A New Adaline Approach for Online Voltage Components Extraction from Unbalanced and Perturbed Power Systems

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Abstract—This work presents theoretical studies and practical results obtained with voltage component extraction. The paper is centered on a new method for estimating the direct, inverse and homopolar voltage components from unbalanced and disturbed power systems. We introduce and develop a new decomposition of the voltages in the $DQ$-space that results in linear expressions explicitly separating AC from DC components. These expressions are learned by Adaline neural networks because of their simplicity and capabilities to approximate linear relationships and to learn online with respect to real-time applications. While learning, the Adalines estimate the amplitude and the phase of the direct, inverse and homopolar voltages of the electrical network and efficiently compensate for the disturbance events, i.e., time-varying nonlinear loads, parameters changes, noise perturbations, fluctuating distortion harmonics. The method was studied and successfully implemented, simulations and experiments under stationary and nonstationary conditions are reported. A demonstrative comparison with other methods is also addressed.

I. INTRODUCTION

A large number of low-power-electronic-based appliances are nonlinear loads that generate considerable disturbance in AC mains. The proliferation of nonlinear loads still continues with the increasing domestic and industrial needs. This results in deterioration of the quality of the voltage waveforms, in the presence of harmonic distortions, in power losses and in the risk of equipment damage.

Since recent years, Active Power filters (APFs) have been studied to compensate for reactive power, harmonics and flicker in industrial power systems [1]. Harmonic compensation with APF generally includes two steps. At first, the harmonic components are identified from the currents and secondly, currents resulting from the distortion harmonics are determined and injected phase opposite in the electrical supply network. Several control methods have been proposed in the past years, including the well-known and powerful Instantaneous Power Theory (IPT). However, the identification of the harmonic components with the IPT strongly depends on the quality of voltage of the electrical power system. APF schemes based on the IPT thus need the voltage components and this is conventionally done with a PLL (Phase Locked Loop) [2].

Existing APFs need much improvement in terms of their versatility, reliability and accuracy. The objective of this paper is to develop an Artificial Neural Network (ANN) approach for identifying the voltage components, i.e., the direct, inverse and homopolar voltages from a three-phase voltage system. The neural approach relies on an original decomposition of the three-phase voltages. These voltages are successively converted into the $\alpha\beta$- and $DQ$-spaces with respectively the Concordia and Park transforms. The $DQ$-space allows to decompose the voltages in linear expressions and to separate the AC components from the DC components from the following voltage components: $v^d_D$, $v^q_Q$, $v^i_D$, $v^i_Q$. The index terms designate the direct and quadrature coordinate frame ($D$ and $Q$), the exponent letter points out the component ($d$ and $i$ for respectively the direct and inverse components).

An Adaline-based architecture is proposed and adopted to learn the linear expressions of the voltages. By iteratively adapting their weights online [10], the Adalines are able to find out the direct, inverse and homopolar voltage components. In order to validate the performance of the method, simulation studies are carried out in the presence of plant variations. Experiments are also presented to show the performance of the proposed neural method under many practical industrial conditions.

This paper is organized in the following way. An overview of voltage component extraction is given in the next section. The proposed voltage decomposition is described in Section III and the induced learning scheme is reported in Section IV. Section V gives some results obtained in simulation and in real-time experiments under various operating conditions. Finally, in Section VI concluding remarks are elaborated and some directions are given for future work.

II. VOLTAGE COMPONENT EXTRACTION

A. PLL for active power filtering

The PLL is present in the architecture of current compensator and voltage controller. Indeed, PLL is used for the synchronization of the APF control with the voltages of the electrical source [2]. Indeed, the PLL enables to estimate the fundamental voltage in a three-phase power system. APF’s
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ANNs are proven to be very efficient, with innumerable possibilities of application in engineering and science. Moreover, their design and implementation are frequently very simple and require little computational effort. More recently, ANNs have been developed and introduced in power/voltage control [3]. Applied in power systems, these techniques now represent a good alternative to conventional strategies in different tasks, e.g., distortion harmonic filtering, frequency estimation, control, etc. As an example, a compensation method for a shunt APF based on ANNs was studied in [9]. This work introduces a new decomposition of the currents. The method is based on the instantaneous active and reactive current components and is completely frequency-independent. Simulation and experimental results are presented and the proposed method shows a good harmonic compensation performance under distorted mains voltages.

