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Research Article

Distribution State Estimation and Its Impact of Load Modeling

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Abstract: To maintain system security and other essential parameters like reliability and quality, continuous monitoring of the system is very important. Considering the distribution network, state estimation (SE) methods can be adopted. The purpose of the method is to identify and estimate unknown variables based on the online measurements of test data. The primary objectives considered in this paper are: To choose the exact SE method and the artificial neural network (back propagation algorithm), which can be used for determination in the islanding mode of distribution network states, the composite load model is considered for the estimation of states and further enhancement. By adopting the system, state variables in terms of error are measured in the 12-bus distribution network with precise measurements and compared with practical values. The SE proposed includes results with the load flow backward-forward sweep method to satisfy the system state variables. Numerical results indicate that the model performs better for error measurement data with states and in the case of state forecasting.

Keywords: distribution network, distribution state estimation, backward-forward sweep load flow, load modeling, composite load model

MSC: 37N40, 90C39, 93A14, 94C60

1. Introduction

In electrical power systems, online monitoring is essential for control and operation applications such as voltage control, load frequency control, and power generation. Parameters required to be controlled are system frequency, optimal dispatch power, voltages, and power flows, which are regularly controlled in the distribution network. The information collected in the control unit by using remote terminal units (RTUs) for real-time or online monitoring was adopted for operation and control applications. A measurement with online data is extensively necessary for proper control of the power system. In practical terms, devices for estimation are very less and necessary because the cost is high. Locations are selected and monitored continuously in the areas that are critical to government administrative centers and industrial applications. In many conventional distribution systems, measuring equipment is identified. A

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commonly monitored distribution network with controlled primary connections and equipment is in a substation to capture the perfect picture of the distribution network for its smooth control operation.

The devices that are monitored with limitations on state conditions in the distribution network are identified with the state estimation (SE) method. SE in distribution networks is considered by implementing constant and steady conditions [1]. In the late 1960s, SE was implemented in power systems [1]. The state estimator method includes proper estimation with approximate load flows (reactive and active powers) and bus voltages that can be measured. The estimation of states in a power system measures electrical quantities like real and reactive load flows in power transmission lines by injecting real and reactive power into the buses [2]. The SE method is one of the main data processing schemes to estimate the easiest way for state variables at instants of time. In the SE program, the energy management system (EMS) has modern processes. The set of measurement data is raw in nature and includes a real-time solution on the basis of advanced functions for system security with monitoring and control [3]. The mathematical relations from the SE method are based on the system state variables and their measurements.

To process the available information and provide the best, the state estimator is used on the SE of the power system. The ability is to achieve SE with robustness and high-level efficiency. It is very important in the electric utility of today's industry, which is mainly interconnected with different loads. From the starting point, an algorithm must be convergent and necessary to solve both ill-conditioned and well-conditioned problems. To address the limitations of the distribution network and to solve the number of measurements, including their limitations, include pseudo-measurements. Pseudo-measurement with customer loads are obtained with historical load forecasting, data, and other similar methods approximated from the point of view of the customer. Hence, a few numbers of real-time measurements in a system are acceptable when using SE. To obtain a solution for SE with various techniques and surveys based on different SE algorithms, which are found in [4], two data types are required for SE: network data and measurement data.

A central control system in real-time can be used to improve the reliability of electrical power systems [5]. In [6], integrated methods like fuzzy SE are presented, as is load flow analysis in distribution networks. A multi-area SE for the distribution network is considered [7]. Local SE is executed in each area of the distribution network with a minimum amount of information about the border, which is to perform the SE of the whole network. A SE algorithm based on the forward-backward propagation of lines with a higher resistance/reactance ratio (R/X) ratio has been considered [8]. An estimation branch based on the SE method suitable for real-time monitoring of the distribution network is presented in [9].

The enhancement of the SE method is considered in this paper, which presents a composite load model by incorporating it into a distribution network application. The composite load model is to compute and incorporate accurate values of active and reactive powers, which include various types of loads such as commercial, industrial, and domestic [10, 11]. The distribution SE (DSE) proposed is based on the weighted least squares (WLS) method to find and capture a network operation point. A minimum number of real-time measurements, as in a practical distribution network, are used in the proposed algorithm. The proposed method is used for pseudo-measurement, which is utilized to limit the number of measurements. Two WLS approaches to the problem of load estimation (LE) in unbalanced power distribution networks are: (1) the WLS load parameter method is restated more rigorously; (2) a constrained DSE-based method is introduced to consider operating and loading constraints. The test results include two distribution networks, which have significantly improved the system state in terms of overall voltage profiles [12-15].

