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Implementation of Autoregressive (AR) Method to Pre-Filter the Set of Measurements

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Abstract— This paper describes an approach to identify and change the measurement weights used in Weight Least Square (WLS) estimation method employed in State Estimation (SE). The individual measurement is assigned with their own weighting factor based on technical experience by the engineers. However, ents could occur in a real time system. Thus, the higher weighting factor or wrongly assigned weighting factor to the measurement could lead to flag the measurement as bad. This paper describes a pre-screening process to identify the bad measurements and the measurement weights before WLS estimation method employed in SE is performed. The autoregressive (AR) method proposed in this paper is used to predict the data and at the same time filtering the logical weighting factors that have been assigned to the identified bad measurements. The AR algorithms known as Burg and Modified Covariance (MC) are used to calculate the one-step-ahead of the predicted values of the state variables. The performance of the AR filter is tested using 5-bus, IEEE 14-bus, IEEE 24-bus, IEEE 57-bus, IEEE 118-bus, IEEE 300-bus system and local utility network consisting 103-bus. Simulation results are presented and compared with the measured values to validate the proposed method.

Keywords—State Estimation (SE), Weight Least Square (WLS), Autoregressive (AR), Burg algorithm, Modified Covariance (MC) algorithm.

I. INTRODUCTION

The state of the power system is described by a collection of bus voltage vector for a given network topology and parameters. Comprehensive discussion of the state of the art and its important in electric power system state estimation is discussed in [1]-[5]. The state variables obtained from State Estimation (SE) rely on the set of measurements that are collected via the Supervisory Control and Data Acquisition (SCADA) system.

Various numerical methods of SE incorporating state filtering are presented in [1] and [6]-[14]. The main objective of these methods is to have a robust numerical estimator, which can suitably improve the gain matrix. Recently, Artificial Intelligent systems such as Fuzzy and Neural Network are being used in SE [15]-[17]. However, these techniques have not been tested on the large-scale power systems.

An important constraint on all existing SE methods is the measurement redundancy. More the redundancy, the better is the filtering and bad data detection. To avoid the system loosing a number of measurements due to the bad measurements, higher weighting factor should be placed on the good measurement devices. Decisions to select the good measurements are always based on the experience of engineers. However, in real time environment, some measurements are inconsistent in producing a good reading. The uncertainty in analog measurements could occur because of the combination between systematic error and random error [18]. This will affect the measurements that are assigned with higher weighting factor since the measurement with higher weighting factor is the priority input for the SE process. If this good measurement is producing bad data, the SE still considered it as priority measurement and it will affect the efficiency of SE.

In order to alleviate these problems, all the measurements are to be processed before SE is performed. Most of the existing commercial software performs a pre-screening process to check whether the measured values are within the reasonable limit or not. The margin of the limitations set in the SCADA subsystem is typically around 15 % [19]. However, this pre-screened process is not fully implemented in large power system networks. An improved algorithm, which adaptively updates the measurement variances, is presented in [20] and [21]. The sensitivity relationship between the measurement variances and the covariance matrix of their residuals was used for this purpose. However, the requirement of calculating all the elements in the sensitivity matrix could increase the computational cost especially for large scale networks.

The proposed AR method can be used to predict the data

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and at the same time filter the logical weighting factors that have been assigned to the trusted measurements. The performance of combination between the proposed method and SE (AR-SE) are also not dependent on any measurement redundancy. It is because the input data for AR-SE is based on forecasted value of historical measurements.

II. REVIEW OF WEIGHT LEAST SQUARE

Most of the SE programs are formulated as over-determined systems of nonlinear equations and solved as Weight Least Square (WLS) problems [1] and [9]. The mathematical model for SE is given by

$$z = h(x) + e \quad (1)$$

$$E(ee^T) = R \quad (2)$$

where

- z is the m dimensional measurement vector (mx1)
- x is the n dimensional state vector (voltage magnitudes and voltage phase angles) (nx1)
- e is the m dimensional measurement error vector (mx1)
- $h(\,)$ is the m dimensional nonlinear vector function relating the state to the ideal measurements
- E is the expectation operator
- R is the (m x m) dimensional diagonal measurement error covariance matrix
- m is the number of measurements
- n is the number state variables

The model assumes that the errors are small and uncorrelated as in (2) and follow normal distributions with zero mean. The errors that do not satisfy category in (2) are considered to be gross errors.

The objective function of the WLS is to minimize the cost function of $J(x)$ given by:

$$J(x) = (z - h(x))^T W(z - h(x)) \quad (3)$$

where $W = R^{-1}$ is the weighting matrix.
The cost function $J(x)$ will be minimized when

$$\frac{\partial J(\hat{x})}{\partial \hat{x}} = H^T(\hat{x})W[z - h(\hat{x})] = 0 \quad (4)$$

where

- $H(x)$ is the Jacobian of $h(x)$ that would result in minimum $J(x)$.
- $\hat{x}$ is defined as the final estimated values.

