An Application of Master-Slave ADALINE for State Estimation of Power System

Zhanshan Wang(✉), Haoyuan Gao, and Huaguang Zhang

School of Information Science and Engineering,
Northeastern University, Shenyang 110819, China
zhanshan_wang@163.com

Abstract. This paper presents two-fold adaptive linear neural networks (ADALINE) to gain the current operating state of power system for a fast and accurate estimation. On the one hand, the Slave-ADALINE applies the fixed and larger step-size least mean square algorithm to accelerate the convergence speed of weights. On the other hand, the Master-ADALINE follows least mean square with a variable step-size factor to achieve the minimum of steady-state error. In this paper the IEEE-30 network of power system is used to verify the effectiveness of the proposed method, and comparisons of simulation results with Particle Swarm Optimization algorithm and single ADALINE are also provided.

Keywords: State estimation · Master-Slave ADALINE · Least mean square (LMS) · Power system

1 Introduction

In the last years, a rapid progress from the conventional electrical grids toward the new smart grids has happened to deal with the increasing requirements of customers [1]. In fact, various power system applications such as optimal power flow, economic dispatch, and security assessment rely on the state variables of power systems under management that are filtered initially by state estimation [2]. Real time monitoring of power systems has therefore become very important, and the timely detection of contingencies has also become important in order to allow the undertaking ofremedial actions to avoidany potentially dangerous situation [3].

F.C. Schweppe, in the 1970s, firstly presented the concept of the power system state estimation and applied weighted least squares (WLS) method to solve this problem [4]. But, with the high development of the Distributed Generations, the complexity of power system, operation and communication will also affect the optimal state estimation. In response to these challenges, various methods especially based on the evolutionary algorithms have been proposed in many

Z. Wang—This work was supported by the National Natural Science Foundation of China (Grant Nos. 61473070, 61433004, 61627809), and SAPI Fundamental Research Funds (Grant No. 2013ZCX01).

F. Cong et al. (Eds.): ISNN 2017, Part II, LNCS 10262, pp. 28–35, 2017.
DOI: 10.1007/978-3-319-59081-3_4

literatures. In the 2015, Reza used the firefly algorithm to solve state estimation problems [1]. A hybrid method based on Particle Swarm Optimization (PSO) was proposed [5,6] for distribution state estimation with the Distributed Generations. Specially for the PSO, many researchers have tried to improve the performance of PSO, focusing on the individual best position (Pbest) and global best position (Gbest) [7,8]. In order to improve the performance of PSO, a new PSO is proposed in [9]. The algorithm can adaptively change the initial trajectory of a particle to make the particle explore a new region. Nevertheless, the above methods still need to use more memory resources.

In recent years, adaptive linear neural network (ADALINE) has been widely used in harmonic analysis [10–14]. In 2014, a new algorithm minimizes an objective function based on weighted square of the error and using a modified recursive Gauss Newton (MRGN) method was introduced by Nanda [15]. The method in [10–15] can minimize the tracking error, and has a faster convergence rate. Meanwhile, its multi-input and single-output structure can reduce the complexity of the system design. However, the ADALINE technique prematurely converges during the estimation of the signal with time-varying parameters, affecting the accuracy of estimation. Therefore, in 2009, G.W. Chang presented a two-stage ADALINE for harmonics and interharmonics measurement [16], but the computing time is double. In this paper, the authors will use a two-fold ADALINE structure, i.e. applying the Master-Slave ADALINE to solve the state estimation of power system. Compared with the reference [16], the proposed method has parallel processing characteristics, which can improve the speed of computation. The IEEE-30 network of power system is used to verify the achievability of the way, and comparisons of simulation results with PSO algorithm [9] and single ADALINE [15] is tested.

The rest of this paper is organized as follows. Section 2 shows the power system state estimation of specific implementation. Section 3 presents the MS ADALINE structure and algorithm. Section 4 presents the simulation results of IEEE-30 network of power system and the simulation results are compared with PSO algorithm and single ADAINE. Section 5 draws some conclusions of the present paper.

2 Specific Accomplishment of State Estimation

Before presenting the master-slave adaptive linear neural network structure and algorithm in detail, we need to get the mathematical model of the state estimation of voltage. So, in this section will introduce the common mathematical model of power lines and branch power flow calculation formula, and the specific processes of state estimation of voltage.