New decompositions of the currents, voltages or powers in power system problems is important in the sense that it changes the point of view of the problem and it brings thus new solutions. A new decomposition is also proposed in [4] to recover the voltage components, i.e., the direct, inverse and homopolar voltage components. The decomposition is learned with Adaline neural networks and good results are obtained.

An harmonic distortion identification and filtering scheme also based on Adalines is associated to the previous "Adaline-based disturbance voltage regulation" in [5]. The objective of this work is clearly to develop a complete and unified neural APF scheme for identifying and compensating for the harmonic distortions introduced by nonlinear loads in power systems. The approach results in a modular decomposition where each module is based on an original decomposition of either the voltages, of the currents or of the powers. Each decomposition is then learned with Adalines. The approach has demonstrated its efficiency and reliability in estimating and compensating for harmonic distortions in AC lines. By their learning capabilities, artificial neural networks are able to take into account time-varying parameters, i.e., nonlinear load changes, and thus appreciably improve the performance of traditional compensating methods.

III. A NEW DECOMPOSITION TO EXTRACT THE VOLTAGE COMPONENTS

A. Model of the unbalanced voltage system

The three voltages measured on the nonlinear load, $v_L$, can be expressed with the direct, inverse and homopolar voltage components $v_d$, $v_i$ and $v_o$:

$$v_L = \begin{bmatrix} v_{L1} \\ v_{L2} \\ v_{L3} \end{bmatrix}^T = v_d + v_i + v_o,$$

These voltage components are expressed by:

$$v_d = V_d \sqrt{2} C_{32}.P(\theta_d). \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

$$v_i = V_i \sqrt{2} C_{32}.P(-\theta_i). \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

$$v_o = V_o \sqrt{2}. \cos(\theta_o). C_{31} = \frac{1}{3}(v_{L1} + v_{L2} + v_{L3}).C_{31},$$

where $V_d$, $\theta_d$, $V_i$, $\theta_i$ and $V_o$ and $\theta_o$ are respectively the amplitude and the phase of the direct, inverse, and homopolar voltage components. Equations (2-3) use the general expression of the Clarke and Concordia transforms with the following parameters:

$$P(\theta) = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix},$$

$$C_{32} = \begin{bmatrix} 1 & 0 \\ -1/2 & \sqrt{3}/2 \\ -1/2 & -\sqrt{3}/2 \end{bmatrix},$$

and $C_{31}$ in (4) is a unit vector, i.e., $C_{31} = [1 \\ 1 \\ 1]^T$.

If $\omega$ represents the (theoretical) pulsation of the power system, the instantaneous phases of the voltage components, $\theta_d$, $\theta_i$ and $\theta_o$ can be expressed through $\omega$ and the phases $\varphi_d$, $\varphi_i$ and $\varphi_o$, which are due to the unbalance of the system:

$$\begin{bmatrix} \theta_d \\ \theta_i \\ \theta_o \end{bmatrix} = \begin{bmatrix} \omega t - \varphi_d \\ \omega t - \varphi_i \\ \omega t - \varphi_o \end{bmatrix}.$$

The voltage $v_L$ can be written with $v_d$, $v_i$ and $v_o$, as follow:

$$v_{L1} = V_d \sqrt{2} \cos(\theta_d) + V_i \sqrt{2} \cos(\theta_i) + V_o \sqrt{2} \cos(\theta_o),$$

$$v_{L2} = V_d \sqrt{2} \cos(\theta_d - 2\pi/3) + V_i \sqrt{2} \cos(\theta_i - 2\pi/3) + V_o \sqrt{2} \cos(\theta_o),$$

$$v_{L3} = V_d \sqrt{2} \cos(\theta_d + 2\pi/3) + V_i \sqrt{2} \cos(\theta_i + 2\pi/3) + V_o \sqrt{2} \cos(\theta_o).$$

B. Extraction of the voltage components in the DQ-space

The objective now consists in extracting the amplitude $V_d$ and $V_i$ and the phases $\theta_d$ and $\theta_i$. The amplitude and phase of the homopolar component can than be deduced from (4).