This system is solved iteratively and the state x is updated at each iteration of k by

$$\Delta x_k = [H^T(\hat{x}_k)WH(\hat{x}_k)]^{-1}[H^T(\hat{x}_k)W(z - h(\hat{x}_k))] \quad (5)$$

This process is repeated until convergence is obtained.

A. Bad Data Identification and Elimination

Bad data identification and elimination technique is processed once the final estimate $\hat{x}$ is obtained. Methods used for detecting and identifying bad data are discussed in details in [10],[22]-[25]. One of the methods used for detecting bad data is Chi-squares, χ^2 test. The sum of weighted squares of $J(x)$ is given as

$$J(\hat{x}) = \sum_{i=1}^{m} \frac{\hat{e}_i^2}{\sigma_i^2} \quad (6)$$

where

- σ is the standard deviation of the error of the i'th measurement.
- α is the detection confidence level

has the Chi-square, χ^2 ,distribution. If the sum of weighted squares as calculated from the (6) lie below the chi-square distribution $\chi^2_{d,\alpha}$,

$$J(\hat{x}) \le \chi^2_{d,\alpha} \quad (7)$$

where $\chi^2_{d,\alpha}$ means the chi-square distribution with d degrees of freedom with probability of false alarm threshold, α, which represents 5 % probability of error for the most of the cases presented in this paper, the set of measurements is said to be in a good condition.

If the constraint given in (7) is not satisfied, then the presence of bad data is suspected. Once bad data are detected in the measurement set, they are identified using normalized residual, r^N test [10], [25]. The normalized residual is given in (8).

$$r_i^N = \hat{e}_i \Big/ \sqrt{r_{ii}} \qquad i = 1,2,\ldots,m \quad (8)$$

where

- $\hat{e}_i$ is the i-th element of the residual vector, $e = z\text{-}h(x)$
- r_{ii} is the i-th diagonal element of the residual covariance matrix $r = R - H(x)\, G^{-1}(x)\, H^T(x)$
- G is the gain matrix H^TWH

The measurement presenting the normalized residual with the largest absolute magnitude is flagged as a bad data. Once the identification process is completed, the bad measurement is eliminated and SE process is repeated until the measurements are free from bad data.

III. AUTOREGRESSIVE (AR) METHOD

An AR technique is used as a pre-estimation filter to detect and identify gross errors in the measurement set, before they can be used for SE process.

AR model is given by [27], [28]:

$$E_m(n) = x(n) + \sum_{k=1}^{m} a_m(k)U(n-k) \quad (9)$$

where

- $a_m(k)$ are the prediction coefficients with $0 \le k \le m - 1$
- m is the number of past measurements/observations
- n is the instant of time
- $E_m(n)$ is an observed sequence
- $x(n)$ is the input to a system that generates $E_m(n)$
- $U(n\text{-}k)$ is equal to ($E(n\text{-}1), E(n\text{-}2), \ldots E(n\text{-}k)$)

The above is called an autoregressive model of order m or, in short, *AR(m)*. Several methods to find the prediction coefficients of the model, $a(k)$ are found in [26]. However due to the ability to minimize the sum of backward and forward prediction errors, the Burg and MC are selected as the AR methods in this paper. The objective of the both methods is to minimize the sum of squares of prediction errors.

$$\varepsilon_m = f_m + g_m \quad (10)$$

where

ε_m is the sum of squares of prediction errors

f_m is the forward error

g_m is the backward error

The basic function of AR filters is to predict the one-step ahead expected value of a measurement from past measurement. For the same instant of time, the difference between predicted and the measured value of the measurement should not exceed a certain pre-determined threshold. If it does not meet the requirement, the measurement is identified as a bad data. If the bad measurements are initially assigned with higher weighting factor, the predicted value obtained from AR algorithm is substituted and the SE is carried out.

In real-time applications, each time a measurement *m* meet the requirement, it replaces the most recent measurement in the vector of past measurements, *x(n)*. The AR parameter are then calculated using Burg or MC, and the one-step ahead predicted value of variable *m* is determined so that, when the next snapshot is available, the filtering procedure can be repeated.

A. Burg method

The Burg method for estimating the AR parameters can be viewed as an order–recursive least-squares lattice method, based on the minimization of the forward and backward errors in linear predictors, with the constraint that the AR parameters satisfy the Levinson-Durbin recursion [27]-[29]. To derive the estimator, consider the data *x(n)*, *n*=0,1,…, *N*-1. The forward and backward linear prediction estimates of order *m* are

$$\hat{x}(n) = -\sum_{k=1}^{m} a_m(k)x(n-k) \tag{11}$$

$$\hat{x}(n-m) = -\sum_{k=1}^{m} a_m^*(k)x(n+k-m) \tag{12}$$

The corresponding forward and backward errors $f_m(n)$ and $g_m(n)$ are defined as $f_m(n) = x(n) - \hat{x}(n)$ and $g_m(n) = x(n-m) - \hat{x}(n-m)$. The least square error is

$$\varepsilon_m = \sum_{n-m}^{N-1}\left[\left|f_m(n)\right|^2 + \left|g_m(n)\right|^2\right] \tag{13}$$

