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Enhancement of Monitoring and Non-technical Power Loss Detection in Power Distribution Networks Using WSN State Estimation

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Abstract. The power distribution network is one of the important parts of the power system needing a precise control and supervision on optimal operation. Given the limitations of the measuring devices, the network faces a monitoring challenge. The paper proposes a new monitoring approach to the power management system. A Wireless Sensor Network (WSN) is used to measure the distribution network voltages and currents. Using the Phasor measurement-based network state-estimation method minimizes the measurement errors and determines the location to install WSNs to continuously monitor the network operation and power consumption at buses. A new method is presented to modify the measured values in observability area and to monitor the entire network to detect measurement failures and founds areas of the network. The energy consumed by the network consumers and non-technical losses are detected. Results of simulations and implementations made on a 33-bus IEEE network are presented.

Keywords: State estimation, WSN, Monitoring, Non-technical power losses

Izboljšava spremljanja izgub v elektroenergetskih omrežjih z uporabo brezžičnega senzorskega omrežja

Distribucijsko omrežje je eden pomembnih delov elektroenergetskega sistema, ki potrebuje natančen nadzor nad optimalnim delovanjem. V prispevku je predlagan nov pristop k spremljanju upravljanja porabe energije. Za merjenje napetosti in tokov distribucijskega omrežja se uporablja brezžično senzorsko omrežje (WSN). Z uporabo metode ocenjevanja stanja omrežja zmanjšamo napake pri merjenju in določimo mesto namestitve WSN. Predstavljeni sta novi metodi za spreminjanje izmerjenih vrednosti in za spremljanje celotnega omrežja za odkrivanje napak pri merjenju. Predstavljeni so rezultati simulacij z uporabo omrežju IEEE.

1 INTRODUCTION

In a distribution network, the measurable values like the current and voltage are not always available due to various reasons such as the lack of the line and bus values and equipment failures. Thus, automation of real-time monitoring of the distribution network is inevitable. Moreover, a high rate of non-technical losses and power theft in the distribution network calls for an advanced monitoring approach.

Given the lack of comprehensive and instantaneous data about of the distribution network buses because of the insufficiency of the measurement devices, the monitoring challenge is considerable. Based on the power system state estimation can be determined, theoretical power losses, voltage and power optimized, network control redesigned, line overloading prevented and so on. Using the state-estimation methods improves monitoring, control, and distribution of the economic load of the distribution network and increases its power and reliability.

So far, many studies have been done for the power network state-estimation which usually uses two approaches. [1] to [4] are statistical methods which usually iterative convergence methods like the Quasi-Newtonian methods and the others are sensitivity analysis methods. They both assume that the objective function or the equations for the distribution network state-estimation can be continuous and differential, but the objective function cannot be a continuous differential given the nonlinear characteristics of the distribution network devices [5]. This makes the traditional methods of state-estimation for the power network difficult. [5] proposes a method based on a particle swarm optimization to solve the problem of non-linear components of the power distribution network. [6] examines the distribution network control system as a function of improvements based on accurate data and fast communication signals. The effect of using a Wi-Max wireless communication system as a rural network control system tool in Italy is examined. There are significant time delays between the control center and the distribution of energy resources and on rainy days the entire communication gets lost. [7] suggests a

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joint filter approach to the static state estimation (bus voltage size and phase) and dynamic state estimation (rotor angle and speed, and generator voltage) using PMU. Using the load and the measuring devices data, [8] predicts the load on a feeder. The prediction for a three-phase feeder is made using the least-squares estimation method. [9] presents an estimation method which takes into account the previous estimates using a converged filter to improve the accuracy of current calculations. [10] presents the state estimation as a part of the distribution network approach based on a nonlinear dynamic system approach. An advanced formulation of limitations of the amplitude measurement and voltage phase angle is used to enhance the accuracy of the amplitude and voltage phase angle. The algorithm is tested on IEEE 123 node test feeders. [11] presents a state estimation formula for a feeder using a quasi-symmetric impedance matrix that incorporates the network structure. As a result, the size of the optimized problem is significantly reduced, but the major problem is using nonlinear equations for state estimation.