In the steady-state analysis of power system, mathematical model of power lines is based on the resistance, reactance, and admittance, serial or parallel conductance through the equivalent circuits. Figure 1 shows the π-type equivalent circuit of transmission line. Among them, $Z = R + jX$, where R is the resistor of power line, X is the inductance of power lines. $Y = jB$ is the admittance

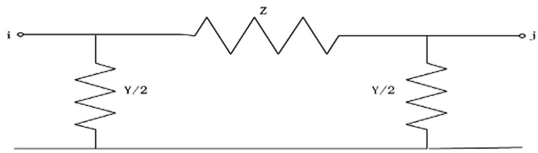

Fig. 1. The π-equivalent circuit of transmission line

of power lines. The active and reactive power calculation formula of the branch from node i to node j is defined as follows,

$$P_{ij} = |V_i|^2|y_{ij}|\cos(-\alpha_{ij}) - |V_i||V_j||y_{ij}|\cos(\delta_i - \delta_j - \alpha_{ij}) \tag{1}$$

$$Q_{ij} = |V_i|^2|y_{ij}|\sin(-\alpha_{ij}) - |V_i||V_j||y_{ij}|\sin(\delta_i - \delta_j - \alpha_{ij}) \tag{2}$$

where, $|V_i|$ and δ_i are the amplitude and phase of the voltage node i, respectively. $|V_j|$, δ_j are the amplitude and phase of the voltage node j. $|y_{ij}|$, α_{ij} are the admittance modulus and phase of the branch from node i to node j ($y_{ij} = |y_{ij}|\angle\alpha_{ij}$), respectively.

By comparing Eq. (1) with (2), let

$$W_1 = 1, W_2 = |V_j|\cos(\delta_j), W_3 = |V_j|\sin(\delta_j) \tag{3}$$

Therefore, from the (1)–(2),we can derive the following formulas,

$$|V_j| = \sqrt{W_2^2 + W_3^2} \tag{4}$$

$$\delta_j = \arctan(W_3/W_2) \tag{5}$$

3 Structure of MS ADALINE

This section will introduce ADALINE method to solve the power system state estimation problem. Figure 1 is the structure diagram of MS ADALINE. The structure is formed by two conventional master ADALINE and slave ADALINE, whose weights are denoted as $\{\hat{w}_{1M}(n), \hat{w}_{2M}(n), \hat{w}_{3M}(n)\}$ and $\{\hat{w}_{1S}(n), \hat{w}_{2S}(n), \hat{w}_{3S}(n)\}$. At the same time, the master and slaver ADALINE have the same reference signal of input and desired output, which is $\{I_1(n), I_2(n), I_3(n)\}$ and $D(n)$, and the corresponding feedback signal of error is $\{E_M(n), E_S(n)$. The error feedback signal is transferred to the decision controller to adjust the real-time weights. The Slave-ADALINE applies fixed, larger step-size least mean square (LMS) algorithm to weights for accelerating the speed of convergence. At the moment, the Master-ADALINE follows least mean square with a variable step-size factor, in order to accomplish the minimum of steady-state error. Finally, after some iterations MS ADALINE weights can be obtained to calculate amplitude and phase of the node j, the formulas are as follows,

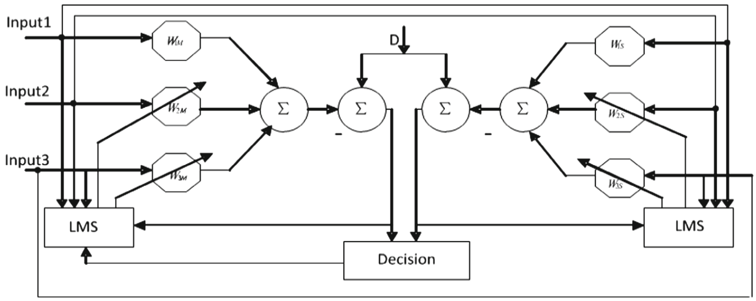

Fig. 2. The framework of MS ADALINE for power state estimation

$$|V_j| = \sqrt{\hat{w}_{2M}(n)^2 + \hat{w}_{3M}(n)^2} \tag{6}$$
$$\delta_j = \arctan(\hat{w}_{3M}(n)/\hat{w}_{2M}(n)) \tag{7}$$

symbols S_i and δ_i are the amplitude and phase of the harmonic i, respectively.
Weights of MS ADALINE are adjusted as follows.