Equations (11) to (13) are the standard equations for forward and backward linear prediction. Thus, those equations will be reused in the MC section later. However, in Burg, the error obtained in (13) is to be minimized by selecting the prediction coefficients, subject to Levinson-Durbin constraint given by

$$a_m(k) = a_{m-1}(k) + K_m a_{m-1}^*(m-k), \quad 1 \le k \le m-1, \quad 1 \le m \le p \tag{14}$$

where $K_m = a_m(m)$ is the *m*th reflection coefficient in the lattice filter realization of the predictor. When (13) is substituted into the expressions for $f_m(n)$ and $g_m(n)$, the result is the pair of order–recursive equations for the forward and backward prediction errors given by

$$\begin{aligned} f_m(n) &= f_{m-1}(n) + K_m g_{m-1}(n-1), \quad m = 1,2,\dots p \\ g_m(n) &= K_m^* f_{m-1}(n) + g_{m-1}(n-1), \quad m = 1,2,\dots p \end{aligned} \tag{15}$$

Now, if we substitute (14) into (13) and perform the minimization of ε_m with respect to the complex-valued reflection coefficient K_m, we obtain the result as

$$\hat{K}_m = \frac{-\sum_{n=m}^{N-1} f_{m-1}(n) g_{m-1}^*(n-1)}{\frac{1}{2}\sum_{n=m}^{N-1}\left[\left|f_{m-1}(n)\right|^2 + \left|g_{m-1}(n-1)\right|^2\right]} \qquad m = 1,2,\dots p \tag{16}$$

The term in the numerator of (16) is an estimate of the cross correlation between the forward and backward prediction errors. With the normalization factors in the denominator of (16), it is apparent that K_m <1, so that the all-pole model obtained from the data is stable. The denominator in (16) is simply the least-squares estimate of the forward and backward errors E_{m-1}^f and E_{m-1}^b, respectively [27], [28]. Hence (16) can be expressed as

$$\hat{K}_m = \frac{-\sum_{n=m}^{N-1} f_{m-1}(n) g_{m-1}^*(n-1)}{\frac{1}{2}\left[\hat{E}_{m-1}^f + \hat{E}_{m-1}^b\right]} \qquad m = 1,2,\dots p \tag{17}$$

where $\hat{E}_{m-1}^f + \hat{E}_{m-1}^b$ is an estimate of the total squared error E_m. The denominator term of (17) can be computed in an order-recursive fashion according to the relation [27]

$$\hat{E}_m = \left(1 - \left|\hat{K}_m\right|^2\right)\hat{E}_{m-1}\left|f_{m-1}(m-1)\right|^2 - \left|g_{m-1}(m-2)\right|^2 \tag{18}$$

where $\hat{E}_m \equiv \hat{E}_m^f + \hat{E}_m^b$ is the total squared error.

To summarize, the Burg algorithm computes the reflection coefficients in the equivalent lattice structure as specified by (17) and (18), and the Levinson-Durbin algorithm is used to obtain the AR model parameters.

B. Modified Covariance method

Consider the data *x(n)*, *n*=0,1,…, *N*-1. To find the prediction coefficients that minimize ε_m, the derivative of ε_m with respect to $a_m^*(l)$ is set to zero for *l* = 1,2,…..,*m* [27] and [30]. Hence

$$\begin{aligned} \frac{\partial E_m}{\partial a_m^*(l)} &= \sum_{n=m}^{N-1}\left[f_m(n)\frac{\partial\left[f_m(n)\right]^*}{\partial a_m^*(l)} + \left[g_m(n)\right]^*\frac{\partial g_m(n)}{a_m^*(l)}\right] \\ &= \sum_{n=m}^{N-1}\left[f_m(n)x^*(n-l) + \left[g_m(n)\right]^* x(n-m+l)\right] = 0 \end{aligned} \tag{19}$$

Substituting (11) to (13) into (19) and simplifying, the normal equations for the MC method are obtained as

$$\begin{aligned} &\sum_{k=1}^{m}\left[c_x(l,k) + c_x(m-k, m-l)\right]a_m(k) \\ &= -\left[c_x(l,0) + c_x(m, m-l)\right] \end{aligned} \tag{20}$$

where $c_x(l,k) = \sum_{n=m}^{N-1} x(n-k)x^*(n-l)$ that are known as autocorrelation coefficients, which dependent only on the absolute value of the difference between l and k, i.e. $c_x(l,k) = c_x(|l-k|)$. However, the autocorrelation matrix is not Toeplitz but it is symmetric [27] and [30].

