

Online State Estimator for Three Phase Active Distribution Networks Displayed on Geographic Information System

Dimas Fajar U. P., Indri Suryawati, Ontoseno Penangsang, Adi Suprijanto, and Mat Syai'in

Abstract—To improve the operating performance of a distribution network, on line monitoring is required. For this purpose, sensors (metering devices) are installed. To reduce the number of sensors, state estimation approach can be used to estimate the voltage of buses which do not have sensors. This paper proposes online state estimator for three phase active distribution networks using Neural Network and displayed the results on Geographic Information System (GIS). Neural Network based state estimation is used to estimate the bus voltages by using learning approach from power flow patterns. K-matrix three phase distribution power flow is used in this method as an analytical tool. The K-matrix approach is combined with Particle Swarm Optimization (PSO) in handling a Distributed Generation (DG) which is operated as a voltage controlled (PV) bus. The test results show that the proposed method can reduce the number of sensors significantly (almost 50%).

Index Terms—State estimator, neural network, K-matrix, PSO and GIS.

I. INTRODUCTION

Electrical distribution systems is a part of power systems that directly connected to the consumers. In some electrical distribution systems, can consist of a huge number of bus. Due to this reason, monitoring and controlling the electrical distribution system for real time becoming very important to improve its operating performance.

To build this automation systems, huge number of sensor are needed to monitor all part in the systems. But if the sensor installed at all buses, investment cost become huge. To reduce the investment cost, the numbers of installed sensor in the bus need to be reduced. To reduce the number of sensors, state estimation approach can be used to estimate the voltage of buses which do not have sensors.

The concept of state estimator was first discovered by Fred Schweppe on the transmission system. The basic idea of the concept is to combine the advantages of measurements using an equations system as to find the conditions that may occur on the network, resulting the minimization of the error of sensor and the delay of sensor readings. Vector estimation in transmission systems consists of voltage magnitude and phase

angle [1]-[3]. In [4]-[6], they were developed state estimation for single phase distribution systems, this concept suitable for distribution areas where have balance load system.

Distribution networks have characteristics such as the radial network topology, the high value of R/X. There is a lateral system (two-phase and single-phase), and usually have unbalanced load system. Newton Raphson power flow and fast decouple which is used to analyze the transmission system can't be applied to the distribution system, these methods are built on the assumption of balanced three-phase system.

Several methods have been developed to analyze the distribution system like FB, loop frame, FFRPF, direct-ZBR, these methods have accurate analysis but can't accommodate PV bus. The integration of renewable energy sources into the distribution system requires an active distribution power flow to analyze a system performance. The three-phase power flow sequence component based method (SPF-NR) easily accommodates PV bus problems. But SPF-NR cannot accommodate lateral system (two-phase network and single phase). K-matrix distribution power flow is a combination of network topology based methods [7] and direct-ZBR method [8]-[12]. K-matrix distribution power flow algorithm is simpler thus more accommodating the changes of the network structure instead of the previous method. In [10] lambda was used to estimate the voltage at some point which is based on the results of measurements of the voltage sensor at other point measurements.

Voltage estimation in [11] is continuation of research on the integration of renewable energy sources (DG) in distribution networks. The operation of the DG as a PV bus, voltage magnitude is maintained at a certain scale. To get the amount of Volt Var, and optimization is done on the PV bus. Meanwhile, to estimate both the voltage magnitude and voltage angle is maintained accordingly measurement results. Then the optimization is done on the value of Watt and Var on the buses to be estimated voltage. Thus no need sensors at each bus to know the voltage of all buses in the distribution system. The method is robust, but slowness in computational.

This paper proposes neural network distribution state estimation for online monitoring integrated by geographic information system (GIS). State estimation is solved using learning approach from K-matrix-PSO load flow patterns. Neural Network (NN) is an intelligent computing algorithm that inspired the workings of nerve cells. All incoming input signal is multiplied by the weighting for each input, then summed and added to the bias. The sum of the incoming activation function of the neuron produces output. NN will be trained to power flow results of K-matrix-PSO, as many as 50 load pattern. The goal is not only improve the accuracy but

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real time measuring. The advantage of GIS for online monitoring; it has two dimension visualization, detailed information of location and flexibility analysis.