Non-technical losses are defined as the difference between total network losses and technical losses. Electricity theft, measurement equipment failure and unidentified consumption are the main causes of non-technical losses. Identifying non-technical losses in each feeder needs an accurate load estimation at the transformer output.

[12] presents an experiment method in the Brazilian power network that improves the detection of non-technical losses by 50%. [13] has uses correlation coefficients, Bayesian networks, and system tree to identify the non-technical losses. [14] takes another perspective. It identifies the feeders with the highest non-technical losses. Contrary to after papers generally using data mining methods to detect electricity theft, a load propagation method with the state estimation is used. The data and consumption patterns of each subscriber type are available. In previous models, the percentage of the network input power consumption is assigned to each feeder. Finally, after calculating the power in each feeder and considering the power cost in each period, the non-technical losses per feeder are calculated. In [15], the development of machine-learning classifiers are proposed to detect anomalous power consumption in the Turkish network. [16] discusses the use of a smart-meter data to increase monitoring in distribution networks. To identify non-technical losses caused by cyber-attacks in a modern distribution network, [17] proposes using multivariate control charts that create a reliable area for monitoring and variance measurement.

Managing the distribution network necessitates the availability of the network data collected by measuring devices installed in the network. One of the major challenges is how to send the measured data to a control center. Due to the structure of the distribution network, it is virtually impossible to send the data to the center directly. A reliable and appropriate mode is needed to send the data to a control center directly.

Another challenge is the number of substations to install measuring devices which involves a financial burden for the network. Moreover, suite many data need to be sent to the control center to assume its proper infrastructure. In case of meter failure, the center receives data for the involved substation which makes the responsibleness difficult.

After receiving an information about a network failure, the measuring device communicates it to the center. If the measuring system is not modified, the network will respond wrongly. The control center needs to properly analyze the data and use them correctly. The data can be used or a ritual measurement of the energy consumed and energy lost to calculate the non-technical energy consumption (illegal consumers).

In our study, WSN is used to increase the availability and reliability of its sensors. Moreover, the paper presents a robust linear WSN-compatible estimator and proposes a new calculation method for the state estimation to be used in case the area control and monitoring is lost for various reasons.

In part 2, The paper presents WSN concepts and its application in the distribution network cost-accounting system. Making the network observable will be examined using it. Part 3 presents concepts and relationships of linear state-estimations compatible with WSN. Part 4 examines monitoring of the network using WSN. Part 5 discusses how to monitor a network when one of its parts cannot be monitored. Part 6 focuses on monitoring the energy of the distribution network. Part 7 identifies the network technical and non-technical losses. In part 8 the above is simulated and run on an IEEE standard network.

2 WSN AND DISTRIBUTION NETWORK MONITORING SYSTEM

The data need to be sent to the control center. To manage and control a network. given the structure of the distribution network, it is necessary that data of each substation or line separately communicates with the server, which in values a large number of routes and causes problems in execution. If one and the sensor connections to the center is interrupted, the affected part of the network is unavailable and cannot it monitored.

Control systems of smart power networks are composed of a combination of similar and diverse components like sensors, actuators, software for monitoring and data collection and other services. As one of the new increasing technologies, WSN produces smart networks with the ability to monitor and make precise decisions by providing many features. WSN is a very effective and flexible tool to obtain power network features for central monitoring and analysis. [18] explores the WSN role in the smart networks.

WSN is composed of thousands of inexpensive small smart sensors. They compute processes and communicate with each other. The reason for being used in our study is its multi-directional communicational capability. Each sensor can send its and other adjacent sensors data to the control center from several different paths so that if any communication path is interrupted, the sensor provides a new way of data transmission. WSN has various applications in industry, transportation, security, medicine, crisis management and so on. Such network acts as a bridge between the physical and virtual space, enabling the monitoring of formerly unseen elements in a large range of a desirable quality [19].

