

A NEW FORMULATION IPCA BASED METHOD FOR BRANCH-CURRENT ESTIMATION IN DISTRIBUTION NETWORKS

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ABSTRACT

This paper introduces a neuro-based branch's current state estimator for distribution networks in which a limited set of real-time data is available. This estimator employs Inverse Principle Component Analysis (IPCA) method. Using the IPCA method leads to some proper models devised so that the distribution network becomes observable and then load estimation will be possible. By determining load consumption in each node and voltage magnitude of the reference bus, load flow program can be run for determining the power flow of all sections, which are called pseudo power measurements. Finally, through incorporation of a certain and finite number of variables including real-time voltage magnitudes in few of buses, current magnitude in the beginning of the feeder and pseudo power flow measurements, the currents of all the network's branches are estimated in real-time via the IPCA and WLS methods with a desired degree of accuracy. A case study on a typical network is considered at the end of paper for better highlighting of the merits of the proposed method. The experimental results show that the proposed neuro-estimator outperforms the previously cited techniques.

INTRODUCTION

By state estimation, the operating point of the distribution network can be determined and shifted to an optimum point, in order to improve the network's operating conditions. By considering the rapid development of distribution networks and power industry restructuring, optimum design and operating of distribution networks become a critical issues. Moreover, presence of new technologies and conditions in distribution systems, including distributed generation (DG) and sensitivity of customers' electrical appliances to power quality, tends to increasing the importance of the load estimation and network monitoring.

Due to the great number of network nodes, the number of variables in the distribution network increases remarkably. Therefore, a large number of real-time data is needed for a precise state and/or load estimation of the network. However, due to technical and economical restrictions, which are mainly related to the communication network, accessing to such a large number of real-time data is almost impossible. On the other hand, applying new technologies in distribution networks, such as network automation, automatic meter reading (AMR), distribution network mechanization, and distribution management system (DMS), has facilitated the use of advanced techniques and

finding optimal solutions to operation of distribution networks. The above facilities have also provided a suitable environment for adoption and realization of more precise load estimation techniques in distribution networks.

In some of the recent studies, with considering the lack of enough real time data, various solutions to the load estimation problem are presented. These solutions include employing pseudo data, using innovative techniques and simplification of network topology in combination with error minimization methods.

The approaches that were presented in [1],[2], use customer's monthly peak load and transformers peak load data for the extraction of load curve. This curve is then used as pseudo data for load estimation. The above methods are suitable for peak load estimation and are not useful for load estimation.

A method for load curve determining, which uses pseudo real-time data, such as AMR data, is addressed in [3]. The resulting load curve is then used for state estimation. By merely using these data, only some of the network variables can be estimated; however due to the AMR restrictions, determination of all of the system variables is not possible. In [4] and [5], by assuming the availability of pseudo data, all nodes' loads are first determined, and then, the states of the network are estimated. The approach uses both the historical data of energy billing and historical load curve data of different load points in the network. In [6], a probabilistic model for estimating the loads of different points (nodes) of the network is developed based on the historical data. This method results a better performance compared to the previously developed methods. A fuzzy logic and neural network based approach, for active load estimation of distribution network, is also proposed in [7], where, the inputs of the neural network are taken as: classified load curves, monthly energy consumption in addition to the real-time measurements.

In some of other studies, the network topology is simplified according to the position of the metering equipments. Then, a sensitivity analysis is employed on historical load data to identify the relationship between the load changes in the different sections of the network. These results are then compared with the historical data of the measurement equipments in each section; accordingly, the load estimation problem is then solved by using a limited set of real-time data [8],[9]. The method can be improved by establishing relations between the load changes of different points and the real-time measurement equipment in the network, and employing data analysis techniques.

Some researchers have developed state estimation methods based on WLS or heuristic optimization techniques such as

hybrid particle swarm optimization (HPSO) by assuming that, enough data is available [10],[11].

In a few studies that has been addressed, with investigating of the load's data in the various points of the network and determining correlation between the load changes in different nodes (by using historical data), more suitable methods for load estimation and meters optimum locating are presented [12],[13].

Using of data mining based techniques [14],[15] for classification of the collected data and exploration of their hidden interrelations are very useful for improving the load estimation in distribution networks, when limited data is available.