2. SE problem formulation

The WLS algorithm with the SE algorithm is necessary to minimize the sum of the squared weighted errors between the actual and estimated measurements in the distribution network. Commercial state estimators in the method include weights, which are selected and directly proportional to the measurement's accuracy. In high-accuracy measurement with a high weight in a power system that includes distribution and transmission systems, the measurement vector is considered a global variable and is indicated by Z [16-20].

$$Z_i = h_i(x) + r_i,\ i = 1, 2, 3, \dots\dots\dots\dots m \tag{1}$$

For a power system with N-bus 'm' measurements, assume 'r' error vector, which is taken from a standard Gaussian that has a mean of zero and covariance of σ. Let i be the index of the measurements. The equations of measurement are considered in equation (1).

Considering Z_i, the measurements of vectors, where the state vector is X, the measurement matrix is $h_i(x)$, including nonlinear functions, and r_i is the measurement error vector, the measurement vector with residual values can be formulated and defined with equation (2), as mentioned below:

$$r_i = Z_i - h_i(x), i = 1, 2, 3, \ldots\ldots\ldots\ldots m \tag{2}$$

By method, the WLS is applied to minimize the objective function, as mentioned in equation (3):

$$J(x) = \sum_{i=1}^{m} Z_i - h_i(x) 2 / R_i \tag{3}$$

Diagonal matrix R_i of $[1/\sigma_1^2, 1/\sigma_2^2, 1/\sigma m^2]$ σm^2 for the mth error measurement of covariance.

X is represented as the state vector and the best solution obtained for the equations. To estimate the required accuracy of the meters measured adopted.

$$[G(x)][\Delta x^{k+1}] = [H(x^k)]^T [R]^{-1} [Z - h(x^k)] \tag{4}$$

The Jacobian matrix is represented by $H(x)$ and is also known as a measurement function. $h(x)$ is considered from equation (1). The gain matrix is represented as $G(x)$ in equation (5), as mentioned below:

$$[G(x)] = [H(x^k)]^T [R]^{-1} [H(x^k)] \tag{5}$$

$$P_i = V_i \sum_{i=1}^{m} (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij}) V_j \tag{6}$$

$$Q_i = V_i \sum_{i=1}^{m} (G_{ij} \sin\theta_{ij} + B_{ij} \cos\theta_{ij}) V_j \tag{7}$$

The equation (4) is used to solve and minimize errors to estimate an optimal estimate, which includes system states to be solved iteratively. SEs like WLS in this paper with mathematical analysis tools are the best iterative solutions, which are interpreted to filter out errors for estimating an optimal estimate of system states in a distribution network. The measurement matrix is the most used measurement in the practical system. Bus power injections, line power flows, bus voltage magnitudes, and line current flows are common measurements in a real power system. The proposed DSE uses line power flows, bus power injections, and bus voltage magnitudes to construct the measurement matrix. Real and reactive power injection, P_i and Q_i, equations at bus ith can be expressed below [21, 22].

The DSE proposed method for measuring voltage is based on a proper selection of an estimation method. The injection of power comes from load flow studies, which are computed with the equations (6), (7), (8), and (9) at different buses in the distribution network. Finally, values are estimated and calculated with the measurement matrix (h_i) for solving equation (4). With the information available in real-time for conventional distribution networks being limited, the state estimator may not achieve convergence. Therefore, measurements of pseudo-nature are estimated with the proper assistance of state estimator convergence in the distribution network. At some buses, the pseudo-measurements may not be real and considered.

3. Modeling of load model by SE

For the modeling of the load model, the parameters considered in real-time are dependent on system frequency and system voltage. Different loads are considered with constant current, constant impedance, and constant power. There are different state estimators, like the open loop. Closed loop and reduced order. To include all models with SE methods for producing precise and reliable estimations. For a variety of composite load models, which include combinations of loads adopted. The values of the composite load are given in Table 1.