The WSN advantages are energy saving, responsiveness, stability, adaptability and automatic updating. The sensors are composed of six main components: the processing unit, memory storage, power supply data, radio module to transmit and receive data, antenna and sensor measuring.

3 LINEAR STATE ESTIMATION USING WEIGHTED LEAST- SQUARES CRITERION

To ensure a reliable operation of power systems which are subject to a wide range of disturbances, the availability of an accurate and timely data at the system level is an important task to done by state estimators. They calculate system variables such as the bus voltage and angles by introducing an objective function and minimizing or maximizing it. the control center receives a variety of target functions to determine the system state, including weighted least squares indicating the least weighted suspended weight, non-quadratic estimators and least-square mean values. The objective function of the weighted least squares is the most useful and the most accurate and fast among the objective functions.

The weighted least- square function estimates the state network by minimizing the sum of squares between the estimated measurements from the actual measurements. In estimating the x parameter using N_m, the objective function of the weighted least- squares method is :

$$min\, J(x) = \sum_{i=1}^{N_m} \frac{[z_i^{meas} - f_i(x)]^2}{\sigma_i^2} \tag{1}$$

where $J(x)$ is the objective function, N_m is the number of independent measurements, z_i^{meas} is the measured quantity number i, $f_i(x)$ is the function used to calculate the measured value from the measurement number i and σ_i^2 is the variance for the i measurement. The function $f_i(x)$ is as follows:

$$f_i(x_1, x_2, \dots, x_{N_s}) = f_i\,(\mathrm{x}) = h_{i1}x_1 + \dots + h_{iN_s}x_{N_s} \tag{2}$$

By placing all f_i functions in a vector, we get:

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_{N_s}(x) \end{bmatrix} = Hx \tag{3}$$

where N_s is the number of unknown parameters estimated and H is matrix $N_m \times N_s$ containing the coefficients of the linear functions $f_i(x)$.

By placing the measured quantities in a vector, Equation (1) takes the following form:

$$min\, J(x) = [z_i^{meas} - f(x)]\; R\; [z_i^{meas} - f(x)]. \tag{4}$$

To obtain a general expression for the minimum in Equation (4) by expanding the equation and zeroing gradient $J(x)$, as the below equation:

$$\nabla J(x) = 0. \tag{5}$$

Finally, the matrix equation is:

$$X^{est} = [(H^T R^{-1} H)^{-1} H^T R^{-1}] Z^{meas} \tag{6}$$

where X^{est} is the vector of the estimated values of bus voltages. Matrix H is derived from the values of the network controls and WSN installation location and includes the network topology. Matrix R is the covariance matrix of the error of the measuring device which is a diagonal matrix. Vector Z^{meas} is the measured values of the voltage and current of some buses and branches, installed at desired locations to read the desired quantities of the monitoring WSN. Matrix H is:

$$H = \begin{bmatrix} K \\ yA + y_s \end{bmatrix}. \tag{7}$$

Matrix K is an $m \times n$ matrix for the voltage measuring devices where n is the number of voltage meters and m is the number of network buses. The matrix rows show the corresponding measuring device and the matrix columns the corresponding bus acts as follows.

To determine the entries, the matrix act as follows. When there is a voltage meter in a monitored bus (column), it is set to one, otherwise to zero. Matrix A is an $n \times m$ matrix where n is the number of the current measuring devices and m the network bus. Matrix y is the admittance matrix between buses of an $m \times m$ matrix where it is m -times the number of the network buses. Matrix y_s is the parallel admittance matrix of the system. This matrix shows the location of each current measuring device for the parallel admittance of the branch on which the current measuring device is located. The parallel admittance matrix is $m \times b$, where m is the number of the current measuring devices and b is the number of buses which the measured current are exited from them. By forming the above matrices and using Equation 6, a linear equation set is obtained that can be solved easily.

4 LOCATING WSN MEASURING DEVICES TO MONITOR THE DISTRIBUTION NETWORK

Given their simple structure and safety issues, distribution networks are often exploited radially or the distribution substation overhead is considered as a baseline and expands radially. Our objective is to measure the parameters of each distribution substation. Suitable points of the network are identified to achieve this goal at the lowest cost and highest efficiency. The data about these points, can monitor the whole network by applying circuit equations.