IV. RESULTS AND DISCUSSION

The performance of the AR methods is tested on 5-bus, IEEE 14-bus, IEEE 24-bus, IEEE 57-bus, 103-bus, IEEE 118-bus and IEEE 300-bus system. The historical data is executed through successive power flow programs to record different types of measurements for the entire IEEE tested network. The simulations were carried out for 24 time samples. Meanwhile for 103-bus network, the data was recorded every 10 minutes. Results of the average errors for all system states relative to power flow solution are shown in Figure 1 to 5. It is clearly shown that average errors of all system states in both methods are below 4 %. The accuracy of the Burg and MC method is obviously illustrated when it is implemented in the IEEE 118-bus and IEEE 300-bus system. The average error of all system states in the both networks are less than 1 % error.

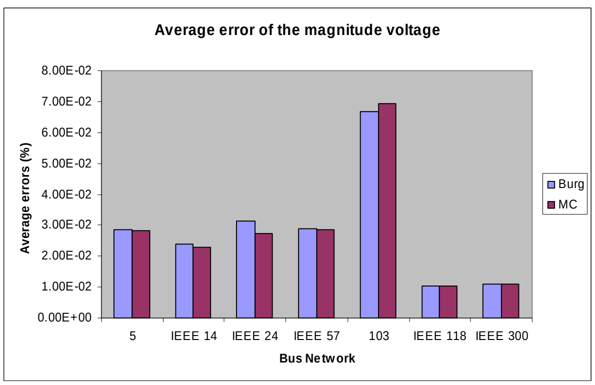

Fig. 1 Average error of the magnitude for tested networks.

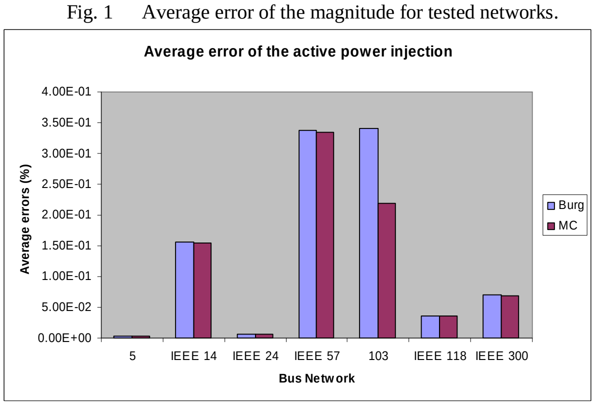

Fig. 2 Average error of the active power injection for tested networks.

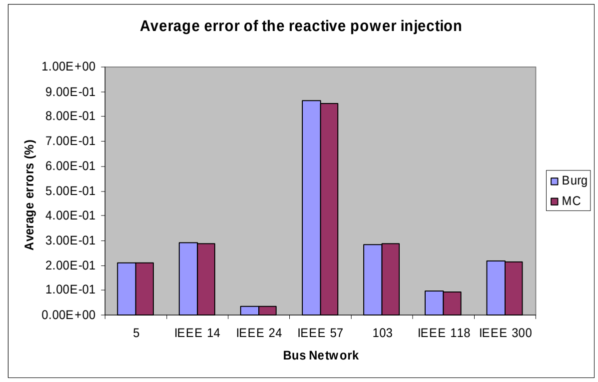

Fig. 3 Average error of the reactive power injection for tested networks.

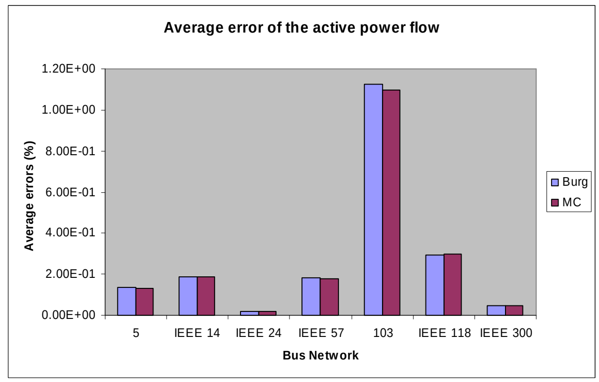

Fig. 4 Average error of the active power flow for tested networks.

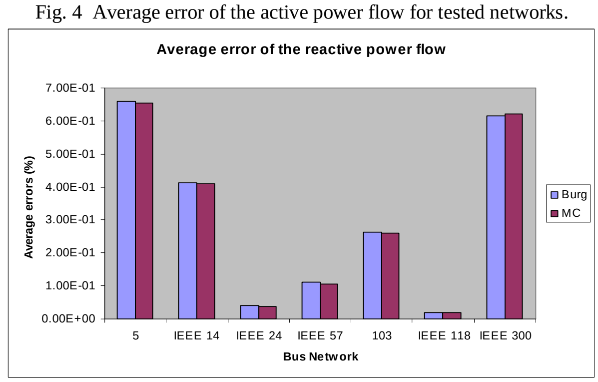

Fig. 5 Average error of the reactive power flow for tested networks.