Step-1: The adjustment of weights $\{\hat{w}_{1S}(n), \hat{w}_{2S}(n), \hat{w}_{3S}(n)\}$ of the Slave-ADALINE.

$$\hat{w}_{1S}(n) = 1 \tag{8}$$
$$\hat{w}_{2S}(n+1) = \hat{w}_{2S}(n) + \mu_S E_S(n) I_2(n) \tag{9}$$
$$\hat{w}_{3S}(n+1) = \hat{w}_{3S}(n) + \mu_S E_S(n) I_3(n) \tag{10}$$
$$E_S(n) = D(n) - Y_S(n) \tag{11}$$
$$Y_S(n) = [\hat{w}_{1S}, \hat{w}_{2S}, \hat{w}_{3S}][I_1, I_2, I_3]^T \tag{12}$$

symbol $D(n)$ is the desired output, $Y_S(n)$ is the output of the Slave-ADALINE respectively.

Step-2: The adjustment of weights $\{\hat{w}_{1M}(n), \hat{w}_{2M}(n), \hat{w}_{3M}(n)\}_{i=1}^{L}$ of the Master-ADALINE.

$$\hat{w}_{1M}(n+1) = 1 \tag{13}$$
$$hatw_{2M}(n+1) = \begin{cases} \hat{w}_{2S}(n+1), if(A_S(m) < A_M(m)) \\ \hat{w}_{2M}(n) + \mu_M E_M(n) I_2(n), else \end{cases} \tag{14}$$
$$\hat{w}_{3M}(n+1) = \begin{cases} \hat{w}_{3S}(n+1), if(A_S(m) < A_M(m)) \\ \hat{w}_{3M}(n) + \mu_M E_M(n) I_3(n), else \end{cases} \tag{15}$$
$$A_S(m) = \sum_{m=0}^{Q} E_S^2(m) \qquad A_M(m) = \sum_{m=0}^{Q} E_M^2(m) \tag{16}$$
$$E_M(n) = D(n) - Y_M(n) \tag{17}$$
$$Y_M(n) = [\hat{w}_{1M}(n), \hat{w}_{2M}(n), \hat{w}_{3M}(n)][I_1(n), I_2(n), I_3(n)]^T \tag{18}$$

symbol $Y_M(n)$ is the output of the Master-ADALINE. After the end of each iteration, $A_S(m)$ and $A_M(m)$ will be calculated. Decision controller based on the results of comparison of the two calculated values is used to predict the Master-ADALINE updated weights.

Step-3: Update the variable step of Master-ADALINE.

$$\mu_M(n+1) = \begin{cases} \frac{\mu_M(n)+\mu_S}{2}, if(A_S(m) < A_M(m)) \\ \max[C_1\mu_M(n), \mu_{\min}], else \end{cases} \tag{19}$$

From the formula (19), one can see taht, if the tracking performance of Master-ADALINE is better, Master-ADALINE step value is the average value of Master-ADALINE step and Slaver-ADALINE step, which makes the Master-ADALINE, converges faster. In order to obtain small steady-state error, the step value of Master-ADALINE should be further reduced.

Step-4: According to the formula (1) and (2), the amplitude and phase of the voltage of the node j can be calculated, respectively.

In order to obtain a good convergence efficiency, the values of C_1, μ_{min}, μ_S and μ_M need to be chosen. The above discussions show that μ_S determines the global convergence of MS ADALINE, μ_M determines the accuracy of convergence, therefore, the selection of these two values plays a key in the performance of the network. These two main values can be determined based on previous experience.

The weights of the Master-ADALINE are updated by the expected outputs until them no long changed obviously, or the maximum number of iterations is reached. The active power and reactive power are alternating as the expected input of the MS ADALINE. The reference input signals as shown in Table 1.

Table 1. The reference input signals

Input signals	Pij	Qij
Input1	$\lvert V_i\rvert^2\lvert y_{ij}\rvert\cos(-\alpha_{ij})$	$\lvert V_i\rvert^2\lvert y_{ij}\rvert\cos(-\alpha_{ij})$
Input2	$-\lvert V_i\rvert\lvert y_{ij}\rvert\cos(\delta_i-\alpha_{ij})$	$-\lvert V_i\rvert\lvert y_{ij}\rvert\sin(\delta_i-\alpha_{ij})$
Input3	$-\lvert V_i\rvert\lvert y_{ij}\rvert\sin(\delta_i-\alpha_{ij})$	$\lvert V_i\rvert\lvert y_{ij}\rvert\cos(\delta_i-\alpha_{ij})$

Remark 1. The proposed method used to deal with the state of power system needs less memory space compared with previous method, like PSO [9]. So, this needs less time to compute the results.

Remark 2. Compared with [16], the proposed method has parallel processing characteristics, which can improve the speed of computation.