Monitoring the distribution network is very important for its state estimation, and the number of the measurements must be greater than the unknowns of the problem to have the desired result. In this section we present a monitoring method using a WSN measurement unit. The WSN unit is assumed to capable of measuring bus voltages and currents of the branches connected to it. Figure 1 shows an example for calculating the node voltages and currents of the nodes and their adjacent branches. It is assumed that in a four-bus network, one can measure the following data by installing a measuring sensor in buses 1 and 4:

- Bus voltage
- Bus input current
- Bus output current
- Bus power consumption

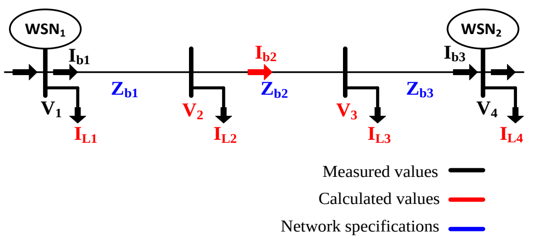

Figure 1. WSN locations to monitor the power distribution network.

Using the above data, one can make the entire network can be monitored with minimally two meters. In the network of Figure 1, the known and unknown network magnitudes are specified (Table 1).

Table 1. Known and unknown distribution network magnitude values

Bus	Bus input current	Bus output current	Bus power consumption	Bus voltage
1	Known	Known	Unknown	Known
2	Unknown	Unknown	Unknown	Unknown
3	Unknown	Unknown	Unknown	Unknown
4	Known	Known	Unknown	Known

To get the network unknown magnitude values using buses whose voltages and currents are read by WSN, the voltage of all buses is determined and then the bus current consumption is calculated which is done according to the below equations:

$$V_2 = V_1 - Z_{b1} I_{b1} \tag{8}$$

$$V_3 = V_4 + Z_{b3} I_{b3} \tag{9}$$

$$I_{b2} = \frac{V_2 - V_3}{Z_{b2}} \tag{10}$$

$$I_{L2} = I_{b1} - I_{b2} \tag{11}$$

$$I_{L3} = I_{b2} - I_{b3} \tag{12}$$

where V is the bus voltage, Z_b and I_b are the branch impedance and current, and I_L is the bus output current towards the consumer. As is seen in the radial network shown in Figure 1, instead of installing a sensor in each bus, the network can be easily monitored with two WSN meters according to the Kirchhoff's circuit laws.

To better understand the usefulness of the theory, see Figure 2.

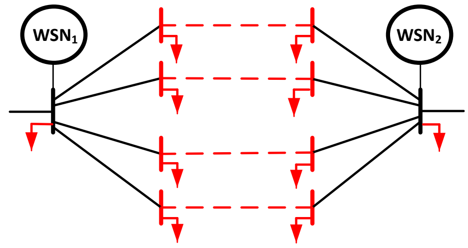

Figure 2. Monitoring enhancement using WSN

By installing two WSNs for every four buses at two points in a network, one can monitor all the magnitudes of this cut from a larger network. The black lines and buses show that WSN has read their current and voltage values. The lines and buses of the dashed line show the buses that can be calculated using the measured values. Thus, by installing two WSNs, one can easily the network voltage for four buses and four branches and three consumption currents.

5 NETWORK MONITORING WHEN THE WSN DATA IS LOST

Sometimes, one or more WSNs data in the network may be lost. This may lead to a loss of the network monitoring. Hence, it is necessary to take the necessary measures. For better understanding, consider Figure 3 as a part of an electrical network.

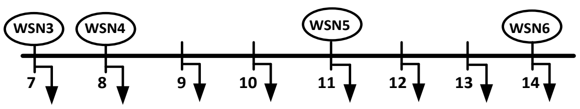

Figure 3. Network monitoring with measuring devices.