The capability of Burg and MC method to predict a step ahead of the system states with less than 4 % error can be the platform for producing high quality pseudo-measurements. The later statement is strengthened by testing the Burg and MC method under two case studies.

1) Case 1

The system is tested for detecting the weighting factor for erroneous measurements assigned with higher weighting factor. The standard variation is calculated using

$$\sigma = 0.005 \cdot |z^t| + 1 \times 10^{-10} \tag{21}$$

where z^t is the measured value.

Meanwhile the weighting factor W is calculated from the respective standard deviation σ as follows:

$$W = \frac{1}{\sigma^2} \tag{22}$$

Any weighting factor that exceeds W value calculated in (22) is considered high.

Due to space limitation, only IEEE 57-bus and IEEE 118-bus systems will be presented in this section. Meanwhile the analysis of IEEE 24-bus and SESB system are provided in [31].In this case study, two and five bad measurements are introduced in IEEE 57-bus and IEEE 118-bus network respectively. In IEEE 57-bus network the directions of Q_8 and active power flow from bus 13 to 49, $p_{13\text{-}49}$ are reversed. The weighting factor of measurement $p_{13\text{-}49}$ was reduce to a value lower than calculated W as in (22). While the five bad measurements introduced in IEEE 118-bus network are V_{22}, Q_{14}, P_{47}, $p_{16\text{-}17}$ and $q_{81\text{-}68}$. Only measurement V_{22} is set as low weighting factor while the rest of the measurements are set as high weighting factor. Table I and Table II summarize the results of AR after introducing bad data to several measurements at time step 23 for both networks.

TABLE I: PERFORMANCE OF THE AR METHOD ON IEEE 57-BUS – CASE 1

Measurement	Measured	Forecasted Burg	Forecasted MC	Identified bad data with more than 5% error
Q_8	0.40078	0.39878	0.39878	-0.40078
$p_{13\text{-}49}$	0.32961	0.32850	0.32850	-0.32961
Analog measurements considered bad and the weighting factor is high.			Q_8	

TABLE II: PERFORMANCE OF THE AR METHOD ON IEEE 118-BUS – CASE 1

Measurement	Measured	Forecasted Burg	Forecasted MC	Identified bad data with more than 5% error
Q_{14}	-0.00970	-0.00969	-0.00969	-0.10970
V_{22}	0.97030	0.97044	0.97044	1.97030
P_{47}	-0.33970	-0.33956	-0.33956	0.33970
$p_{16\text{-}17}$	-0.17480	-0.17620	-0.17620	-0.27480
$q_{81\text{-}68}$	-0.75380	-0.73723	-0.73743	0.75380
Analog measurements considered bad and the weighting factor is high.			Q_{14}, P_{47}, $p_{16\text{-}17}$ and $q_{81\text{-}68}$	

It should be noted that the predicted values depend on the past historical data. In the first run of SE, the Burg and MC algorithm detected a few analog measurements with wrong readings compared with predicted values, typically more than 5 % error, as depicted in Table I and Table II. Two different conditions of result are presented in this section.

1) The identified bad measurements are replaced with the predicted value obtained from AR algorithm and then the SE is carried out.

2) All the higher weighting factor for the identified bad measurements are set to 20 % lower than W in (22) which indicating the measurements are not reliable, and then the SE is carried out.

Condition 1: The result of IEEE 57-bus is summarized in Table III. All the measurements identified by AR methods as bad measurements are replaced with the predicted values obtained in AR methods. After SE is carried out, the final output shows that there no bad data is detected in the system even though in the first place two bad measurements are introduced in the system. With the accuracy of predicted values provided by both AR methods, as shown in Figure 1 to 5, the bad data is eliminated without reducing the number of available measurements. Thus, it will maintain the accuracy of normal SE since the measurement redundant is maintained.

TABLE III: THE MEASURED, PREDICTED AND NRSE VALUES OF STATE VARIABLES FOR IEEE 57-BUS NETWORK AFTER SUBSTITUTING THE BAD DATA WITH PREDICTED VALUE – CASE 1 (1ST CONDITION)