Remark 3. Compared with the single ADALINE [15], the proposed method has a two-fold structure, i.e. master ADALINE and slave ADALINE. The slave ADALINE mainly is used to improve the speed of convergence, at the same time, the master ADALINE could accomplish the minimum of steady-state error.

4 Simulation Results

A IEEE-30 network of power system is used to verify the achievability of the proposed method. Meanwhile, some comparisons of simulation results with PSO [9] and single ADALINE [15] are presented. Then the simulation results indicate that the proposed method has better accuracy than the PSO algorithm and the single ADALINE, and convergence rate of which is faster than the single ADALINE.

Figure 3 shows the comparisons between the results of the MS ADALINE and PSO algorithms and the single ADALINE. MS ADALINE and single ADAINE have better performance than PSO for the ability of voltage amplitude and phase estimation. What's more, MS ADALINE voltage amplitude estimated average error is 0.0015769, phase estimated average error is 0.0047077. PSO voltage amplitude estimated average error is 0.035515, phase estimated average error is 0.022969. The single ADALINE voltage amplitude estimated average error is 0.0022536, phase estimated average error is 0.021897. So MS ADALINE results are better than the PSO algorithm and single ADALINE. MS ADALINE results are more accurate, and MS ADALINE model has obvious advantages on simulation time, whose value is 0.015 s, and PSO is 0.103 s (CPU 887 1.5 GHz).

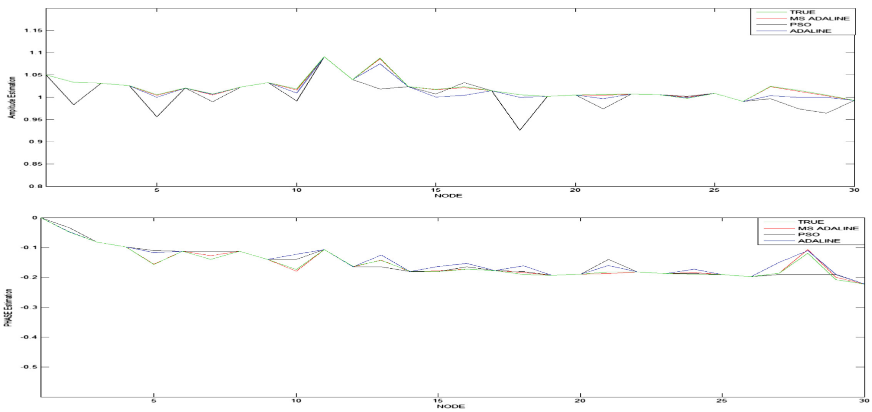

Fig. 3. The comparisons of estimated voltage amplitude and phase

Figure 4 shows the comparisons of tracking performance of MS ADALINE, Single ADALINE and PSO. The PQ_{12} is the actual measured value. It can be seen from the right simulation diagram that MS ADALINE coincides with the expected waveform after 16 iterations, PSO converges after the 37th iteration, and single ADALINE converges to the expected value after the 25th iteration. The left diagram is a comparison of the MS ADALINE and PSO algorithms of node 2, the horizontal axis is the number of iterations, and the vertical axis is the error degree. The error degree is defined as $\Delta = (\hat{V}_i(k) - V_{imeas})^2 + (\hat{\delta}_i(k) - \delta_{imeas})^2$, where, $\hat{V}_i(k)$, $\hat{\delta}_i(k)$ are the estimated values of each iteration

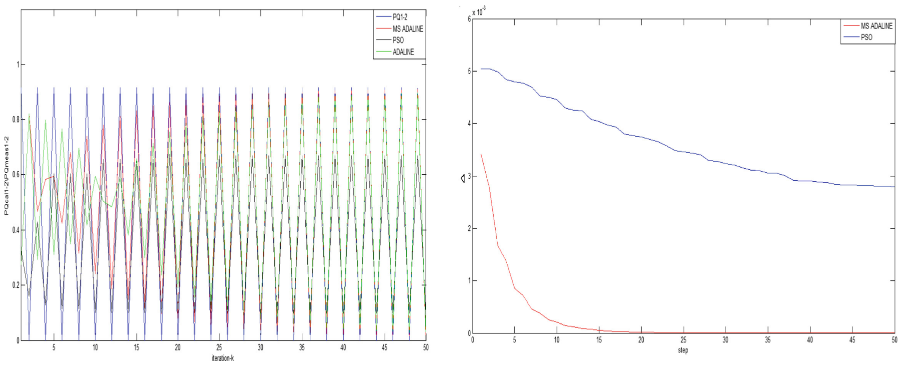

Fig. 4. The comparisons of tracking performance of MS ADALINE, Single ADALINE and PSO

and V_{imeas}, δ_{imeas} are the actual measured values of the node. Above, the PSO algorithm has a lower convergence rate, and the estimation accuracy is worse. The estimation precision of MS ADALINE is better than PSO and single ADALINE. Therefore, MS ADALINE not only can improve the accuracy of the estimate, but also could ameliorate convergence rate.

