mathbf{x}^*(k)$ vector based on found frequencies in first step
2. Train $Q2$ network and find $\mathbf{w}^*(k)$
3. If error is not acceptable go to 2
4. Phases = $atan(w_k/w_{k+1})$ (k is odd value)
5. Amplitudes = $\sqrt{(w_k{}^2 + w_{k+1}{}^2)}$ (k is odd value)

End of Stage-2

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3. Simulations

In this section, simulations are realized with ADALINE and back-propagation networks. The flowchart of designed simulator is given in Fig. 3. Designed simulator is run on MATLAB and Deep Learning Toolbox [14, 19]. In order to show an example, ADALINE and non-linear network (which is implemented in this simulator) can be compared. Sampling period of test signal which is derived from mathematical model of P&O MPPT method is selected as 1 s time duration is specified as 0.6 s. Step voltage of PV system is 12 V and MPPT frequency is 20 Hz.
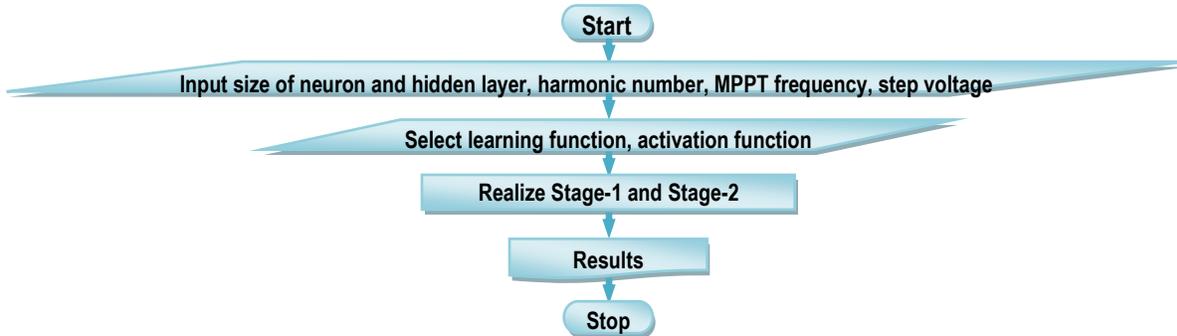
Figure 3. The flowchart of designed simulator
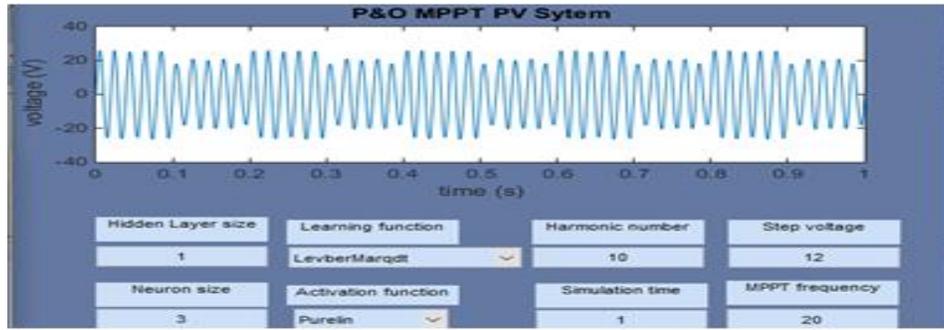
Figure 4. Simulation screen

In ADALINE simulation, 750 inputs are used. In back-propagation, 400 inputs are used. Back-propagation model consists of one input layer, one output layer and one hidden layer with 3 neurons. In complex amplitude calculation, two times of found frequency components should be fed to input of second neural network as stated in Equation (9). Therefore, 400 hundred inputs are changed to 800 hunders inputs for second network which uncovers complex amplitude values. Obtained results are shown in Table 1. Simulation screens for ADALINE and different form of back-propagation algorithm is shown in Fig. 4.

Table 1. Obtained results with ADALINE and back-propagation for frequency estimation ($V_{step} = 12V$ and $f_{MPPT} = 5Hz$)

Real/True value	ADALINE		Back-propagation	
Frequency (Hz)	Estimation (Hz)	Relative error (%)	Estimation (Hz)	Relative error (%)
5	4.8989	2.0220	5.0000	~0
15	17.3109	15.4060	15.0000	~0
25	23.1178	7.5288	25.0000	~0
35	35.4164	1.1897	35.0000	~0
45	44.0699	2.0669	45.0000	~0
50	49.4533	1.0934	50.0000	~0
55	55.1027	0.1867	55.0000	~0
65	65.3665	0.5638	65.0000	~0
75	76.8383	2.4511	75.0000	~0
85	86.4204	1.6711	85.0000	~0
95	97.8306	2.9796	95.0000	~0

It is important to note that this simulator gives opportunity to its users how new neural topology could be designed with differentiating existing one. ADALINE is a linear network, and every input has one weight. But, in back-propagation, 3 neurons are used and every input has weights to each neuron (400x3 weights). In back-propagation, sum of weight which is directly connected to specific input should be considered as Prony polynomial coefficients and this procedure is given in Equation (10).

Conclusions

In this work, an educational simulator is designed for frequency estimation, using ANNs. It is designed in MATLAB and Deep Learning Toolbox. In this simulator, various ANN types with different learning function, neuron size, layer size, etc. can be designed and investigated. It gives opportunity to its users to analyze existing topologies and creating new schemes in order to adapt new problems.

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