Measured		Burg		MC		NRSE	
V (pu)	θ (deg)	V (pu)	θ (deg)	V (pu)	θ (deg)	V (pu)	θ (deg)
1.040	0	1.040	0	1.040	0	1.042	0
1.010	-1.180	1.010	-1.180	1.010	-1.180	1.011	-1.124
0.985	-5.970	0.985	-5.970	0.985	-5.970	0.986	-5.909
0.981	-7.320	0.981	-7.320	0.981	-7.320	0.982	-7.210
0.976	-8.520	0.976	-8.520	0.976	-8.520	0.978	-8.439
0.980	-8.650	0.980	-8.650	0.980	-8.650	0.981	-8.577
0.984	-7.580	0.984	-7.580	0.984	-7.580	0.985	-7.520
1.005	-4.450	1.005	-4.450	1.005	-4.450	1.007	-4.441
0.980	-9.560	0.980	-9.560	0.980	-9.560	0.982	-9.551
0.986	-11.430	0.986	-11.430	0.986	-11.430	0.988	-11.431
0.974	-10.170	0.974	-10.170	0.974	-10.170	0.976	-10.175
1.015	-10.460	1.015	-10.460	1.015	-10.460	1.017	-10.452
0.979	-9.790	0.979	-9.790	0.979	-9.790	0.981	-9.786
0.970	-9.330	0.970	-9.330	0.970	-9.330	0.972	-9.338
0.988	-7.180	0.988	-7.180	0.988	-7.180	0.990	-7.167
1.013	-8.850	1.013	-8.850	1.013	-8.850	1.016	-8.842
1.017	-5.390	1.017	-5.390	1.017	-5.390	1.020	-5.393
1.001	-11.710	1.001	-11.710	1.001	-11.710	0.992	-14.681
0.970	-13.200	0.970	-13.200	0.970	-13.200	0.970	-15.218
0.964	-13.410	0.964	-13.410	0.964	-13.410	0.968	-14.805
1.008	-12.890	1.008	-12.890	1.008	-12.890	1.011	-13.268
1.010	-12.840	1.010	-12.840	1.010	-12.840	1.010	-12.946
1.008	-12.910	1.008	-12.910	1.008	-12.910	1.009	-12.992
0.990	-13.250	0.990	-13.250	0.990	-13.250	1.000	-13.028
0.982	-18.130	0.982	-18.130	0.982	-18.130	0.957	-21.733
0.959	-12.950	0.959	-12.950	0.959	-12.950	0.960	-12.728
0.982	-11.480	0.982	-11.480	0.982	-11.480	0.983	-11.357
0.997	-10.450	0.997	-10.450	0.997	-10.450	0.998	-10.360
1.010	-9.750	1.010	-9.750	1.010	-9.750	1.011	-9.673
0.962	-18.680	0.962	-18.680	0.962	-18.680	0.939	-22.039
0.936	-19.340	0.936	-19.340	0.936	-19.340	0.918	-22.045
0.949	-18.460	0.949	-18.460	0.949	-18.460	0.943	-20.109
0.947	-18.500	0.947	-18.500	0.947	-18.500	0.941	-20.149
0.959	-14.100	0.959	-14.100	0.959	-14.100	0.954	-14.465
0.966	-13.860	0.966	-13.860	0.966	-13.860	0.963	-14.155
0.976	-13.590	0.976	-13.590	0.976	-13.590	0.974	-13.844
0.985	-13.410	0.985	-13.410	0.985	-13.410	0.984	-13.616
1.013	-12.710	1.013	-12.710	1.013	-12.710	1.013	-12.803
0.983	-13.460	0.983	-13.460	0.983	-13.460	0.982	-13.654

0.973	-13.620	0.973	-13.620	0.973	-13.620	0.972	-13.866
0.996	-14.050	0.996	-14.050	0.996	-14.050	0.998	-14.103
0.966	-15.500	0.966	-15.500	0.966	-15.500	0.969	-15.600
1.010	-11.330	1.010	-11.330	1.010	-11.330	1.012	-11.348
1.017	-11.830	1.017	-11.830	1.017	-11.830	1.018	-11.905
1.036	-9.250	1.036	-9.250	1.036	-9.250	1.038	-9.279
1.060	-11.090	1.060	-11.090	1.060	-11.090	1.061	-11.131
1.033	-12.490	1.033	-12.490	1.033	-12.490	1.035	-12.549
1.027	-12.570	1.027	-12.570	1.027	-12.570	1.029	-12.656
1.036	-12.920	1.036	-12.920	1.036	-12.920	1.038	-12.964
1.023	-13.390	1.023	-13.390	1.023	-13.390	1.025	-13.423
1.052	-12.520	1.052	-12.520	1.052	-12.520	1.055	-12.520
0.980	-11.470	0.980	-11.470	0.980	-11.470	0.982	-11.402
0.971	-12.230	0.971	-12.230	0.971	-12.230	0.972	-12.159
0.996	-11.690	0.996	-11.690	0.996	-11.690	0.998	-11.643
1.031	-10.780	1.031	-10.780	1.031	-10.780	1.033	-10.759
0.968	-16.040	0.968	-16.040	0.968	-16.040	0.969	-16.130
0.965	-16.560	0.965	-16.560	0.965	-16.560	0.965	-16.656

Meanwhile, for IEEE 118-bus system, the average errors of all variables are low or in other word the accuracy of both AR methods are high. This can be illustrated in the curve of the predicted value and measured value for measurements $p_{15\text{-}23}$, P_2 and Q_{12}. The results are shown in Figure 6 to 8.