As known, the AC-component can easily be separated from the DC-component in the DQ-space. The voltage of the nonlinear load $v_L$ will thus be expressed in the DQ-space.

The voltage of the power system, represented by the direct and inverse voltage components, are first converted into the $\alpha\beta$-space with the Concordia transform:

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = T_{32}^T \cdot v_L,$$

$$= V_d \sqrt{3}. P(\theta_d). \begin{bmatrix} 1 \\ 0 \end{bmatrix} + V_i \sqrt{3}. P(\theta_i). \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = T_{32}^T \cdot v_L,$$

$$= V_d \sqrt{3}. P(\theta_d). \begin{bmatrix} 1 \\ 0 \end{bmatrix} + V_i \sqrt{3}. P(\theta_i). \begin{bmatrix} 1 \\ 0 \end{bmatrix}.$$

The voltages $v_{\alpha}$ and $v_{\beta}$ are then converted into the $DQ$-space with the Park transform with an angle $-\theta_d$. The direct components on the $DQ$-voltages is thus given by:

$$
\begin{bmatrix}
v_D^d \\
v_Q^d
\end{bmatrix} = P(-\theta_d) \begin{bmatrix}
v_{\alpha} \\
v_{\beta}
\end{bmatrix} = \begin{bmatrix}
V_d\sqrt{3}\cos(\theta_d - \theta) + V_i\sqrt{3}\cos(-\theta_i - \theta_d) \\
V_d\sqrt{3}\sin(\theta_d - \theta) + V_i\sqrt{3}\sin(-\theta_i - \theta_d)
\end{bmatrix}.
\tag{7}
$$

The inverse components on the $DQ$-voltages are calculated with the Park transform with an angle $\theta_i$, and thus

$$
\begin{bmatrix}
v_D^i \\
v_Q^i
\end{bmatrix} = P(\theta_i) \begin{bmatrix}
v_{\alpha} \\
v_{\beta}
\end{bmatrix} = \begin{bmatrix}
V_d\sqrt{3}\cos(\theta_d + \theta) + V_i\sqrt{3}\cos(-\theta_i + \theta_i) \\
V_d\sqrt{3}\sin(\theta_d + \theta) + V_i\sqrt{3}\sin(-\theta_i + \theta_i)
\end{bmatrix}.
\tag{8}
$$

The instantaneous phases $\hat{\theta}_d$ and $\hat{\theta}_i$ are estimated online with a Voltage-Controlled Oscillator (VCO, see Section III-C). One can see that an estimation $\hat{\theta}_d$ very close to $\theta_d$ leads to:

$$
\begin{bmatrix}
v_D^d \\
v_Q^d
\end{bmatrix} \approx \begin{bmatrix}
V_d\sqrt{3} + V_i\sqrt{3}\cos(-\theta_i - \theta_d) \\
V_d\sqrt{3}\sin(-\theta_i - \theta_d)
\end{bmatrix}.
\tag{9}
$$

In the same way, if $\hat{\theta}_i$ is very close to $\theta_i$ then

$$
\begin{bmatrix}
v_D^i \\
v_Q^i
\end{bmatrix} \approx \begin{bmatrix}
V_d\sqrt{3}\cos(\theta_d - \theta_i) + V_i\sqrt{3} \\
V_d\sqrt{3}\sin(\theta_d + \theta_i)
\end{bmatrix}.
\tag{10}
$$

In (9), the terms depending on $(-\theta_i - \hat{\theta}_d)$ are time-varying and represent the AC components of the direct voltages $v_D^d$ and $v_Q^d$ in the $DQ$-space. On the other side, $V_d\sqrt{3}$ that is present in $v_D^d$ is a DC component. Thus, by separating the AC component from the DC component of $v_D^d$, one can extract the real value of $V_d$.