The Principal component analysis (PCA) method is one of the widely-used data analysis techniques in data mining studies. This method explores the relations and extracts features of different variables in huge sets of data in order to reduce the dimensions of the problem. Identification of governing patterns between the variables, results in more precise solutions while less data have been used [16], [17]. Comparisons of six different short-term load forecasting (STLF) methods in [18] show that using PCA can considerably improve the precision.

In [19], a method based on Inverse Principal Components Analysis (IPCA) has been recently developed by the authors for load estimation of distribution network. In this method, the governing patterns between load variables are first extracted by means of the conventional PCA method, and then the loads of all network nodes are estimated through IPCA using a limited real-time data set and the above extracted patterns as well.

Determining of load's variables relationships makes the network observable and facilitate load estimation. Then, by using the relationship models as well as the IPCA method, the load of all the nodes will be estimated.

This paper introduces a new intelligent method for current estimation of the network's branches, based on IPCA. In this method, the load of all the network nodes is estimated by the IPCA technique at first. Then, by using magnitude of the voltage at the reference bus and the load of various nodes, network will be observable and running the load flow program will be can possible. So we can determine the power flow in the various lines of the network. These results are called pseudo power measurements and are used of them for observable state estimation problem in distribution network. By using pseudo power measurements, voltage magnitude measurements in few nodes and current magnitude in the beginning of a feeder, the problem of branches' currents estimation can be modeled and then will be solved by using WLS error minimization method. In figure 1, the comprehensive model of the proposed method is presented.

A new formulation of the problem is proposed in this paper, the state variables which, takes into account magnitude and angle of all branches' current and also, voltage magnitude of reference bus.

The results of applying the presented method for solving the state estimation problem of typical distribution network,

while limited data are available, reveals that the calculations have proper accuracy.

The rest of the paper is organized as the following:

In section 2, a summary description of the IPCA method is discussed. Section 3 is devoted to measurement functions and the algorithm of solving the problem. In section 4 the proposed method is applied to a sample network as a case study, and finally section 5 discusses ideas for the future researches.

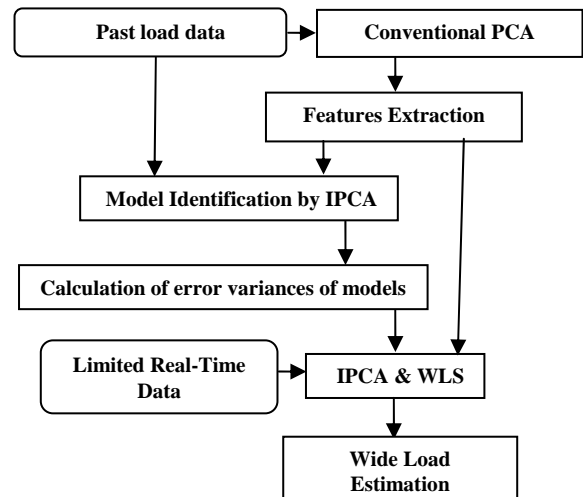


Fig. 1: A comprehensive outline of the proposed method.

INTRODUCING THE IPCA METHOD

This section is devoted to a brief description of the IPCA method. The most important limitation that the state/load estimation of the distribution networks faces with, is the lack of enough real-time data. Beside measurement equipments, real-time data gathering needs to the availability of communication infrastructures. Considering the day to day reduction of the cost of electronic measurement equipments vast replacing of analog measurement devices by the electronic ones in distribution networks has become reasonable. The electronic measurement equipments provide facilities such as precise measurement and logging of network's electrical parameters. Based on the studies of EPRI, the greatest part of investments that is spent to establishment of communication infrastructures is allocated to building of communication channels [20].

Here, it is assumed that monitoring of the real-time data is possible only in a limited set of the network's nodes. Also, it is assumed that load's data on the other nodes are collected and logged by metering and data logging devices and then will be downloaded in a periodical and non-automatic manner. So, the initial conditions for constructing the past load data matrix "S" is available. This matrix can be defined as:

$$S = \begin{bmatrix} s_{1,1} & s_{1,2} & \cdots & s_{1,n} \\ s_{2,1} & s_{2,2} & \cdots & s_{2,n} \\ \vdots & \ddots & \ddots & \ddots \\ s_{r,1} & s_{r,2} & \cdots & s_{r,n} \end{bmatrix} \quad (1)$$

where:

S : past loads data matrix

n : number of load nodes

r : number of load samples in each node

$s_{i,j}$: i -th load sample of the j -th node load

The so-called adjusted load matrix, " S_a " is then calculated as,

$$\bar{S} = \left\{ \frac{1}{r} \sum_{i=1}^r a_{i,j} \right\}_{j=1}^n \quad (2)$$

$$S_a = \{Row_i(S) - \bar{S}\}_{i=1}^n$$

In which, \bar{S} denotes the average value of the samples of nodal loads, and $Row_i(S)$ represents the i -th row of the matrix " S ". Now, the covariance matrix " C " is calculated by:

$$C = \frac{1}{r} (A_a^T \cdot A_a) \quad (3)$$

Since the above matrix is a symmetric one, it is a positive semi-definite with " n " unit eigenvectors which are corresponding to " n " non-negative real eigenvalues. By selecting a set of larger eigenvalues, we can compose a matrix denoted by " T " as given below, in order to build the principal components of the matrix " C ".

$$T = [\phi_1 \quad \phi_2 \cdots \phi_i \quad \cdots \quad \phi_k] \quad (4)$$

where:

T : PCA projection matrix

ϕ_i : the i -th eigenvector corresponding to the i -th eigenvalue

k : the number of selected eigenvalues

The matrix " T ", which is called as "PCA projection matrix", defines a strong linear relationship between the variables of data matrix [19]. Since the ϕ_i vectors, which construct the matrix " T ", are orthogonal and it can be shown that the inverse of " T " is equal to its transpose.

Now, we can define the load variables of the network as:

$$\begin{aligned} S(t_0) &= [Z(t_0) \quad X(t_0)] \\ Z(t_0) &= [z_1(t_0) \quad z_2(t_0) \quad \cdots \quad z_m(t_0)] \\ X(t_0) &= [x_1(t_0) \quad x_2(t_0) \quad \cdots \quad x_{n-m}(t_0)] \end{aligned} \quad (5)$$

where:

$S(t_0)$: vector of nodal loads at t_0

$Z(t_0)$: vector of known loads at t_0

$X(t_0)$: vector of unknown loads at t_0

$z_i(t_0)$: the value of i -th node load measurement at t_0

$x_j(t_0)$: j -th node unknown load at t_0

m : number of nodes that their real-time measurements is available

By using Eq.2, we can modify and calculate $S(t_0)$ vector.

Then we can project it by applying " T " matrix therefore, the "PCA" matrix will be come as:

$$S_{PCA}(t_0) = \bar{S}(t_0) \cdot T \quad (6)$$

where:

$\bar{S}(t_0)$: adjusted real-time load variables' matrix

$P_{PCA}(t_0)$: projection of $\bar{S}(t_0)$ to the PCA space

As mentioned before, the inverse of T matrix is equal to its' transposed matrix. So, by using Eq.7, we can define load relationships in the network's nodes.

$$\begin{aligned} S'(t_0) &= P_{PCA}(t_0) T^T + \bar{S} \\ S'_j(t_0) &= \sum_{i=1}^k \left(\sum_{j=1}^m z_j T_{(1,j)} + \sum_{j=1}^{n-m} \hat{x}_j T_{(1,j+m)} \right) T_{(i,j)} \end{aligned} \quad (7)$$

where:

$S'(t_0)$: approximation of real time load variables' vector

$S'_j(t_0)$: approximation of real-time j -th load variable

By neglecting the small difference between $S'(t_0)$ and $S(t_0)$, we can write:

$$S_j(t_0) = \sum_{i=1}^k \left(\sum_{j=1}^m z_j T_{(1,j)} + \sum_{j=1}^{n-m} \hat{x}_j T_{(1,j+m)} \right) T_{(i,j)} \quad (8)$$

By arranging the above equation, we can define " n " virtual equations among the load variables. This will make the network observable and so we can estimate the load of all the network's nodes, even if only limited data is available.

BRANCHES' CURRENT ESTIMATION

In distribution networks, generally the magnitude and phase of lines' currents are chosen as state variables. Therefore, in a " n " bus radial distribution network, it leads to $2 \times n - 2$ state variables. But, for a " n " bus network to become completely observable, we need to $2 \times n - 1$ state variable. In most of the previous works, this important point was not considered and so, the precision of calculations has been decreased [21]. In the new formulation which is presented in this paper, the voltage magnitude of reference bus is added to the branches' currents state variables. Therefore, the state variables are chosen as the magnitude and phase of lines' currents and the magnitude of the reference bus voltage.