The model is considered in DSE by substituting the load power with a constant value, which eventually depends on the following equations:

$$P_i = P_{i_0} * \left(C_1 + C_2 V_i + C_3 |V_i|^2\right), i = 1, 2, \ldots, m \tag{8}$$

$$Q_i = Q_{i_0} * \left(d_1 + d_2 |V_i| + d_3 |V_i|^2\right), i = 1, 2, \ldots, m \tag{9}$$

Constant load compositions of power like c_1, d_1, and c_2 and d_2 are constant load compositions of current, and constant load compositions of impedance like c_3 and d_3. By considering P_{i_0} and Q_{i_0} of the nominal powers with rated voltages, model parameters of load like P_{i_0} and Q_{i_0} were considered with the initial values of system operating conditions. The proposed DSE includes the load values, which are to be updated with the number of iterations. In Figure 1, the radial distribution network represents the line model with loads connected as i and j at both ends of the load line. The calculated value of load is adopted in equations (10) and (11).

$$P(V) = P_0 (V / V_0)^{\alpha} \tag{10}$$

$$Q(V) = Q_0 (V / V_0)^{\beta} \tag{11}$$

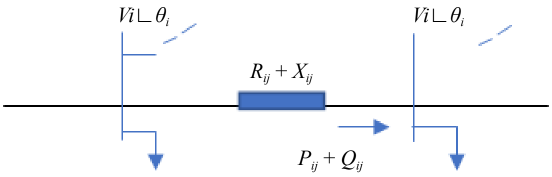

Figure 1. Model of line section of radial distribution system

In the composite load model, the constant variable is considered as shown in Table 1. Noncritical (redundant) and critical measurements make up the two main categories of measurements (nonredundant). A critical measurement is one that, when removed from the set of measurements, makes the network impossible to observe. Noncritical measurements feature nonzero residuals, allowing detection and perhaps identification of their errors. Critical measurements contain negligible residuals, making it impossible to identify their inaccuracies. If the removal of any measurement from a set of measures makes the remaining measurements important, the set is said to be a minimally dependent set (MDS) [23-28]. The absolute values of the normalized residuals for each measurement in an MDS are equal. Each bus's voltage and angle magnitudes are depicted in Figures 1 and 2 depict about the voltages and angles at buses, which are estimated by load flow methods. A practical 12-bus distribution system with composite loads is considered, as shown in Figure 2. Three findings are shown in each table from 2 to 8: DSE with and without a load model, and load flow with a load model (% of error). The backward-forward sweep method is the foundation of the load flow. As seen, the voltage profile produced by the DSE with load modeling is fairly similar to the voltage profile produced by the load flow. Similar to the voltage profile, the phase angle profile exhibits the same pattern. The system state accuracy is likewise seen to be deteriorating as the bus distance increases from the measurement place.

Table 1. Description of parameters

Load type	c_1 and d_1	c_2 and d_2	c_3 and d_3
Active power	0.4	0.3	0.2
Reactive power	0.4	0.3	0.2

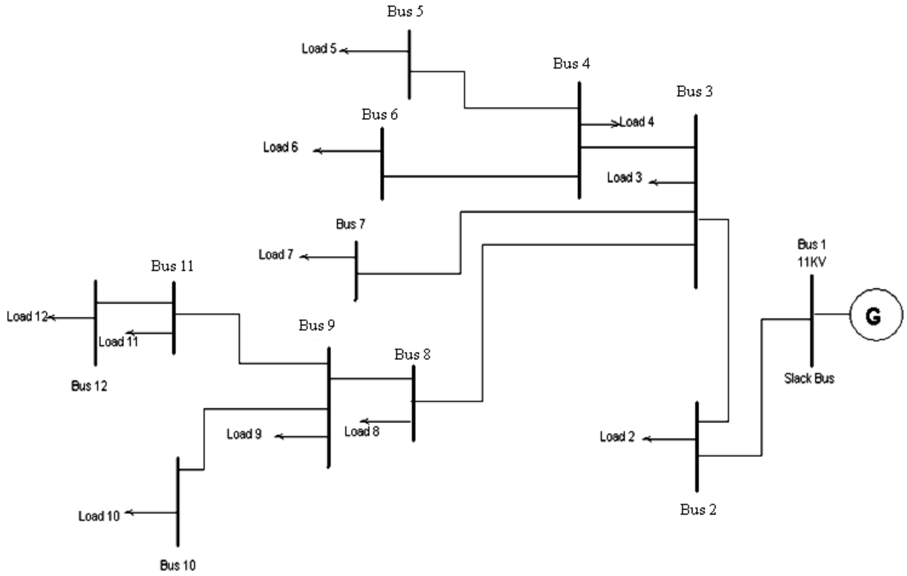

Figure 2. Practical 12-bus distribution system

The load types considered composite loads are active power and reactive power, with a variation of coefficients within the range of 0.3 to 0.4.

3.1 *SE method: Load flow with load (backward-forward sweep method)*

The SE method is an algorithm considered for reducing % of error by considering load modeling by initiating backward sweep and forward sweep and settled at seven iterations (Table 2).