In (10), the terms depending on $(\hat{\theta}_d - \hat{\theta}_i)$ are time-varying and represent the AC components of the direct voltages $v_D^i$ and $v_Q^i$ in the $DQ$-space. $V_i\sqrt{3}$ is present in $v_Q^i$ and is a DC component. Thus, by separating the AC component from the DC component of $v_Q^i$, one can extract the real value of $V_i$.

The complete Adaline-based decomposition which is used to estimate the amplitudes $V_d$ and $V_i$ is shown in detail by Fig. 1. This block-diagram needs online estimates of the instantaneous phases $\theta_d$ and $\theta_i$.

C. Online estimation of the instantaneous phases $\theta_d$ and $\theta_i$

The design of the estimation of the instantaneous phases $\theta_d$ and $\theta_i$ relies on well-known clock extraction circuitry. Indeed, a VCO is phase locked on the incoming data stream and runs at the same rate as the input signal. If the data rate fluctuates, the error voltage from the phase detector will cause the oscillator to shift in frequency and "follow" the data. Adjustment of the loop gain in the PLL structure will control how fast and how far the incoming data can deviate from its nominal rate without preventing the VCO from tracking. Clock extraction circuits are often based upon a PLL architecture, which includes a phase detector and a VCO. Conventional and enhanced PLL can be used [2] and we also have shown that ANNs can be used [4].

In this work, a VCO compatible with the real-time constraint.

Fig. 1. Block diagram of the extraction of the direct and inverse voltage components with the Adaline-based approach.
is used to online deliver $\hat{\theta}_d$ and $\hat{\theta}_i$ at different levels in the architecture of Fig. 1.

IV. FILTERING THE AC COMPONENTS IN THE DQ-SPACE

Separating AC from DC components can be done with conventional low-pass filters. We also propose to use Adaline neural networks for their self-adjustment capabilities and their robustness. Moreover, we also want an APF based on an homogeneous computational structure composed with only neural units working in parallel, i.e., with ANNs such as Adalines [7].

We first introduce the use of low-pass filters and then detail the Adaline-based filtering scheme.

A. Filtering with low-pass filters

Signals from (9) and (10) are filtered with four power low-pass filters in order to separate the AC-voltage component from the DC-voltage component. The order of the filters determines the dynamics and the efficiency of the whole method. We choose second-order filters to achieve the best compromise between total performance and size and cost. Indeed, higher-order filters represent computational costs not compatible with a hardware implementation for an online application. The cutoff frequency, $f_0 = \omega_0/2\pi$, is chosen to separate the terms $V_d\sqrt{3}$ and $V_i\sqrt{3}$ from the AC-voltage components.

B. Filtering with Adalines

In this neural approach, both expressions (9) and (10) are proposed to be learned with Adalines. If we consider the $DQ$-space, both direct voltage components given by (9) can be written with vectorial notations as follow:

$$
\begin{bmatrix}
\hat{v}_D^d \\
\hat{v}_D^i
\end{bmatrix} =
\begin{bmatrix}
W_{D}^{dT} X_{D}^{d}(t) \\
W_{D}^{iT} X_{D}^{i}(t)
\end{bmatrix}.
$$

The two inverse voltage components given by (9) can be written in the $DQ$-space with vectorial notations as follow:

$$
\begin{bmatrix}
\hat{v}_Q^d \\
\hat{v}_Q^i
\end{bmatrix} =
\begin{bmatrix}
W_{Q}^{dT} X_{Q}^{d}(t) \\
W_{Q}^{iT} X_{Q}^{i}(t)
\end{bmatrix}.
$$