Determination of measurement functions

Measurement function determines the relationships between the measured values and the network's state variables. We can define this relationship as:

$$z = h(X) + e \quad (9)$$

where, the Z is the vector of measured values, the h is measurement function and X is the vector of state variables. If we consider the simplified model of the line as Fig.2, we can define relationship between each variable and other variables of the network as the following equations.

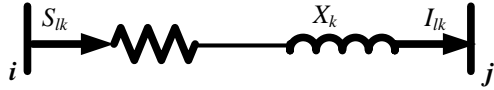


Fig. 2: The model of Kth section distribution line.

i-th bus voltage measurement function

$$\begin{aligned} \vec{V}_i &= V_0 - \sum_{m \in S_i} \vec{Z}_m \times \vec{I}_m \\ &= V_0 - \left[\sum_{m \in S_i} Z_m I_m \cos(\theta_m + \delta_m) + j \sum_{m \in S_i} Z_m I_m \sin(\theta_m + \delta_m) \right] \quad (10) \\ &= V_0 - \sum_{m \in D_i} Z_m I_m \cos(\theta_m + \delta_m) - j \sum_{m \in S_i} Z_m I_m \sin(\theta_m + \delta_m) \end{aligned}$$

where:

\vec{V}_i : value of i -th bus's voltage

V_0 : value of the reference bus's voltage

\vec{Z}_m : m -th line impedance

\vec{I}_m : m -th line current

Z_m, θ_m : magnitude and phase of m -th line's impedance

I_m, δ_m : magnitude and phase of m -th line's current

D_i : set of buses which exist in the path of i -th bus feeder

i-th bus current measurement function

If the K -th line is fed from i -th bus, we can calculate the K -th line power flow by the following equations:

$$\begin{aligned} \vec{S}_{lk} &= V_i \vec{I}_k^* \\ P_{lk} + jQ_{lk} &= (V_0 - \sum_{m \in D_i} \vec{Z}_m \vec{I}_m) \vec{I}_k^* \\ P_{lk} &= V_0 I_k \cos(\delta_{lk}) - \sum_{m \in D_i} Z_m I_m I_k \cos(\theta_m + \delta_m - \delta_{lk}) \quad (11) \\ Q_{lk} &= -V_0 I_k \sin(\delta_{lk}) - \sum_{m \in D_i} Z_m I_m I_k \sin(\theta_m + \delta_m - \delta_{lk}) \end{aligned}$$

where :

\vec{S}_{lk} : injected complex power to the K -th line

P_{lk} : injected active power to the K -th line

Q_{lk} : injected reactive power to K -th line

\vec{I}_k^* : conjugate of Injected current to K -th line

Measurement function of the bus injected current

We can define measurement function of the bus injected current as below:

$$I(meas) = I_f \quad (12)$$

where, $I(meas)$ is the current magnitude which is the beginning of the feeder.

Considering this equation, we can define a measurement function for all of the metering equipments.

Determining of the Jacobean matrix

Jacobian matrix of the elements show the sensitivity of the measurement functions relative to a partial change in state variables. We can show this relationship as the following equation:

$$H = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial I} & \frac{\partial P}{\partial V_0} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial I} & \frac{\partial Q}{\partial V_0} \\ \frac{\partial V}{\partial \delta} & \frac{\partial V}{\partial I} & \frac{\partial V}{\partial V_0} \\ \frac{\partial \delta}{\partial \delta} & \frac{\partial \delta}{\partial I} & \frac{\partial \delta}{\partial V_0} \\ \frac{\partial I}{\partial \delta} & \frac{\partial I}{\partial I} & \frac{\partial I}{\partial V_0} \\ \frac{\partial \delta}{\partial \delta} & \frac{\partial \delta}{\partial I} & \frac{\partial \delta}{\partial V_0} \end{bmatrix} = \begin{bmatrix} \frac{\partial P}{\partial \delta} & \frac{\partial P}{\partial I} & \frac{\partial P}{\partial V_0} \\ \frac{\partial Q}{\partial \delta} & \frac{\partial Q}{\partial I} & \frac{\partial Q}{\partial V_0} \\ \frac{\partial V}{\partial \delta} & \frac{\partial V}{\partial I} & \frac{\partial V}{\partial V_0} \\ 0 & 1 & 0 \\ 0 & 1 & 0 \end{bmatrix} \quad (13)$$