Table 2. SE with load modeling

Iteration number	Process	Result
1	Initiating backward sweep Initiating forward sweep	Not converged
2	Initiating backward sweep Initiating forward sweep	Not converged
3	Initiating backward sweep Initiating forward sweep	Not converged
4	Initiating backward sweep Initiating forward sweep	Not converged
5	Initiating backward sweep Initiating forward sweep	Not converged
6	Initiating backward sweep Initiating forward sweep	Not converged
7	Initiating backward sweep Initiating forward sweep	Converged and calculating losses

The SE method is an algorithm considered for reducing % of error without load modeling by initiating backward sweep and forward sweep and settling at eight iterations, which is comparably higher than with load modeling (Table 3).

Table 3. SE without load modeling

Iteration number	Process	Result
1	Initiating backward sweep Initiating forward sweep	Not converged
2	Initiating backward sweep Initiating forward sweep	Not converged
3	Initiating backward sweep Initiating forward sweep	Not converged
4	Initiating backward sweep Initiating forward sweep	Not converged
5	Initiating backward sweep Initiating forward sweep	Not converged
6	Initiating backward sweep Initiating forward sweep	Not converged
7	Initiating backward sweep Initiating forward sweep	Not converged
8	Initiating backward sweep Initiating forward sweep	Converged and calculating losses

Table 4 describes the voltages and bus angles with load modeling at all the buses to see the variation of voltage states and bus angles w.r.t. change in algorithm and with load modeling.

Table 4. Bus voltages and bus angles with load modeling - 1

Bus voltage values		Bus angle values	
Bus no.	Bus voltage	Bus no.	Bus angles
1.0000	1.0000	1.0000	-0.0000
2.0000	0.9958	2.0000	-0.0673
3.0000	0.9925	3.0000	-0.1216
4.0000	0.9877	4.0000	-0.2609
5.0000	0.9839	5.0000	-0.3705
6.0000	0.9808	6.0000	-04625
7.0000	0.9746	7.0000	-0.7188
8.0000	0.9704	8.0000	-0.8913
9.0000	0.9655	9.0000	-1.1007
10.000	0.9630	10.000	-1.2063
11.000	0.9619	11.000	-1.2516
12.000	0.9615	12.000	-1.2707

Table 5 describes the voltages and bus angles without load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. change in algorithm and without load modeling.

Table 5. Bus voltages and bus angles without load modeling - 1

Bus voltage values		Bus angle values	
Bus no.	Bus voltage	Bus no.	Bus angles
1.0000	0.9985	1.0000	0.0000
2.0000	0.9918	2.0000	0.0007
3.0000	0.9878	3.0000	0.0012
4.0000	0.9827	4.0000	0.0026
5.0000	0.9782	5.0000	0.0037
6.0000	0.9732	6.0000	0.0046
7.0000	0.9667	7.0000	0.0072
8.0000	0.9621	8.0000	0.0089
9.0000	0.9567	9.0000	0.0110
10.000	0.9541	10.000	0.0121
11.000	0.9528	11.000	0.0125
12.000	0.9521	12.000	0.0127

3.1.1 *Load flow with load modeling - 2*

Calculating losses:

Table 6 describes the voltages and bus angles with load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. change in algorithm and load modeling.

Table 6. Bus voltages and bus angles with load modeling - 2

Bus voltage values		Bus angle values	
Bus no.	Bus voltage	Bus no.	Bus angles
1.0000	0.9992	1.0000	0.0000
2.0000	0.9940	2.0000	0.0673
3.0000	0.9898	3.0000	0.1216
4.0000	0.9846	4.0000	0.2609
5.0000	0.9805	5.0000	0.3705
6.0000	0.9764	6.0000	0.4625
7.0000	0.9690	7.0000	0.7188
8.0000	0.9636	8.0000	0.8913
9.0000	0.9552	9.0000	1.1007
10.000	0.9526	10.000	1.2063
11.000	0.9491	11.000	1.2516
12.000	0.9478	12.000	1.2702

Table 7 describes the voltages and bus angles with load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. change in algorithm and without load modeling.