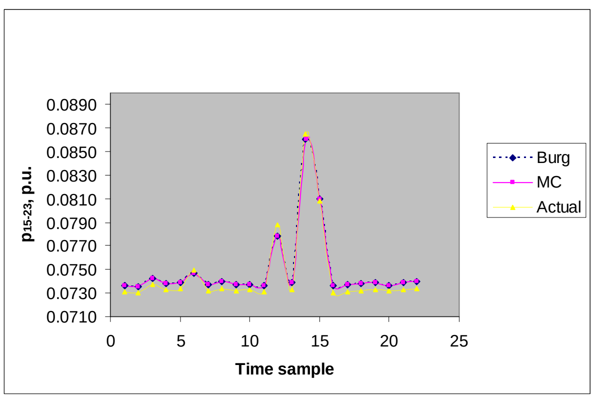

Fig. 6 Active power flow from bus 15 to 23 – relative to power flow solution (actual value).

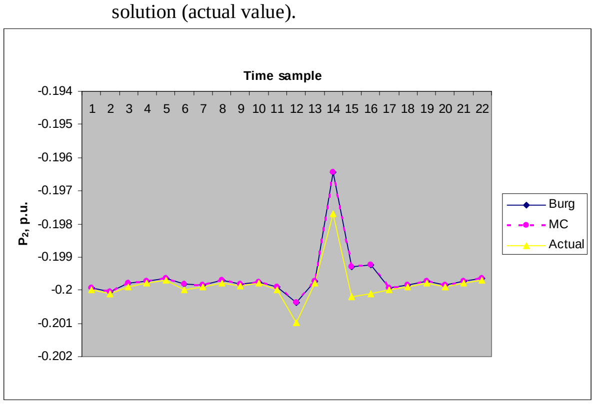

Fig. 7 Active power injected at bus 2 – relative to power flow solution (actual value).

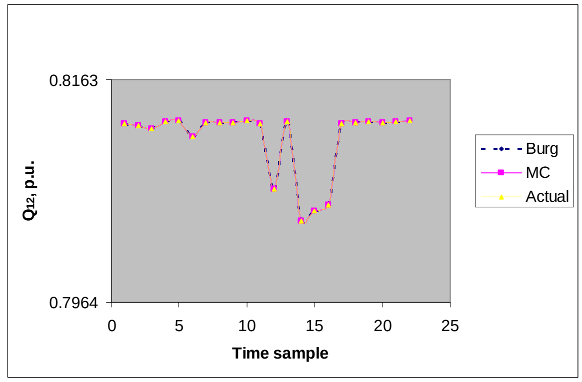

Fig. 8 Reactive power injected at bus 12 – relative to power flow solution (actual value).

Figure 6 to 8 illustrates the final output of SE for measurements $p_{15\text{-}23}$, P_2 and Q_{12} respectively after those bad measurements detected by AR methods (see Table II) are replaced with predicted results obtained in AR method. The average errors of the measurements $p_{15\text{-}23}$, P_2 and Q_{12} are 0.41 %, 0.15 % and 0.037 % respectively. With the error below than 1 %, it is shown that the predicted value which obtained from both AR methods produces high quality of prediction value. Hence, this can guarantee that the SE will produce an accurate final estimate by not reducing the number of measurements and at the same time maintaining the redundancy.

Condition 2: Table IV and Table V show the summarized results of second condition for IEEE 57-bus and IEEE 118-bus system respectively. As shown in Table I and Table II, the bad measurements with higher weighting factor are identified as Q_8 for IEEE 57-bus and Q_{14}, P_{47}, $p_{16\text{-}17}$ and $q_{81\text{-}68}$ for IEEE 118-bus system. The SE program is carried out after the higher weighting factor of the bad measurements are reduced. The bad measurements are eliminated one by one. Multiple interacting bad data is detected in IEEE 118-bus, where Q_{14} and $q_{14\text{-}15}$ are identified as bad measurements (see Table V). However, only measurement Q_{14} is eliminated, since Q_{14} was intentionally created as a bad measurement. The final estimation will end up in reduced number of measurements from 305 to 303 for IEEE 57-bus and 526 to 521 for IEEE 118-bus system. As a result, the redundancy of the measurement is reduced and it will affect to the accuracy of final estimated state variables as shown in Table VI. The average error between the final state estimation and measured data of second condition is increased due to the reducing of redundancy or number of measurements.

TABLE IV: THE RESULTS OF SE PROCESS ON IEEE 57-BUS SYSTEM – CONDITION 2

Est. No	Bad Data	Weight sum of square, J	Chi-square distribution, $\chi^2_{k,a}$	Iter.
1	$p_{13\text{-}49}$	2.378E+05	2.253E+02	7
2	Q_8	8.753E+04	2.242E+01	7
3	None	1.502E+02	2.232E+02	7

TABLE V: THE RESULTS OF SE PROCESS ON IEEE 118-BUS SYSTEM – CONDITION 2

Est. No	Bad Data	Weight sum of square, J	Chi-square distribution, $\chi^2_{k,a}$	Iter.
1	P_{47}	1.360E+05	3.318E+02	14
2	p_{16-17}	2.446E+04	3.307E+02	7
3	$Q_{14}(q_{14-15})$	1.361E+04	3.296E+02	7
4	V_{22}	4.580E+03	3.286E+02	7
5	q_{81-68}	3.325E+02	3.275E+02	7
6	None	2.710E+02	3.264E+02	7

TABLE VI: ANALYSIS OF AVERAGE ERRORS OF STATE VECTORS BETWEEN THE FIRST CONDITION AND SECOND CONDITION.