The elements of matrix H , can be calculated from the following equations:

$$\frac{\partial P_i}{\partial \delta_j} = \begin{cases} 0 & \text{if } j \neq m \\ -V_0 I_i \sin \delta_i - \sum_{m \in S_i} Z_m I_m I_i \sin(\theta_m + \delta_m - \delta_i) = Q_i & \text{if } j = i \\ Z_j I_j I_i \sin(\theta_j + \delta_j - \delta_i) & \text{if } j \neq i \text{ and } j \in m \end{cases} \quad (14)$$

$$\frac{\partial P_i}{\partial I_j} = \begin{cases} 0 & \text{if } j \neq m \\ V_0 \cos \delta_i - \sum_{m \in S_i} Z_m I_m \cos(\theta_m + \delta_m - \delta_i) = \frac{P_i}{I_i} & \text{if } j = i \\ -Z_j I_j \cos(\theta_j + \delta_j - \delta_i) & \text{if } j \neq i \text{ and } j \in m \end{cases} \quad (15)$$

$$\frac{\partial P_i}{\partial V_0} = I_i \cos \delta_i = \text{Re}al(\vec{I}_i) \quad (16)$$

$$\frac{\partial Q_i}{\partial \delta_j} = \begin{cases} 0 & \text{if } j \neq m \\ -V_0 I_i \cos \delta_i + \sum_{m \in S_i} Z_m I_m I_i \cos(\theta_m + \delta_m - \delta_i) = -P_i & \text{if } j = i \\ -Z_j I_j I_i \cos(\theta_j + \delta_j - \delta_i) & \text{if } j \neq i \text{ and } j \in m \end{cases} \quad (17)$$

$$\frac{\partial Q_i}{\partial I_j} = \begin{cases} 0 & \text{if } j \neq m \\ -V_0 \sin \delta_i - \sum_{m \in S_i} Z_m I_m \sin(\theta_m + \delta_m - \delta_i) = \frac{Q_i}{I_i} & \text{if } j = i \\ -Z_j I_j \sin(\theta_j + \delta_j - \delta_i) & \text{if } j \neq i \text{ and } j \in m \end{cases} \quad (18)$$

$$\frac{\partial Q_i}{\partial V_0} = -I_i \sin \delta_i = -\text{Im}ag(\vec{I}_i) \quad (19)$$

Evaluation of equation (10) reveals that the imaginary part is very small and by neglecting of it, we can simplify the relationship among voltage variations and state variables. The simplified equation is:

$$V_i = V_0 - \sum_{m \in S_i} Z_m I_m \cos(\theta_m + \delta_m) \quad (20)$$

By using the above equation, we can calculate value of other elements, of H -matrix:

$$\frac{\partial V_i}{\partial \delta_j} = \begin{cases} 0 & \text{if } j \notin S_i \\ Z_m \cdot I_m \cdot \sin(\theta_m + \delta_m) & \text{if } j \in S_i \end{cases} \quad (21)$$

$$\frac{\partial V_i}{\partial I_j} = \begin{cases} 0 & \text{if } j \notin S_i \\ -Z_m \cdot \cos(\theta_m + \delta_m) & \text{if } j \in S_i \end{cases} \quad (22)$$

According by employing an iteration solution of the above problem can be obtained based Newton – Raphson together with WLS method.

$$\begin{aligned} x_{k+1} &= x_k + G \cdot H^T \cdot W \cdot [f(Z) - h(x_k)] \\ G &= [H^T \cdot W \cdot H]^{-1} \quad \& \\ H &= \frac{\partial(Z - h(X))}{\partial X} \end{aligned} \quad (23)$$

where:

x_k : state variables vector, which includes magnitude and phase of lines' currents and voltage of reference bus.

x_{k+1} : state variables vector in the next iteration.

The flowchart of the proposed algorithm is represented in Fig 3.

In the next section, a case study is presented for the valuation of the performance.

NUMERICAL STUDIES

In order to performance evaluation of the proposed method for estimating of lines' currents magnitude and phase, a typical network is considered. This network is a simple one which contains eleven buses. A single-line diagram of the study system is shown in Fig.4.

In this network, one current meter has been installed in the beginning of the feeder, 3 voltage meters have been installed in the buses 1,4 and 9 and finally 2 power meters have been installed in lines 4 and 9.