II. METHODOLOGY

A. K-Matrix Power Flow

Submit your manuscript electronically for review. For ease of illustration, the simple three phase radial distribution system is shown in Fig. 1. There are five bus and bus no 3 as PV bus. but for this step PV bus is ignored. In other hand the network is passive. The system can be easily analyzed using the K - matrix power flow method.

K - matrix is a square matrix with size nbranch x (nbus - 1). nbranch is the number of branches and nbus is the number of bus. The principle of K-matrix, are looking for the route from bus to reference (bus 1). K-matrix would be worth-C if the branch is located on the opposite lane with reference, C is a diagonal matrix (3x3) with diagonal elements are 1 in accordance with the number of phase. K-matrix formed Fig. 1 is expressed in equation (1) as follows:

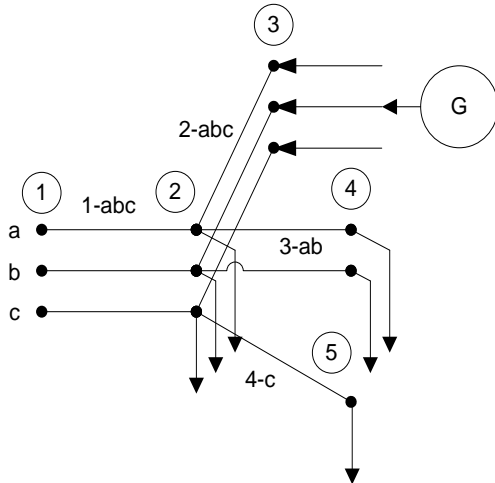


Fig. 1. A simple three phase radial distribution system.

$$K = \begin{matrix} \text{Bus} & \begin{matrix} 2 & 3 & 4 & 5 \end{matrix} \\ \begin{matrix} \text{Branch} \\ a & b & c \end{matrix} & \begin{matrix} abc & abc & ab0 & 00c \end{matrix} \end{matrix} \begin{bmatrix} \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{matrix} \\ \hline \begin{matrix} 2 & b & c \\ 3 & a & b \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{matrix} \\ \hline \begin{matrix} 4 & b & 0 \\ 5 & 0 & c \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{matrix} & \begin{matrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{matrix} \end{bmatrix} \quad (1)$$

K-matrix power flow algorithm:

1. Input load and network data
2. Build K-matrix
3. Build BCBV matrix, BCBV is negative transpose K-matrix multiply with full branch matrix [].
4. Build DLF matrix, DLF is BCBV multiply with - (K-matrix)

5. Then inflows of at each bus was calculated by equation (2)

$$I_{bus(l)}^{(k)} = \left(\frac{P_{(l)}^{sh} + jQ_{(l)}^{sh}}{V_{bus(l)}^{(k)}} \right) \quad (2)$$

Equation (3) is updated every iteration. Along with the update iteration, it is the result of multiplying the voltage difference between DLF and I_{bus}

$$\Delta V^k = DLF \cdot I_{bus}^k \quad (3)$$

$$V^{k+1} = V_{bus_noload} - \Delta V^k \quad (4)$$

V_{bus_noload} is the voltage at each bus in the initial conditions, it is set equal to the reference voltage.

6. Check if $\Delta V_{Bus}^{(k+1)}$ are less than a preset tolerance then iteration stop. If it more than a preset tolerance back to point 5.

B. K-Matrix –PSO Power Flow for Active Distribution

When you submit your final version, after your paper has been accepted, prepare it in two-column format, including figures and tables. K-matrix distribution power flow must be combined with optimization algorithm to estimate the Var value on PV bus. PSO was chosen in this research considering on literature [9]-[21] PSO is robust and simple optimization algorithm

Particle Swarm Optimization (PSO) is heuristic algorithm that inspired by swarm of birds looking for food source [22]. PSO in K-matrix power flow is used for tuning Var in PV bus and keep the voltage constant.