According to the above equations stated in the previous section, the bus 8 data is lost when the WSN 4 data in the network is lost. However, by measuring the adjacent bus measurements measured with WSN 3, the bus 8 data can be easily calculated. Consider the case where the WSN 5 data is lost. According to Figure 4, the access to the data of the buses 10, 11, and 12 will generally be lost too. The paper proposes a new approach to solve the problem of missing data and to resume the network monitoring.

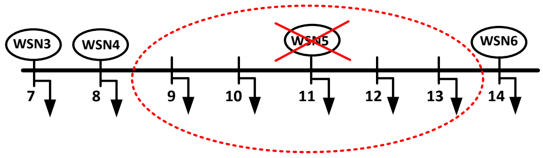

Figure 4. Determining a non-monitored area.

As the historical date of the bus power consumption is available, and on the other hand, the measurements of buses 8 and 14 are available, one can estimate the voltage values of buses 9, 10, 11, 12 and 13 using the innovative Pseudo Gauss-Seidel Iteration method. The method is based on a numerical iteration. However, only the unread values are updated here in iterations: the read values of the bus voltages 8 and 6 remain constant in the calculation and the bus voltages 9 to 13, whose values are not measured, are updated for iterations. The iterations are calculated using Equation (13).

$$V_n = \frac{1}{Y_{nn}}\left(\frac{P_n + iQ_n}{V_{n-1}} - \sum_{k=1}^{m} Y_{nk}V_k\right) \qquad (13)$$

where V_n is the bus voltage read, Y_{nn} is the sum of the admittances connected to bus n, P_n and Q_n are the active and reactive power of loads connected to bus n, bus admittances Y_{nk} are connected to bus n and k. V_{n-1} is the previous voltage of bus n, V_k is the bus voltage k adjacent to bus n and m is the number of buses connected to bus n. This equation applies for each bus in a non-monitored area. The algorithm used in this equation is shown in Figure 5.

6 Energy Monitoring Using WSN

After locating and installing wireless sensors, as well as analyzing and executing the monitoring network and consumer data is fully available, by considering measurement errors and the likelihood of the data loss of some WSNs after performing the state estimation, the following data can be obtained:

- The energy injected into the distribution network
- The energy consumed by subscribers
- The technical and non-technical energy lost in the network

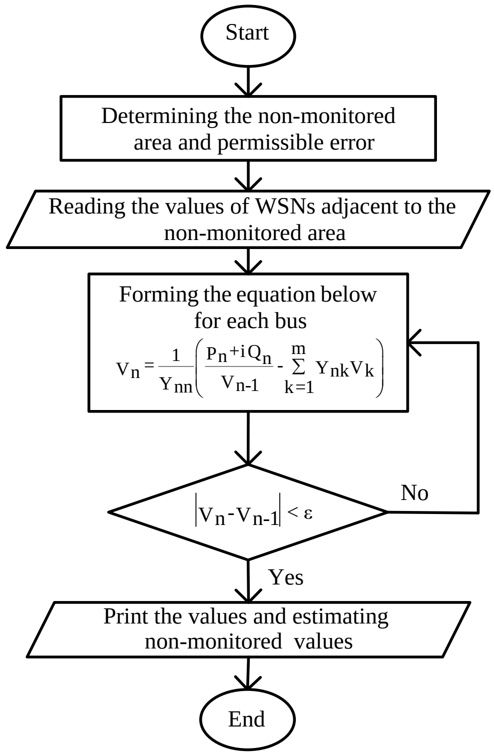

Figure 5. Algorithm to estimate the values of the non-monitored area

- The energy consumed in each area to optimize each area, an unproved energy control, values continuous monitoring of each subscriber and illegal energy consumed can be easily calculated.