For making the network observable, first by applying the IPCA method, each node's load has been estimated. Results are presented in table (1). Then, by using estimated power consumptions, load flow equations have been solved and each line's power flow is calculated. The calculated results are presented in table (2), against the real values.

Other real-time data show in Table (3) that reference bus's voltage has been measured 1.02 per unit by using a voltage meter which has been installed in the beginning of the feeder. However, the real value is 1.01 per unit.

Table (2): The power which flow in all branch's network

With real-time data measurements and pseudo power measurements which get of IPCA method, the calculation of error between measurements and measurements functions is possible and we can run the proposed method for branch-current state estimation in the underlying distribution network.

Table 4, represent the results of branch-current state estimation together with the estimated value of the magnitude of the voltage of the reference bus. As it can be seen a reasonable result is obtained.

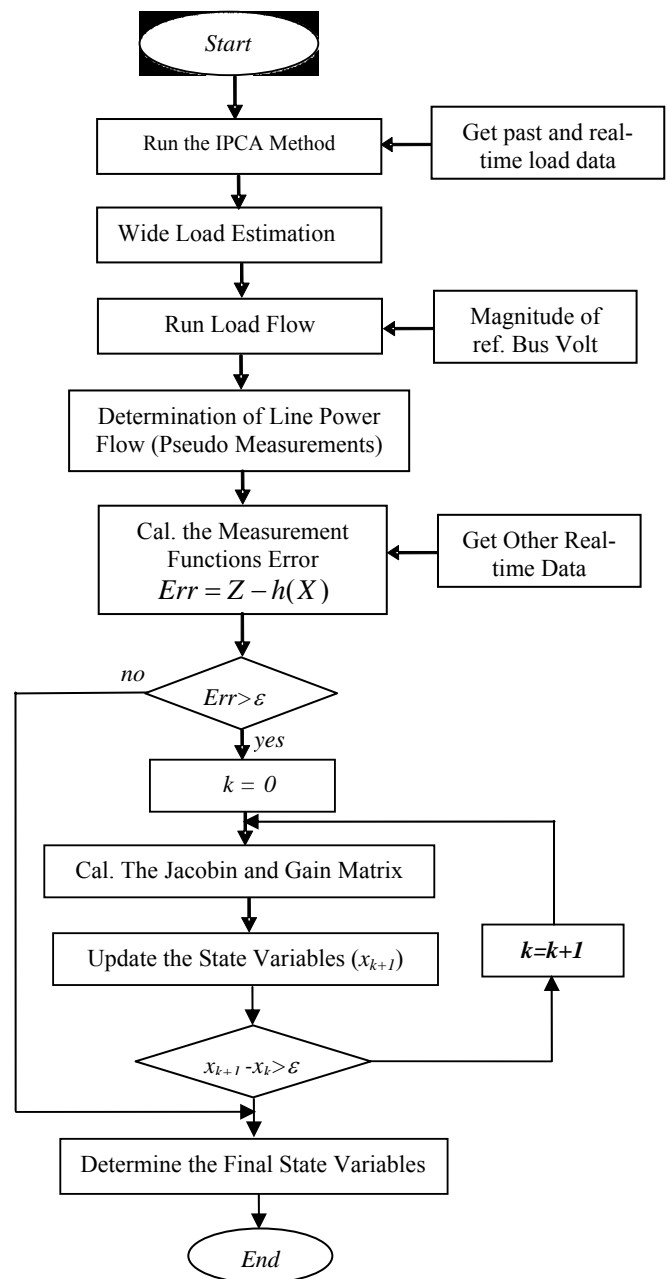


Fig3: The proposed algorithm for branch-current state estimation

Table (1): Results of load estimation with IPCA method

Bus number	Power consumption value	
	approximated	Real
B1	1.309 + 0.458i	1.269 + 0.444i
B2	0.609 + 0.183i	0.648 + 0.194i
B3	0.827 + 0.182i	0.837 + 0.184i
B4	0.662 + 0.099i	0.662 + 0.099i
B5	0.783 + 0.274i	0.797 + 0.279i
B6	0.921 + 0.286i	0.945 + 0.293i
B7	0.37 + 0.089i	0.351 + 0.084i
B8	1.128 + 0.169i	1.067 + 0.16i
B9	0.999 + 0.18i	0.999 + 0.18i
B10	0.601 + 0.18i	0.608 + 0.182i