K-matrix-PSO power flow algorithm:

1. Input load, line and generation data
2. Input PSO parameter
3. Random initialization of Var(Q) for each PV bus.
4. K-matrix Power Flow
5. Evaluate the fitness
6. Getting the best particle (Pbest) and best global particle (Pgbest).
7. Update velocity and Position by equation:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 x(Pbest_i^k - X_i^k) + c_2 r_2 x(Gbest_i^k - X_i^k) \quad (5)$$

$$X_i^{k+1} = V_i^k + V_i^{k+1} \quad (6)$$

V_i^k = velocity particle i at k iteration

ω = weight parameter

c_1, c_2 = acceleration coefficient

r_1, r_2 = random value between 0 until 1

$r_1 X_i^k$ = particle position at k iteration

$Pbest_i^k$ = Pbestparticle i atiterasi k

$Gbest_i^k$ =Gbest particle i iterasi k

8. Check constrains Qmin and Qmax.

9. Check *stopping* criteria, there are two stopping criteria; maximum iteration and tolerance.

C. Neural Network Distribution State Estimator

Neural Network Distribution State Estimator (NNDSE) is designed and tested for real distribution system. It used one of feeder in Surabaya Indonesia. There are ten bus, six bus is load bus and four bus is no load bus. Sensor was placed on two or more bus.

K-matrix power flow patterns divided training and testing, 70% data as training and 30% data as testing. In all data use 50 power low patterns. One hidden layer ten node Neural Network back propagation was design.

Artificial neurons are a processing element that functions like neurons in a neural network structure. A number of the input signal is multiplied by each corresponding weights. Then do the sum of all activation function to get the output signal. Suppose there is an input signal and the weights, the output function of the neuron is according the following equation.

$$F_{(x_1w)} = f(w_1x_1 + \dots + w_nx_n) \quad (7)$$

Set of neurons made into a network that will serve as a computational tool. The amount of weight between each neuron is connected to be determined the network trained using a set of sample data.

Complete research step is described in Fig. 2. Step 1 until 4 is part of stage A and B. magnitude and angle voltage from 50 load flow pattern from each stage as input and output training testing neural network (step 5). This network was used distribution state estimation (step 6). Module NDSE will export estimation data to database and integrated with GIS to show detail information of location and utility.

III. TEST AND DISCUSSIONS

First step result is validation power flow design with commercial software, ETAP. The average different values for all design are 0.001. That's mean that all design of power flow are feasible.

Neural network distribution state estimation was tested for following test cases.

A. Single Phase Distribution Network

There are ten bus in feeder of kaliasin (Fig. 3). bus no 3, 5, 6, 8 and 10 are load bus (see Table I).

Case 1 voltage estimation for bus no 5 and 8 consider three input sensor from bus no 3, 6 and 10.

Case 2 voltage estimation for bus no 5, 6 and 10, sensor was placed on bus no 3 and no 8.

B. Passive Three Phase Distribution Network

Case B is state estimation for three phase distribution unbalance network. The data was used is feeder of Kaliasin Surabaya Indonesia. Same with Case A but it consist of three phase unbalance load (see Table II).

Case 1 voltage estimation for bus no 5 and consider three input sensor from bus no 3, 6 and 10.

Case 2 voltage estimation for bus no 5, 6 and 10, sensor

was placed on bus no 3 and 8.

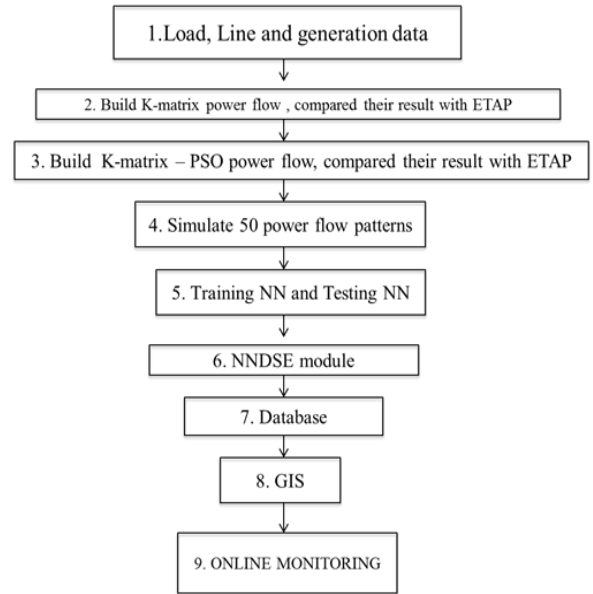


Fig. 2. Flow chart NN state estimation for active distribution systems.