Using Equation (14) an instantaneous power consumption of a bus is determined:

$$P_B = V_B \times I_B \qquad (14)$$

where P_B is the bus power, V_B is the bus voltage and I_B is the bus current. (15) is used to calculate the total energy consumption of a bus for any hour of a month:

$$W_n = \sum_{t=1}^{720} (V_{n_t} \times I_{n_t}) \qquad (15)$$

where W_n is the energy consumed by a bus in one month. V_{n_t} and I_{n_t} are the voltage and current consumed by a bus at a specific hour, and t is the sampling hour. (16) is used to calculate the total power consumption by all the network buses in one month:

$$W_{total} = \sum_{n=1}^{m} W_n \qquad (16)$$

where m is the number of the network buses.

7 DETECTING THE NON-TECHNICAL LOSSES OF THE DISTRIBUTION NETWORK USING WSN

An effort should be made to avoid the non-technical losses in power distribution network. One of the major challenges in the distribution network is to identify illegal consumers and to calculate the energy consumed by them. Ranking areas according to technical and non-technical losses enables power distribution utilities to eliminate and reduce of the losses at a minimal cost. One of the objectives of the paper is to estimate installation of measuring devices of any transformer.

One of the measures to identify modifying or manipulating the energy measuring system is to study the history of the shared consumption in similar periods in previous years. In other words, if a shared consumption has changed dramatically over the same period, subscribers should be is examined and the measuring devices checked.

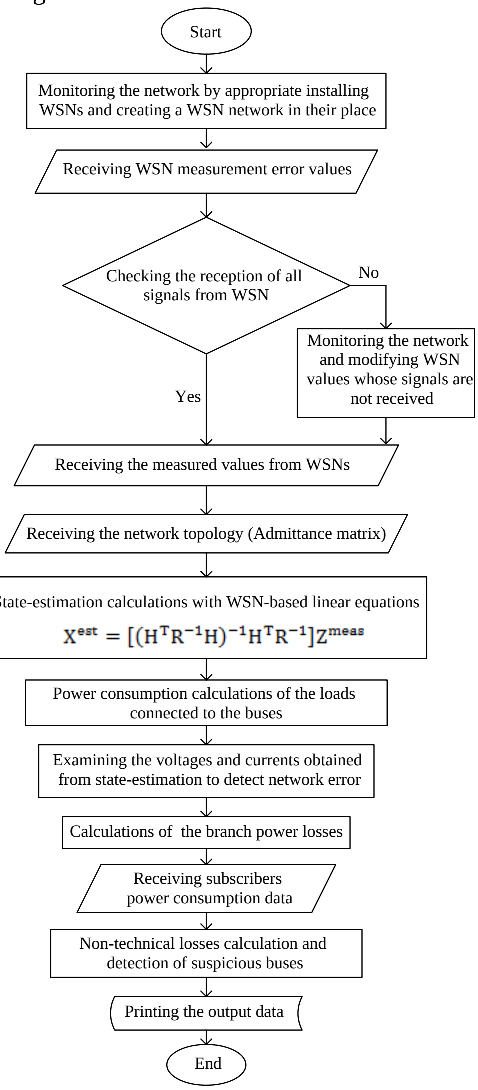

Figure 6. State estimation algorithm using WSN to determine network losses.

The objective of the paper is to determine the non-technical losses by monitoring each subscriber on a continuous basis and to calculate the illegal energy consumption. By comparing the subscribers' bills with the WSN readings of a monthly energy consumption, the non-technical network losses are identified. The algorithm used for this purpose is shown in Figure 6.

8 SIMULATIONS AND RESULTS

Figure 7 shows a 33-bus IEEE network used to test and validate the proposed method to reviewing the network state-estimation. The first step is to examine the WSN location to monitor the distribution network. The second step is to perform the network state-estimation using the WSN measurement. The third step is to examine the effect of deleting the WSN1 and WSN5 data on the estimator. The fourth step is to calculate the energy sold and delivered to the network. The final step is to detect the network non-technical losses.

The locations for installing WSN meters making the network monitoring are shown in Figure 7. The measuring device placed at the beginning of each branch and the meter placement on the branches follows the Figure 1. The network is fully monitored by installing 12 WSN measuring devices which measure the voltage amplitude and angles, as well as the values of the active and reactive power in buses installed as input state estimators.