	1st Condition			2nd Condition		
	Average error		η	Average error e		η
System	|V|	θ	m/n	|V|	θ	m/n
IEEE 57	0.32%	2.83%	2.70	0.32%	2.84%	2.68
IEEE 118	0.43%	7.43%	2.24	0.71%	10.23%	2.22

Note: η is the ratio m/n, known as redundancy.

2) Case 2

Considering a not-convergent system due to the incorrect assigning of weighting factor, the convergence of SE normally relies on the tolerance, the number of measurements and the weighting factors assigned to the individual measurements. In this case, the IEEE 57-bus network is found to be not converging by intentionally changing the weighting factors for all measurements of line flow and bus power injection. In the first run of SE, i.e. without AR filter process, the result is not converging when the tolerance, number of measurements and maximum number of iteration are 0.001, 305 and 50 respectively. It is because of the inability of SE algorithm to identify the measurements that are initially assigned with incorrect weighting factor. However, this problem is solved when the outputs from Burg or MC are used as the input of SE. As a result after the Burg or MC outputs are used, the number of measurements is increased to 491, i.e. equal to maximum number of measurements, and the redundancy was also increased in number related with number of measurements. Thus, the accuracy of the final estimated value of the state variables are also increased as compared is the final estimated of the state variables when number of measurement is 305 as in Case 1. The results are shown in Table VII.

TABLE VII: THE COMPARISON OF THE STATE VECTORS AVERAGE ERRORS BETWEEN CASE 1 AND CASE 2- IEEE 57-BUS SYSTEM.

Case Study	Number of measurements	Average error for the voltage magnitude	Average error for the phase of angle
Case 1	305	0.32 %	2.83 %
Case 2-Output from Burg	491	0.019 %	1.08 %
Case 2-Output from MC	491	0.019 %	1.08 %

Similarly, after SE is carried by changing the weighting factor for a few of measurements in IEEE 118-bus system, the result obtained does not converge for the tolerance, number of measurements and maximum number of iteration are 0.001, 526 and 50 respectively. In the second run, the output from Burg and MC are taken as the input to SE and it successfully converged when the tolerance, number of measurements and maximum number of iteration are 0.001, 1098 and 50 respectively. The comparison of the average error of the state variables between Case 1 and Case 2 is shown in Table VIII.

TABLE VIII : THE COMPARISON OF THE STATE VECTORS AVERAGE ERRORS BETWEEN CASE 1 AND CASE 2- IEEE 118-BUS SYSTEM.

Case Study	Number of measurements	Average error for the voltage magnitude	Average error for the phase of angle
Case 1	526	0.43 %	7.43 %
Case 2-Output from Burg	1098	0.013 %	0.561 %
Case 2-Output from MC	1098	0.013 %	0.561 %

Apart from these two case studies, the output from the Burg and MC, also can be effectively used as pseudo-measurements to replace the lost measurement in the network in the case of the network is unobservable. It is important to ensure network observability, before a SE can be performed. The simulated results of the use of AR method for network observability are presented in our papers in [29] and [30]. The analysis of Case 1 and Case 2 can also be represented by the analysis of unobservable system for IEEE 57-bus and IEEE 118-bus system. It is applied when the condition of number of measurements is less than number of state ($m<n$), also known as under-determined system, is occurred. Thus, to overcome the problem, the output of AR method is used as pseudo-measurements to replace or to add more measurements in the system.

V. CONCLUSION

The development of pre-estimation filter using autoregressive model to identify the gross measurement errors are presented in this paper. The identification of the errors is accomplished by making a comparison between the measured values and the predicted values of the measurements. If the difference exceeds 5 % error, the measured data is assumed to be grossly erroneous and is replaced by its predicted value in the measurement set. The simulated results are discussed in case 1.

Two methods of AR namely as Burg and MC have been implemented in this paper. Both the methods are used to calculate the one-step-ahead predicted values of the state variables. The simulation results show that both the methods are able to accurately predict the behavior of the system variables.

The AR model offers a measurement pre-screening ability that can complement other post-estimation detection /identification techniques by processing the raw measurements before estimation is performed. As shown in simulated result in case 1, this method may occasionally identify the good measurements as bad; however it will always detect any gross errors existing in the measurement. The proposed method is also capable of identifying those measurements that are identified as bad assigned with the higher weighting factor. As discussed in case 1 and case 2, the AR method will provide the necessary pseudo-measurements for those measurements that are identified as bad data. Thus, the strength of Burg and MC algorithm in the field of SE is also established.

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