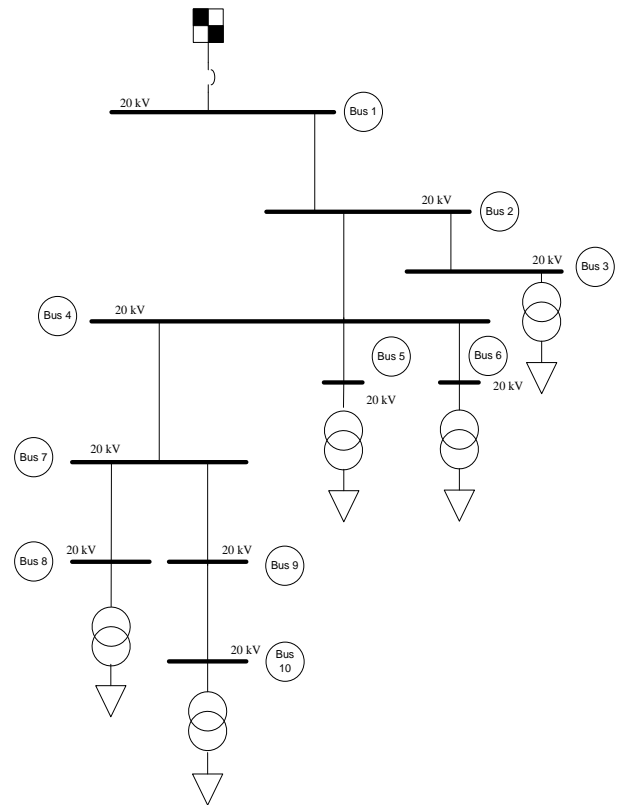


Fig. 3. Real distribution system, feeder of Kaliasin Surabaya Indonesia.

C. Active Three Phase Distribution Network

Case C is state estimation for three phase active distribution network. The data was used is feeder of Kaliasin. Same with Case B but it addition DG as PV bus at bus no 3(see Table III).

Case 1 voltage estimation for bus no 5 and consider three input sensor from bus no 3, 6 and 10.

Case 2 voltage estimation for bus no 5, 6 and 10, sensor was placed on bus no 3 and 8. Similar result between target and NNDSE are obtained. The proposed method accurately solves. The state estimation is displayed on GIS, it is shown in Fig. 4. Normal, under voltage and over voltage condition will

be known. In Fig. 4 is an example that bus is under voltage. Fig. 5 showed the added menu in GIS to display the voltage magnitude and voltage angel for a node/bus in the systems.

For the next research will be combined between Neural Network and others Artificial Intelligent method to improve estimation result.

TABLE I: NN STATE ESTIMATION IN SINGLE PHASE DISTRIBUTION NETWORK

Case 1					Case 2				
		Voltage (pu)					Voltage (pu)		
		Angle					Angle		
Input	V_2	0.99935	θ_2	-0.0180	V_2	0.99935	θ_2	-0.0180	
	V_5	0.99920	θ_5	-0.0222	V_5	0.99916	θ_5	-0.0233	
	V_{20}	0.99906	θ_{20}	-0.0253					
Target	V_5	0.99916	θ_5	-0.0222	V_5	0.99920	θ_5	-0.0222	
	V_2	0.99916	θ_5	-0.0233	V_5	0.99920	θ_5	-0.0222	
					V_{20}	0.99096	θ_{20}	-0.0253	
NNDES	V_5	0.99937	θ_5	-0.0223	V_5	0.99950	θ_5	-0.0227	
	V_5	0.99927	θ_5	-0.0238	V_5	0.99970	θ_5	-0.0229	
					V_{20}	0.99916	θ_{20}	-0.0260	
Error	V_5	0.017%	θ_5	0.45%	V_5	0.03%	θ_5	2.25%	
	V_5	0.011%	θ_5	2.14%	V_5	0.05%	θ_5	3.153%	
					V_{20}	0.872%	θ_{20}	2.77%	