Table 7. Error table with and without load modeling - 1

Bus no.	SE without load modeling	SE with load modeling	Load flow with load modeling	Error %
1.0000	1.0000	0.9997	0.9997	-0.0000
2.0000	0.9958	0.9955	0.9929	0.0026
3.0000	0.9925	0.9911	0.9894	0.0018
4.0000	0.9877	0.9862	0.9828	0.0034
5.0000	0.9839	0.9810	0.9790	0.0021
6.0000	0.9808	0.9778	0.9720	0.0059
7.0000	0.9746	0.9714	0.9657	0.0059
8.0000	0.9704	0.9558	0.9591	0.0079
9.0000	0.9655	0.9610	0.9524	0.0089
10.000	0.9630	0.9571	0.9495	0.0080
11.000	0.9619	0.9544	0.9481	0.0066
12.000	0.9615	0.9520	0.9475	0.0047

Figure 3 describes the % of error with and without load modeling at all the buses for the variation of voltage states and bus angles w.r.t. the change in algorithm for all the 12 buses in the radial distribution system.

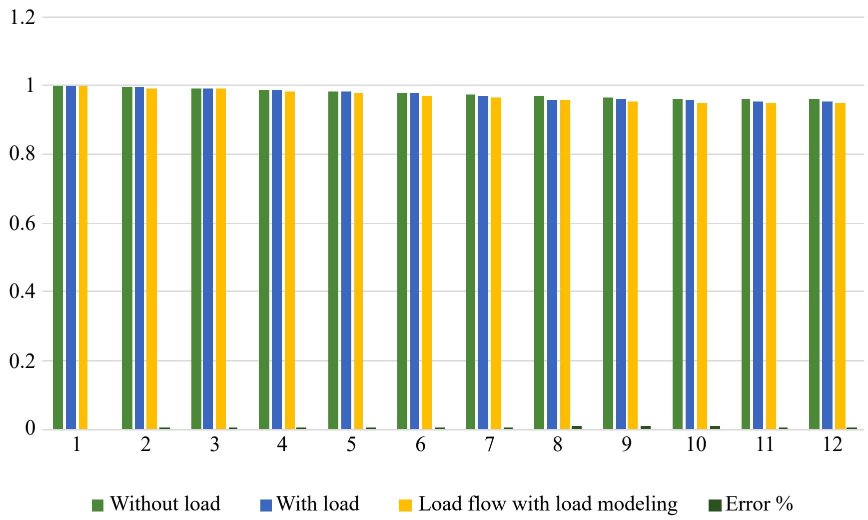

Figure 3. Error estimation with and without load modeling (x-axis is the bus number and y-axis voltage states)

Table 8 describes about the comparison of load flow with and without loadings.

Table 8. Load flow with and without load modeling - 2

Bus no.	SE without load modeling	SE with load modeling	Load flow	Error %
1	1	0.999714	0.999718	0
2	0.995829	0.995493	0.992911	0.002594
3	0.992476	0.991117	0.989377	0.001755
4	0.987670	0.986171	0.982822	0.003394
5	0.983917	0.981008	0.978965	0.002082
6	0.980782	0.977761	0.972033	0.005857
7	0.974564	0.971388	0.965685	0.005872
8	0.970421	0.966782	0.959104	0.007941
9	0.965457	0.960972	0.952412	0.008906
10	0.962982	0.957089	0.94946	0.007971
11	0.961945	0.954409	0.948142	0.006566
12	0.961534	0.951996	0.947491	0.004732

The outcome in Figure 4 demonstrates that for buses where measurements are taken, the voltage magnitudes are close to one another. When comparing the SE and artificial neural network (ANN) algorithms with and without load modeling to the load flow, it can be seen that there has been a considerable improvement when compared to the SE without the load model. Both test cases showed that the suggested DSE approach with load modeling greatly increased the anticipated voltage and angle to be nearly identical to those in load flow with load modeling.

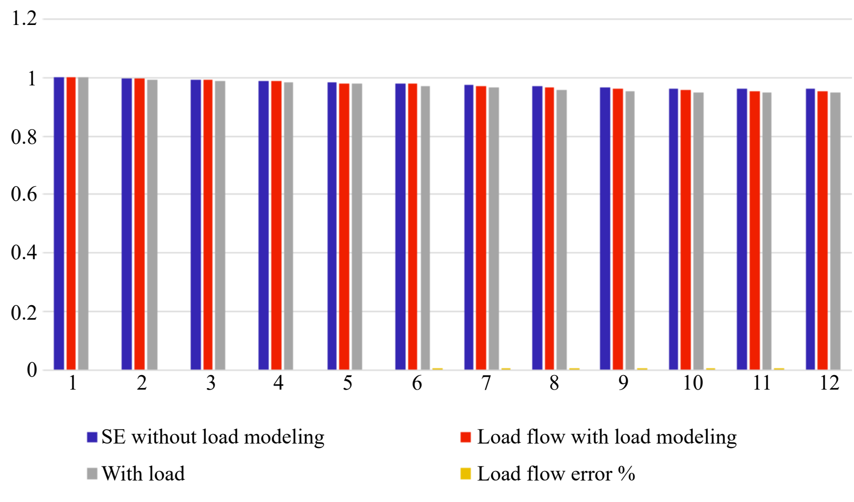

Figure 4. SE with and without load modeling (x-axis is the bus number and y-axis voltage states)