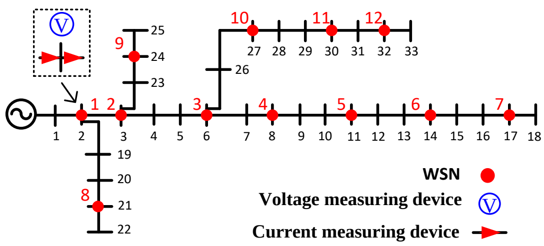

Figure 7. Location of WSNs installed in the 33-bus network

As the actual network, data are not available for the needs of our study, the voltage and phase angle values used to our comparison obtained by applying the load flow over the network. By randomly making these error values, they are assumed quantized values of the voltage and angle in the buses on which the WSNs are installed. Employing the state-estimation algorithm, the simulation results of the load flow and state estimation method using measuring devices data are shown in diagrams of Figures 8 and 9. The difference between the values obtained in Figures 10 and 11 show an error in estimating the state at the angle and voltage. Its value being very small, the state estimation is highly accurate.

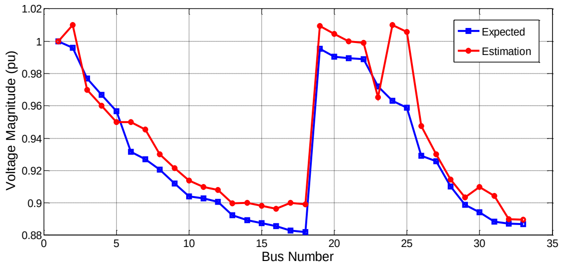

Figure 8. Voltage values of each bus.

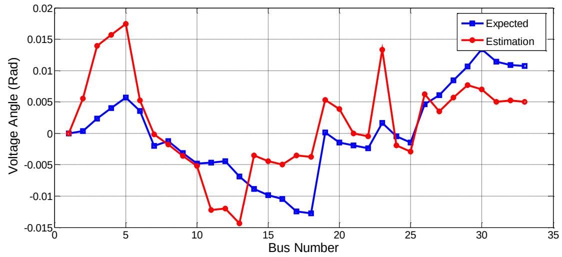

Figure 9. Voltage values of each bus

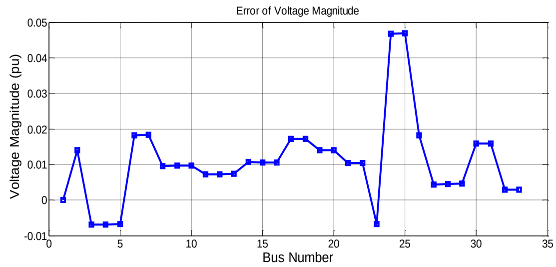

Figure 10. Voltage values error.

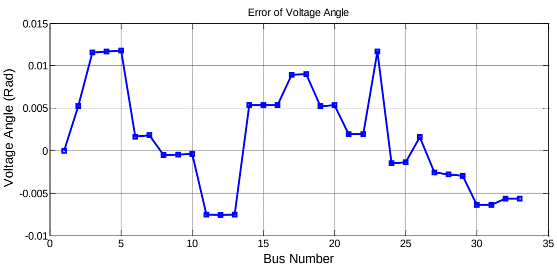

Figure 11. Voltage angle error.

Figures 12 and 13 shows diagrams of line active and reactive losses obtained with two computational modes i.e. load flow and state-estimation using measuring device data are shown.

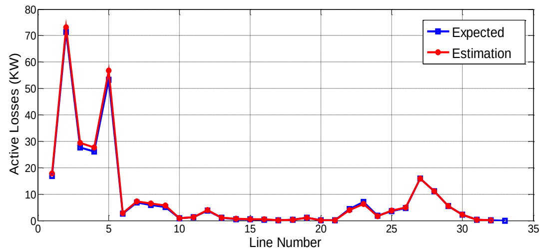

Figure 12. Active line losses.