TABLE II: NN STATE ESTIMATION IN PASSIVE THREE PHASE DISTRIBUTION NETWORK

		Phasa A				Phasa B				Phasa C			
		Voltage (pu)		Angle		Voltage (pu)		Angle		Voltage (pu)		Angle	
Case 1	Input	V_2	0.9995	θ_2	-0.0180	V_2	0.9993	θ_2	-120.0197	V_2	0.9992	θ_2	119.9821
		V_5	0.9992	θ_5	-0.0222	V_5	0.9989	θ_5	-120.0242	V_5	0.9991	θ_5	119.9778
		V_{20}	0.9990	θ_{20}	-0.0253	V_{20}	0.9990	θ_{20}	-120.0276	V_{20}	0.9989	θ_{20}	119.9748
	Target	V_5	0.9994	θ_5	-0.0222	V_5	0.9992	θ_5	-120.0242	V_5	0.9915	θ_5	119.9779
		V_5	0.9991	θ_5	-0.0233	V_5	0.9902	θ_5	-120.0255	V_5	0.9903	θ_5	119.9770
	NNDSE	V_5	0.9993	θ_5	-0.0225	V_{20}	0.9994	θ_5	-120.0280	V_5	0.9925	θ_5	119.9400
		V_5	0.9992	θ_5	-0.0240	V_5	0.9916	θ_5	-120.0600	V_5	0.9908	θ_5	119.9960
	Error	V_5	0.01%	θ_5	1.35%	V_5	0.02%	θ_5	0.38%	V_5	0.1%	θ_5	0.006%
		V_5	0.01%	θ_5	3%	V_5	0.14%	θ_5	0.028%	V_5	0.05%	θ_5	0.015%
	Input	V_2	0.9993	θ_2	-0.0180	V_2	0.9993	θ_2	-120.0197	V_2	0.9993	θ_2	119.9821
		V_5	0.9991	θ_5	-0.0233	V_5	0.9991	θ_5	-120.0255	V_5	0.9991	θ_5	119.9960
Case 2	Target	V_5	0.9992	θ_5	-0.0222	V_5	0.9992	θ_5	-120.0280	V_5	0.9992	θ_5	119.9400
		V_5	0.9993	θ_5	-0.0222	V_5	0.9992	θ_5	-120.0242	V_5	0.9992	θ_5	119.9778
		V_{20}	0.9909	θ_{20}	-0.0253	V_{20}	0.9909	θ_{20}	-120.0276	V_{20}	0.9909	θ_{20}	119.9749
	NNDSE	V_5	0.9994	θ_5	-0.0226	V_5	0.9996	θ_5	-120.0300	V_5	0.9998	θ_5	119.9000
		V_5	0.9995	θ_5	-0.0226	V_5	0.9994	θ_5	-120.0200	V_5	0.9993	θ_5	119.9600
		V_{20}	0.9910	θ_{20}	-0.0251	V_{20}	0.9923	θ_{20}	-120.0400	V_{20}	0.9920	θ_{20}	119.9800
	Error	V_5	0.02%	θ_5	1.8%	V_5	0.04%	θ_5	0.001%	V_5	0.06%	θ_5	0.03%
		V_5	0.03%	θ_5	1.8%	V_5	0.02%	θ_5	0.003%	V_5	0.01%	θ_5	0.01%
		V_{20}	0.01%	θ_{20}	0.88%	V_{20}	0.14%	θ_{20}	0.01%	V_{20}	0.11%	θ_{20}	0.004%