The two previous expressions use the following vectors:

$$W_{D}^T = \begin{bmatrix} V_d\sqrt{3}\cos(\theta_d - \hat{\theta}_d) & V_i \end{bmatrix},$$

$$W_{Q}^T = \begin{bmatrix} V_d\sqrt{3}\sin(\theta_d - \hat{\theta}_d) & V_i \end{bmatrix},$$

$$X_{D}^d(t) = \frac{1}{\sqrt{3}} \cos(-\theta_i - \hat{\theta}_d),$$

$$X_{Q}^i(t) = \frac{1}{\sqrt{3}} \sin(-\theta_i - \hat{\theta}_d).$$

We propose to learn the linear expressions (11) and (12) with Adalines neural networks. Each component, $\hat{v}_D^d$, $\hat{v}_D^i$, $\hat{v}_Q^d$ and $\hat{v}_Q^i$, is learned with an Adaline. Vectors $W_{D}^d$, $W_{Q}^d$, $W_{D}^i$ and $W_{Q}^i$ represent the weights while $X_{D}^d(t)$, $X_{Q}^d(t)$, $X_{D}^i(t)$ and $X_{Q}^i(t)$ are the inputs of the Adalines.

The Adalines are trained by an online learning process based on the LMS learning rule, which is an error minimization algorithm [10]. We used the modified LMS learning rule given by (17) to update the weight $W(k)$, where the index $k$ corresponds to the instant $kT$ ($T$ is the sampling period), $\mu$ is the learning rate of the neuron, $\epsilon$ is the error between the output of the neuron and the desired output ($\epsilon = y_d - y$). $X(k)$ is the input vector:

$$W(k+1) = \begin{cases} W(k) + \frac{\mu\epsilon(k)Y(k)}{\lambda + X^T(k)Y(k)} & \text{if } X^T(k)Y(k) \neq 0 \\ W(k) & \text{if } X^T(k)Y(k) = 0 \end{cases}$$

where $Y(k) = \frac{1}{2} (\text{sgn}(X(k)) + X(k))$ and $\lambda$ is an appropriate not-null constant to ensure (17) to avoid a division by zero.

Adalines are thus very simple and powerful neural networks. Online learning can be achieved to estimate $V_d$, $V_i$, $\theta_d$ and $\theta_i$, and this neural architecture is well suited for a real-time hardware implementation.

C. Discussion

Finally, the homopolar voltage component $v_o$ defined by $V_o$ and $\theta_o$ can be deduced from the estimated values of $V_d$, $V_i$, $\theta_d$ and $\theta_i$ through expression (1) but it can also be deduced directly from (4).

This neural method is different with the one proposed in [4]. If both methods are based on Adaline neural networks and online learning, each neural method relies on a different original decomposition of the voltages. Moreover, the new neural method is able to estimate the frequency online and, on the other hand, the approach in [4] needs an online frequency estimation. This can be done by either estimating the frequency with a VCO/PLL or estimating the frequency by a neural approach as proposed in [6].

This new neural approach has numerous advantages over a conventional PLL and also over the PLL enhanced with a RST controller and proposed in [2]. While PLLs can only compensate for some small deviations from a nominal frequency, the new neural method is able to compensate for every frequency fluctuations, even sudden changes. While PLLs can only estimate the direct voltage component, the new neural method is able to estimate the direct, the inverse and the homopolar voltage components.

V. RESULTS

A. Simulation results

The direct, inverse and homopolar voltage components are first extracted in simulation. An electrical network with a three-phase power supply is simulated with a frequency of 50 Hz and a sample period $T = 0.5$ ms. A nonlinear load with resistive and capacitive parts is also simulated ($R_L = 2\Omega$ and $C_L = 45mF$). The new neural method is used to estimate online the different voltage components even while the nonlinear load is changed or even while the frequency suddenly changes. We also propose to compare the results with those obtained with a PLL enhanced with a RST controller.
as proposed in [2] and with those obtained with the neural approach introduced in [4]. The PLL method will serve as a reference in terms of performance. We used a constant learning rate $\mu = 0.008$ and $\lambda = 0.01$ for the proposed neural approach.