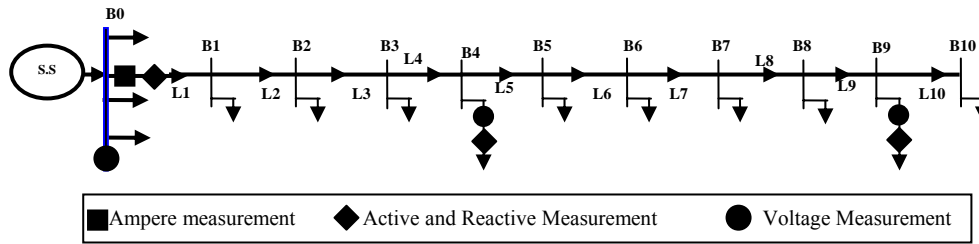


Fig 4: Single line diagram of the typical

Table (2): The power which flow in all branch's network

Line number	Lines power flow		
	Measured value	Real value	Difference
L1	8.32 + 2.22i	8.3 + 2.21i	-0.026 - 0.0009i
L2	6.99 + 1.74i	7.01 + 1.75i	0.0138 + 0.0128i
L3	6.36 + 1.53i	6.33 + 1.53i	-0.026 + 0.0012i
L4	5.51 + 1.32i	5.47 + 1.32i	-0.036 - 0.001i
L5	4.83 + 1.21i	4.80 + 1.21i	-0.0360 - 0.001i
L6	4.04 + 0.92i	3.99 + 0.92i	-0.05 - 0.006i
L7	3.11 + 0.63i	3.03 + 0.62i	-0.0738 - 0.0128i
L8	2.73 + 0.54i	2.69 + 0.53i	-0.0546 - 0.0076i
L9	1.60 + 0.36i	1.61 + 0.36i	0.0067 + 0.0017i
L10	0.60 + 0.18i	0.61 + 0.18i	0.0069 + 0.0019i

Table 3: Other real-time data measurements

Location	Variable	Measurement Value	Real Value	Dif.
B0	Volt.	1.02	1.01	0.01
L 1	Current	8.52	8.5016	-0.0184
B4	Volt.	0.989	0.9952	0.0062
B9	Volt.	0.987	0.9853	-0.0017

Table 4: The state estimation results

State variable	initial value	Estimated value	Actual value	Dif.
V_0	1.02	1.0109	1.01	-0.001
$I_{l,1}$	8.58 - 2.53i	8.58 - 2.52i	8.53 - 2.48i	0.0768
$I_{l,2}$	8.49 - 2.5i	8.23 - 2.19i	8.22 - 2.19i	0.1842
$I_{l,3}$	7.19 - 2.04i	6.93 - 1.73i	6.96 - 1.75i	0.1676
$I_{l,4}$	6.58 - 1.84i	6.33 - 1.55i	6.31 - 1.55i	0.1486
$I_{l,5}$	5.74 - 1.64i	5.50 - 1.36i	5.47 - 1.36i	0.1288
$I_{l,6}$	5.06 - 1.51i	4.84 - 1.26i	4.81 - 1.26i	0.1206
$I_{l,7}$	4.25 - 1.19i	4.05 - 0.97i	4.01 - 0.97i	0.1235
$I_{l,8}$	3.29 - 0.85i	3.13 - 0.67i	3.06 - 0.66i	0.0944
$I_{l,9}$	2.9 - 0.73i	2.76 - 0.58i	2.7 - 0.57i	0.0081
$I_{l,10}$	1.70 - 0.49i	1.62 - 0.39i	1.62 - 0.39i	0.0037

Conclusion

In this paper, a new method for state estimation of distribution network was developed by using the IPCA and WLS approaches.

In the proposed method, by defining the proper state variables of the network, calculating of measurement functions and considering the real time conditions as well as its' limitations, a precise estimation of network's states was presented, based on branches' currents.

One of the important characteristics of the introduced method is the application of reference bus's voltage as the network's state variable where more precise results can be achieved.

Further work is currently under the study for presenting a better algorithm in which, the load flow stage eliminated from the process.