5 Conclusion

This study introduces a master-slave adaptive linear neural network (ADALINE) approach to deal with power system state estimation problem. MS ADALINE has a two-fold structure, and the characteristics of parallel processing. This paper uses a IEEE-30 network to verify the achievability of the way, and comparisons of simulation results with Particle Swarm Optimization algorithm and single ADAINE. Simulation results shows MS ADALINE not only can improve the accuracy of the estimate, but also could ameliorate convergence rate.

References

1. Khorshidi, R., Shabaninia, F., Niknam, T.: A new smart approach for state estimation of distribution grids considering renewable energy sources. Energy **94**, 29–37 (2016)
2. Choi, S., Sakis Meliopoulos, A., Ratnesh, K.: Autonomous state estimation based diagnostic system in smart grid. In: IEEE PES Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, pp. 1–6 (2013)
3. Asprou, M., Kyriakides, E., Chakrabarti, S.: The use of a PMU-based state estimator for tracking power system dynamics. In: IEEE PES General Meeting - Conference & Exposition, National Harbor, MD, pp. 1–5 (2014)
4. Schweppe, F.C., Wildes, J.: Power system static-state estimation. Part I-III: Exact Model IEEE Trans. Power Appar. Syst. **89**(1), 120–135 (1970)

5. Naka, S., Genji, T., Yura, T., Fukuyama, Y.: A hybrid particle swarm optimization for distribution state estimation. In: IEEE Power Engineering Society General Meeting (IEEE Cat. No. 03CH37491) 2 (2003)
6. Liu, Z., Ji, T., Tang, W.H., Wu, Q.H.: Optimal harmonic estimation using a particle swarm optimizer. IEEE Trans. Power Deliv. **23**(2), 1166–1174 (2008)
7. Liu, Z., Zhang, J., Zhou, S., Li, X., Liu, K.: Coevolutionary particle swarm optimization using AIS and its application in multiparameter estimation of PMSM. IIEEE Trans. Cybern. **43**(6), 1921–1935 (2013)
8. Liu, Z., Li, X., Wu, L., Zhou, S., Liu, K.: GPU-accelerated parallel coevolutionary algorithm for parameters identification and temperature monitoring in permanent magnet synchronous machines. IEEE Trans. Ind. Inform. **11**(5), 1220–1230 (2015)
9. Liu, Z., Wei, H., Zhong, Q.C., Liu, K., Xiao, X., Wu, L.: Parameter estimation for VSI-Fed PMSM based on a dynamic PSO with learning strategies. IEEE Trans. Power Electron., to be published. doi:10.1109/TPEL.2016
10. Sarkar, A., Choudhury, S., Sengupta, S.: A self-synchronized ADALINE network for on-line tracking of power system harmonics. Meas **44**(4), 784–790 (2011)
11. Marei, M., El-Saadany, E., Salama, M.: A processing unit for symmetrical components and harmonics estimationbased on a new adaptive linear combiner structure. IEEE Trans. Power Deliv. **19**(3), 1245–1252 (2004)
12. Joorabian, M., Mortazavi, S., Khayyami, A.: Harmonic estimation in a power system using a novel hybrid least square-Adaline algorithm. Electr. Power Syst. Res. **79**(1), 107–116 (2009)
13. Garanayak, P., Panda, G.: Fast and accurate measurement of harmonic parameters employing hybrid adaptive linear neural network and filtered-x least mean square algorithm. IET Gener. Transm. Distrib. **10**(2), 421–436 (2016)
14. Dash, P., Swain, D., Routray, A., Liew, A.: Harmonic estimation in a power system using adaptive perceptrons. IEEE Proc. Gener. Transm. Distrib. **143**(6), 565–574 (1996)
15. Nanda, S., Biswal, M., Dash, P.K.: Estimation of time varying signal parameters using an improved Adaline learning algorithm. Int. J. Electron. Commun. **68**(2), 115–129 (2014)
16. Chang, G.W., Chen, C.I., Liang, Q.W.: A two-stage ADALINE for harmonics and interharmonics measurement. IEEE Trans. Ind. Electron. **56**(6), 2220–2228 (2009)