3.2 *SE method – Load flow with load modeling (including optimization technique)*

M-file code for estimation at each bus in radial distribution system:

```
% Voltage measurements are phase to phase
% Current measurements are per phase
%% General information of the system
    noBranches = 32;              % number of branches
```

```
    noNoP = 5;                   % number of normally-open points (tielines)
    noBuses = 12;                % number of buses
    noMeaurements = noBranches;     % number of V and I measurements
  %% Initialization of the circuit breaker input vector
  % Simulation time 0.2 s with step size of 1 ms
    timeTS = (0:0.001:0.2)';
  % Set the circuit breaker status, close all branches and open all NoPs
  % (syntax is like that in the MATPOWER case branch data)
    CBStats = [ones(length(timeTS), noBranches), zeros(length(timeTS),noNoP)];
  % Change the CBStats variable to change the branch connections in the system
  % EXAMPLE: disconnect Branch 16, close all other branches and open all NoPs
  % CBStats = [ones(length(timeTS),15),zeros(length(timeTS),1),...
  %    ones(length(timeTS),noBranches-16),zeros(length(timeTS),noNoP)];
  % initialize the timeseries for simulation input
    siminCB = timeseries (CBStats,timeTS);
  %% Simulation phase
  % Prepare simulation
    simName = 'IEEE33BusTestSystem';
    simIn = Simulink.SimulationInput(simName);
    simIn = simIn.setVariable('siminCB',siminCB);
  % Run simulation
    simout = sim(simIn);
  % Output: Voltage and Current Measurements
  % Each output matrix has 32 branches x 3 phases = 96 entries
    ISimMat = simout.simOutputI.data;
    VSimMat = simout.simOutputV.data;
  % Obtain the average of the three phases for each branch
  % 96 entries / 3 phases = 32 branches
    IRMSMat = zeros(size(ISimMat,1),size(ISimMat,2)/3);
for iterS = 1:size(ISimMat,2)/3
    IRMSMat(:,iterS) = mean(ISimMat(:,(iterS-1)*3+1:(iterS-1)*3+3),2);
end
    VRMSMat = zeros(size(VSimMat,1),size(VSimMat,2)/3);
for iterS = 1:size(VSimMat,2)/3
    VRMSMat(:,iterS) = mean(VSimMat(:,(iterS-1)*3+1:(iterS-1)*3+3),2);
end
```

Table 9 describes the voltages and bus angles with and without load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. change in algorithm with optimization techniques, which is more efficient than without optimization.

Table 9. Comparison of different load modeling methods

Bus no.	SE without load modeling	SE with load modeling	Load flow with load modeling and optimization	Error %
1	1	0.999714	1.0000	0.0113
2	0.995829	0.995493	0.9992	0.0103
3	0.992476	0.991117	0.9925	0.0094
4	0.987672	0.986172	0.9900	0.0082
5	0.983917	0.981008	0.9845	0.0075
6	0.980782	0.977762	0.9824	0.0069
7	0.974564	0.971388	0.9798	0.0049
8	0.970421	0.966782	0.9773	0.0029
9	0.965457	0.960974	0.9752	0.0023
10	0.962982	0.957089	0.9749	0.0016
11	0.961945	0.954409	0.9746	0.0012
12	0.961534	0.951996	0.9738	0.0006

Figure 5 describes the voltages and bus angles with and without load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. change in SE algorithm with optimization techniques, which is more efficient than without optimization.