At first, the three-phase power system is balanced with only a direct voltage component, i.e., with an null inverse voltage component. After 1.4 seconds, the power supply is disturbed by the nonlinear load, the direct voltage component is reduced by 25%, an non-zero inverse voltage component is introduced, resulting thus to an non-zero homopolar voltage component and to an unbalanced system. After this instant, the electrical network parameters are: $V_d = 0.75 \times 230\sqrt{2} \, \text{V}$, $V_i = 0.25 \times 230\sqrt{2} \, \text{V}$, $V_o = 50 \, \text{V}$, and $\varphi_d = \pi/2 \, \text{rds}$, $\varphi_i = \pi/3 \, \text{rds}$ and $\varphi_o = \pi/5 \, \text{rds}$. One can notice that these conditions are very improper and unfavorable.

The parameters of the direct and inverse voltage components, $V_d$, $V_i$, $\theta_d$ and $\theta_i$ are used to online estimate $V_o$ and $\varphi_o$, and also $v_d$, $v_i$, and $v_o$. These voltage components are represented by Fig. 2. The proposed Adaline strategy succeeded in detecting the transients and in identifying the effects resulting from the nonlinear load changes. The proposed Adaline strategy can be considered to be fast. Fig. 4 shows the online estimation of the direct component $V_d$ with the different methods. One can clearly see that the proposed neural method is the faster one. Indeed, the estimation of the direct voltage component is done after 3.3 ms with the new Adaline strategy against 20.6 ms with the neural approach given in [4] and 46.6 ms with the enhanced PLL.

The proposed neural approach is able to compensate for the variation of the nonlinear load but also for other changing parameters. We now propose to estimate the voltage components when the frequency suddenly changes. Fig. 5 shows the frequency of the previous unbalanced system which suddenly increases from 50 to 51 Hz at time 1.4 s. This figure also shows the estimated frequency which is deduced from the proposed neural approach. Indeed, $\omega$ is obtained with the estimated value of $\theta_d$ and by derivating (5). One clearly notices that the proposed neural approach instantaneously follows the sudden change of frequency.

**B. Experimental results**

Experimental results are now given to illustrate the performance of the Adaline-based method to online extract the voltage components from an electrical three-phase power system. The experimental setup is composed of a three-phase power supply with low voltages (100 V) and a nonlinear load, i.e., a Graetz bridge of six valve functions and a RL-circuit and a power variator. The voltage component extractor is implemented on a DS 1104 DSPACE board, the sample period in all the experiments is $T = 0.5 \, \text{ms}$. This experimental
platform thus reproduces exact industrial conditions.

Several experiments have been conducted in order to evaluate the proposed neural architecture. Results are presented by Fig. 6. One can see the voltage $v_L$ measured at the nonlinear load and the direct voltage component $v_d$ estimated with the proposed neural approach. The Adalines succeeded well in estimating the voltage component parameters.

The new neural approach has been evaluated in more severe cases, for example when the nonlinear load changes over time or when important distortion harmonics are present. This last case is illustrated by Fig. 7 which shows the voltage $v_L$ measured at the nonlinear load and the estimated direct voltage $v_d$. One can see the voltage of the unbalanced system disturbed by distortion harmonics up to rank 11 and the efficiency of the neural approach to online estimate the voltage components.

The experiments demonstrate the efficiency and the robustness of the Adaline approach to estimate online the voltage components, i.e., the direct, inverse and homopolar components. All the experiments also prove that the neural approach is well suited for a hardware real-time application.

VI. CONCLUSION

This paper introduces a neural disturbance detection and identification approach. The proposed approach detects voltage components from unbalanced and perturbed power systems. It is thus well suited for active power filter schemes. Based on a new decomposition of the voltages in the $DQ$-space, linear expressions, explicitly separating AC from DC components, are learned with Adaline neural networks. By their simplicity and their online learning capabilities, the Adalines allow the proposed approach to be significantly faster and more precise in detecting and discriminating the disturbance events than conventional approaches and other neural approaches. The method was studied and successfully implemented in simulation and in experiments both under stationary and nonstationary conditions. Comparisons demonstrate the effectiveness of the proposed method, especially in the presence of uncertainties, parameter changes and noise perturbations.

REFERENCES