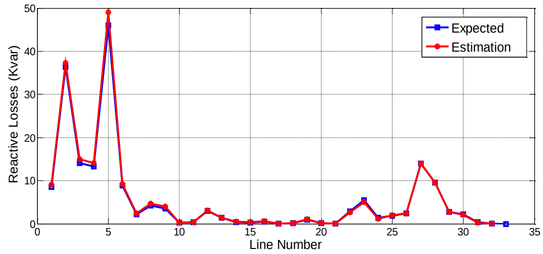

Figure 13. Reactive line losses.

The effect of not using the WSN on network state-estimation data is examined to show the efficiency of the state-estimation method and network monitoring algorithm at a WSN data loss. The effect of not using WSN1 installed on bus 2 does not impair monitoring. The effect of not using WSN5 installed on bus 11 and monitoring of the area is examined. Figures 14 and 15 show the size and angle graphs of the bus voltages after removing the monitoring device and re-executing the state-estimation algorithm,

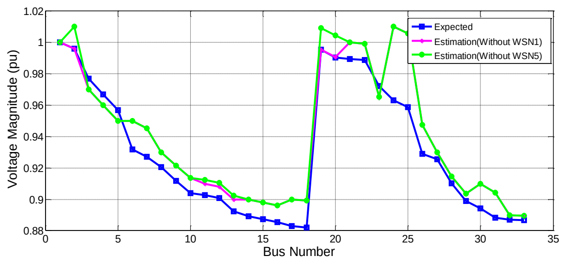

Figure 14. Voltage values of each bus in absence of the WSN1 and WSN5 modes

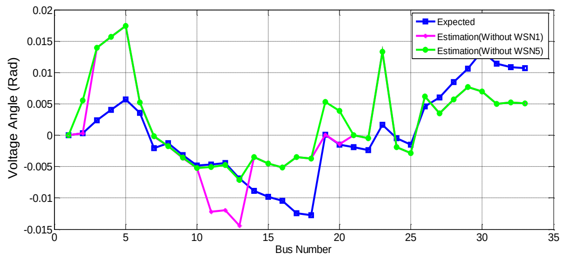

Figure 15. Voltage angle of each bus in absence of the WSN1 and WSN5 modes

As seen from the outputs of the bus voltages, in absence of WSNs, the state-estimation method and the monitoring algorithm are effective and the responses are still very close to reality. Moreover, by comparing the energy obtained from WSNs and the state-estimation using subscriber bills, the non-technical network losses are identified (see Figure 16). A monthly consumed energy by network buses is shown in Figure 17.

Figure 16 shows illegal energy consumption in buses 15 and 25. The measurement results are shown in Table 2.

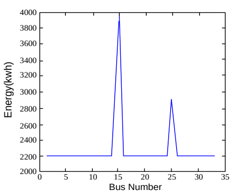

Figure 16. Non-technical losses

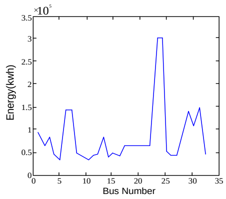

Figure 17. Bus energy

Table 2. Monthly network energy.

The total energy input to the network	2946130 kWh
Network technical energy losses	136612 kWh
Network non-technical energy losses	53214 kWh
The energy delivered to subscribers based on bills	2756304 kWh
Estimated energy sold to subscribers	2798528 kWh

9 Conclusion

The paper presents a method of monitoring the power distribution network by using WSN equipped with a minimum number of measuring devices to operate in times of crisis. Inappropriate and overlapping data are identified and their effect minimized at the state-estimator output by modifying linear state-estimation equations that create a powerful and accurate tool for monitoring and estimating the power distribution network.

The method monitors the monthly energy as well as a continuous monitoring of each parameter. Comparing the subscriber bills and values measured with the proposed method, the non-technical network energy losses are identified. The losses of 53214 kWh are identified in buses 15 and 25 in which there are no measuring devices used. these devices continuously monitor the disruptions that are likely happen in either buses or branches. Based on the study results and using the proposed method significantly improves power distribution network reliability features and upgrades it into a smart distribution network.

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