TABLE III: NN STATE ESTIMATION IN ACTIVE THREE PHASE DISTRIBUTION NETWORK

		Phasa A				Phasa B				Phasa C			
		Voltage (pu)		Angle		Voltage (pu)		Angle		Voltage (pu)		Angle	
Case 1	Input	V_3	1	θ_3	-0.0721	V_3	1	θ_3	-120.0781	V_3	1	θ_3	119.9237
		V_6	0.9997	θ_6	-0.0752	V_6	0.9997	θ_6	-120.0815	V_6	0.9996	θ_6	119.9205
		V_{10}	0.9994	θ_{10}	-0.0783	V_{10}	0.9994	θ_{10}	-120.0848	V_{10}	0.9994	θ_{10}	119.9176
	Target	V_5	0.9997	θ_5	-0.0752	V_5	0.9997	θ_5	-120.0814	V_5	0.9996	θ_5	119.9206
		V_8	0.9996	θ_8	-0.0763	V_8	0.9996	θ_8	-120.0828	V_8	0.9995	θ_8	119.9197
		V_5	0.9997	θ_5	-0.0760	V_5	0.9997	θ_5	-120.0700	V_5	0.9995	θ_5	119.3000
	NNDSE	V_8	0.9997	θ_8	-0.0770	V_8	0.9998	θ_8	-120.7500	V_8	0.9954	θ_8	119.9400
		V_5	0.02%	θ_5	1.06%	V_5	0.02%	θ_5	0.0095%	V_5	0.01%	θ_5	0.52%
	Error	V_8	0.02%	θ_8	0.917%	V_8	0.01%	θ_8	0.55%	V_8	0.4%	θ_8	0.017%
		V_3	1	θ_3	-0.0721	V_3	1	θ_3	-120.0781	V_3	1	θ_3	119.9237
Case 2	Input	V_8	0.9991	θ_8	-0.0763	V_8	0.9991	θ_8	-120.0828	V_8	0.9996	θ_8	119.9197
		V_5	0.9997	θ_5	-0.0752	V_5	0.9997	θ_5	-120.0814	V_5	0.9996	θ_5	119.9206
		V_6	0.9997	θ_6	-0.0752	V_6	0.9997	θ_6	-120.0815	V_6	0.9996	θ_6	119.9205
	Target	V_{10}	0.9994	θ_{10}	-0.0763	V_{10}	0.9994	θ_{10}	-120.0848	V_{10}	0.9994	θ_{10}	119.9176
		V_5	0.9997	θ_5	-0.0752	V_5	0.9997	θ_5	-120.0814	V_5	0.9996	θ_5	119.9206
		V_6	0.9997	θ_6	-0.0752	V_6	0.9997	θ_6	-120.0815	V_6	0.9996	θ_6	119.9205
	NNDSE	V_{10}	0.9997	θ_{10}	-0.0752	V_{10}	0.9994	θ_{10}	-120.0848	V_{10}	0.9996	θ_{10}	119.9176
		V_5	0.01%	θ_5	0.27%	V_5	0.03%	θ_5	0.008%	V_5	0.01%	θ_5	0.008%
	Error	V_6	0.01%	θ_6	0.93%	V_6	0.01%	θ_6	0.0079%	V_6	0.01%	θ_6	0.0004%
		V_{10}	0.01%	θ_{10}	0.13%	V_{10}	0.01%	θ_{10}	0.012%	V_{10}	0.02%	θ_{10}	0.019%

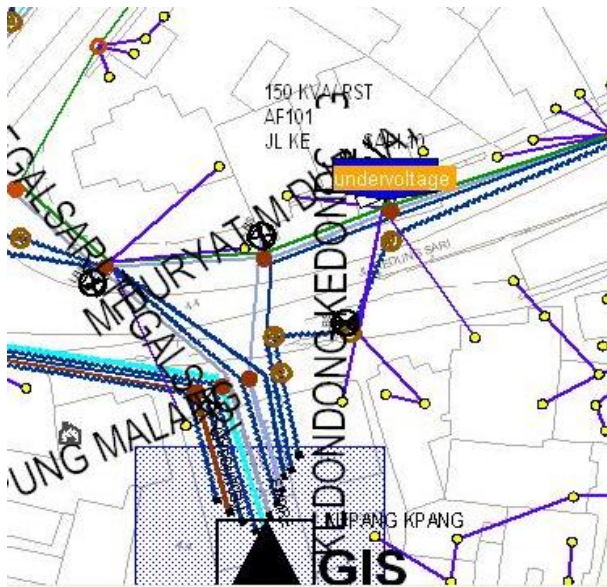


Fig. 4. State estimation displayed in GIS.

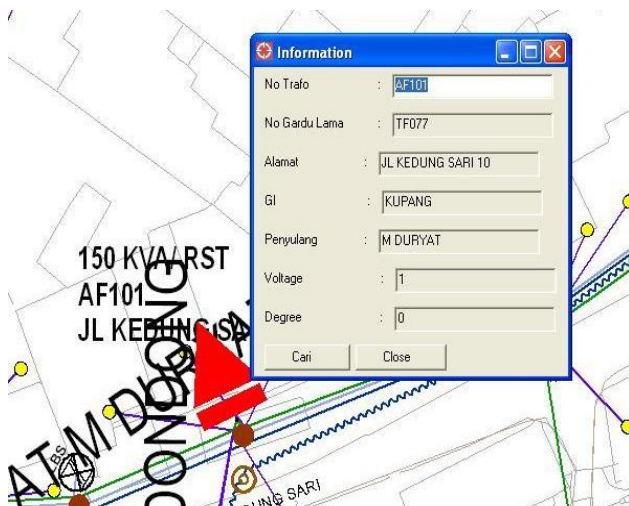


Fig. 5. State estimation information.

IV. CONCLUSION

The proposed method which is a new approach to solve for active unbalanced distribution networks accurately. The simulation results show that proposed method can accommodate PV bus. State estimation using neural network for all case have error under 4% and reduce sensor almost 50%.

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