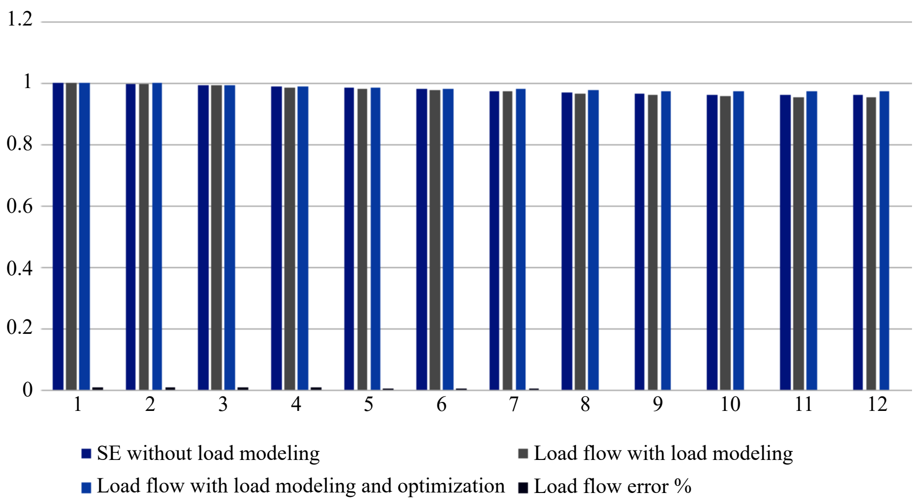

Figure 5. Load flow with and without load modeling (x-axis is the bus number and y-axis voltage states)

3.2.1 *SE method – Load flow with load modeling (fast decoupled method)*

The SE problem may be formulated and solved by distinct methods, with fast-decoupled WLS being the most widely applied technique in control centers around the world. The controller's equivalent reactance is included in the active sub-problem of the proposed fast-decoupled formulation as a new state variable along with the conventional system states.

Table 10 describes the voltages and bus angles with and without load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. changes in algorithms like SE and load flow with fast decoupled optimization techniques, which is more efficient than without optimization.

Table 10. Load flow with fast decoupled

Load flow with fast decoupled	SE without load modeling	SE with load modeling	Load flow with load modeling and optimization	Error %
1	1	0.999714	1.0600	0
2	0.995829	0.995493	1.0450	0.0870
3	0.992476	0.991117	1.0100	0.2223
4	0.987677	0.986177	1.0142	0.1790
5	0.983917	0.981008	1.0172	0.1529
6	0.980782	0.977763	1.0700	0.2516
7	0.974564	0.971388	1.0503	0.2312
8	0.970421	0.966782	1.0900	0.2312
9	0.965457	0.960973	1.0337	0.2588
10	0.962982	0.957089	1.0325	0.2625
11	0.961945	0.954409	1.0474	0.2591
12	0.961534	0.951996	1.0535	0.2664

Figure 6 describes the voltages and bus angles with and without load modeling at all the buses, foreseeing the variation of voltage states and bus angles w.r.t. changes in algorithms like SE and load flow with fast decoupled optimization techniques, which is more efficient than without optimization.

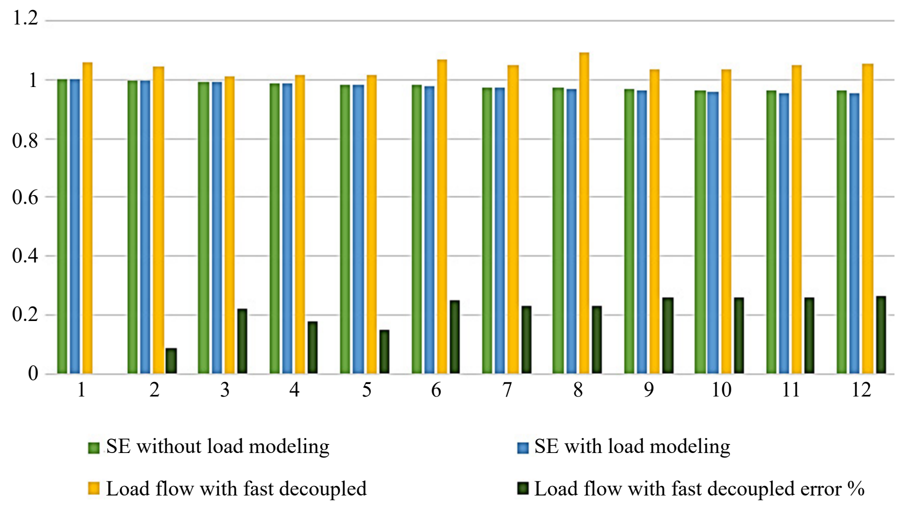

Figure 6. Load flow with fast coupled (x-axis is the bus number and y-axis voltage states)

The percentage of error for load flow with load modeling obtained by three algorithms (backward-forward sweep method, optimization method, and fast decoupled method) is shown in Figure 7. From the tabular column (Table 11), it is observed that load flow with load modeling, including optimization methods, has less than 0.0006% error reduction for the IEEE 12-bus system by minimizing losses.