REFERENCES

- [1] V. Borozan and N.Rajakovic, "Minimum loss distribution network configuration: Analyses and management", Electricity Distribution Part1 : 14th International Conference and Exhibition on Electricity Distribution (CIRED 1997 - Distributing Power for the Millennium) ,No. 438, Vol.6, pp.6-18, June 1997.
- [2] R.P.Broadwater, A.H.Khan, H.E.Shaalan and R.E.Lee, "Time varying load analysis to reduce distribution losses through reconfiguration", IEEE Trans. Power Delivery, Vol. 8, No. 1, pp. 294 – 300, Jan. 1993.
- [3] H.Wang, N. Suhulz, "A load modeling algorithm for distribution system state estimation", T&D Conference and Exposition, 2001IEEE/PES, Vol:1, pp.102-105, 2001.
- [4] M.E.Baran and A.W. Kelley, "State estimation for Real-time monitoring of distribution systems", IEEE Trans. Power Systems, Vol. 9, No.3, pp. 1601-1609, Aug. 1994.
- [5] T.Wang and M.Fan, "A Novel load estimation method in distribution network", Proceeding 1998 International Conference on Power Sys. Tech., Vol. 1, No. 1, pp. 567-571, Aug 1998.
- [6] Atish K. Ghosh, David L, Lubkeman, Rober H. Jones, "Distribution state estimation using A probabilistic approach", IEEE Trans. on Power Systems, Vol. 12, No. 1, pp. 45-51, Feb. 1997.
- [7] D. M. Falcao and H. O. Henriques, "Load estimation in radial distribution systems using neural network and fuzzy set techniques", Power Engineering Society Summer Meeting Volume 2, pp. 1002 - 1006, 2001.
- [8] Jie Wan and Karen Man Miu, "A zonal load estimation for unbalance, radial distribution networks", IEEE Trans. Power Delivery, Vol. 17, pp. 1106 - 1112, Oct. 2002.
- [9] H.Liu, D.Yu, H.D. Chiang, "A heuristic meter placement method for load estimation", IEEE Trans. On Power Systems. Vol. 17, No. 3, pp. 913 - 917, Aug. 2002.
- [10] Jie Wan and Karen Man Miu, "Weighted least squares methods for load estimation in distribution networks", IEEE

- Trans. On Power Systems, Vol. 18, No.4, pp. 1338 – 1345, Nov. 2003.
- [11] Shigenori Naka, Takamu Genji, Toshiki Yura, and Yoshikazu Fukuyama, “A hybrid particle swarm optimization for distribution state estimation”, IEEE Trans. On Power Systems, Vol. 18, No. 1, Feb. 2003.
- [12] M.E. Baran, Lavelle A. A. Freeman and Frank Hanson, “Load estimation for load monitoring at distribution substation”, IEEE Transactions on Power Systems, Vol. 20, No. 1, Feb. 2005.
- [13] **A.A.Yaghoti**, M. Parsa and V. J. Majde, “State estimation in distribution systems”, 18TH Conference and Exhibition on Electricity Distribution, IEE , June 2005.
- [14] Yongjian Fu, “Data mining” ,Potentials, IEEE, Vol. 16, Issue 4, pp. 18 – 20, Oct-Nov 1997.
- [15] Zohreh Nazeri, Jianping Zhang, “Mining aviation data to understand impacts of severe weather On airspace system performance”, Coding and Computing, 2002. Proceedings International Conference, pp. 518 – 523, April 2002.
- [16] I. Higuchi, S. Eguchi, “Robust principal component analysis with adaptive selection for tuning parameters”, Journal of Machine Learning Research5, pp. 453-471, 2004.
- [17] M. Tipping and C. Bishop, “Probabilistic principal component analysis”. Journal of the Royal Statistic Society, 61(3), pp. 611-622, Sep.1999.
- [18] J.W. Taylor, L.M. Menezes and P.E.McSharry, “A comparison Of univariate method for forecasting electricity demand up to a day ahead”, Elsevier, International Journal of Forecasting 22, pp. 1– 16, 2006.
- [19] **A.A. Yaghoti**, M.P.Moghaddam, M.R.Haghifam, V.J.Majd, “Load estimation of distribution networks by means of Inverse PCA”, Amirkabir Journal of Science and Technology, Vol. 16, no.67,Fall 2007-Winter 2008.
- [20] EPRI Research, “Plan for Advanced Distribution Automation”, IEEE General Meeting, June 14, 2005.
- [21] Haibin Wang , Noel N. Schulz, “A Revised Branch Current-Based Distribution System State Estimation Algorithm and Meter Placement Impact”, IEEE Transactions on Power Systems, Vol. 19, No. 1, February 2004.