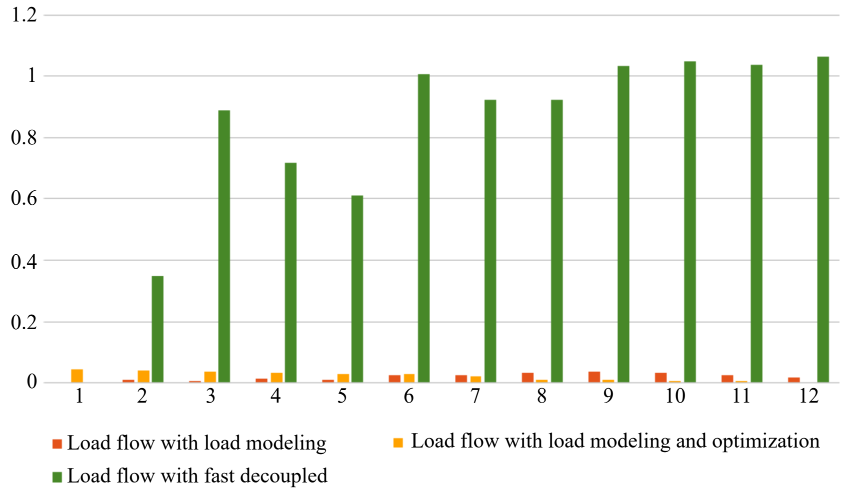

Figure 7. Comparison of three different algorithms (x-axis is the bus number and y-axis voltage states)

Table 11. Comparison of load flow algorithms combined error (%) for three load modeling

	Error %		
Bus no.	Load flow with load modeling	Load flow with load modeling and optimization	Load flow with fast decoupled
1	0	0.0113	0
2	0.002594	0.0103	0.0870
3	0.001755	0.0094	0.2223
4	0.003394	0.0082	0.1790
5	0.002082	0.0075	0.1529
6	0.005857	0.0069	0.2516
7	0.005872	0.0049	0.2312
8	0.007941	0.0029	0.2312
9	0.008906	0.0023	0.2588
10	0.007971	0.0016	0.2625
11	0.006566	0.0012	0.2591
12	0.004732	0.0006	0.2664

3.3 *ANN*

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the function of the network is determined largely by the connections between elements. Neural networks are trained to perform a particular function by adjusting the values of the connections (weights) between elements. Commonly, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. There, the network is adjusted based on a comparison of the output and the target until the network output matches the target. Typically, many such input/target pairs are used in supervised learning to train a network.

Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after the presentation of each individual input vector. Incremental training is sometimes referred to as training. Neural networks have been trained to perform complex functions in various fields of application, including pattern recognition, identification, classification, speech, and vision and control systems. Today, neural networks can be trained to solve problems that are difficult for conventional computers or human beings.

Supervised training methods are commonly used, but other networks can be obtained from unsupervised training techniques or from direct design methods. Unsupervised networks can be used, for instance, to identify groups of data. Certain kinds of linear networks and Hopfield networks are designed directly. The back propagation algorithm is considered for a 12-bus load flow study with composite loads, as shown in Figures 8 and 9.

```
load n
k1=max(i');
k2=max(o1');
P=i'/k1;
T=o1'/k2;
n=157128;
net = newff(minmax(P),[5 1],{'tansig' 'purelin'});
net.trainParam.epochs = 200;
net = train(net,P,T);
Y = sim(net,P);
plot (P,T,P,Y,'o')
gensim(net,-1)
function [ mean_timeline_ANN ] = get_ann_result_from_trainedANN_model00( ...
    trained_ANN, ...
    d_inMicroMeters, ...
    tx_r_inMicroMeters, ...
    rx_r_inMicroMeters, ...
    D_inMicroMeterSqrPerSecond, ...
desired_delta_t, tend, ntx )
system_params_1.distance_inMicroMeters      = d_inMicroMeters;
system_params_1.r_tx_inMicroMeters         = tx_r_inMicroMeters;
system_params_1.r_rx_inMicroMeters         = rx_r_inMicroMeters;
system_params_1.D_inMicroMeterSqrPerSec     = D_inMicroMeterSqrPerSecond;
system_params_1.ntx                        = ntx;
modelfunc = str2func('model_function_00_primitive');
f_1 = @(b,t) modelfunc(b,t,system_params_1);
tval = desired_delta_t: desired_delta_t: tend;
% Get ANN Output
input_params = [d_inMicroMeters  tx_r_inMicroMeters  rx_r_inMicroMeters  D_inMicroMeterSqrPerSecond];
nn_output = trained_ANN(input_params');
nn_output = nn_output';
mean_timeline_ANN = f_1(nn_output, tval);
end
```

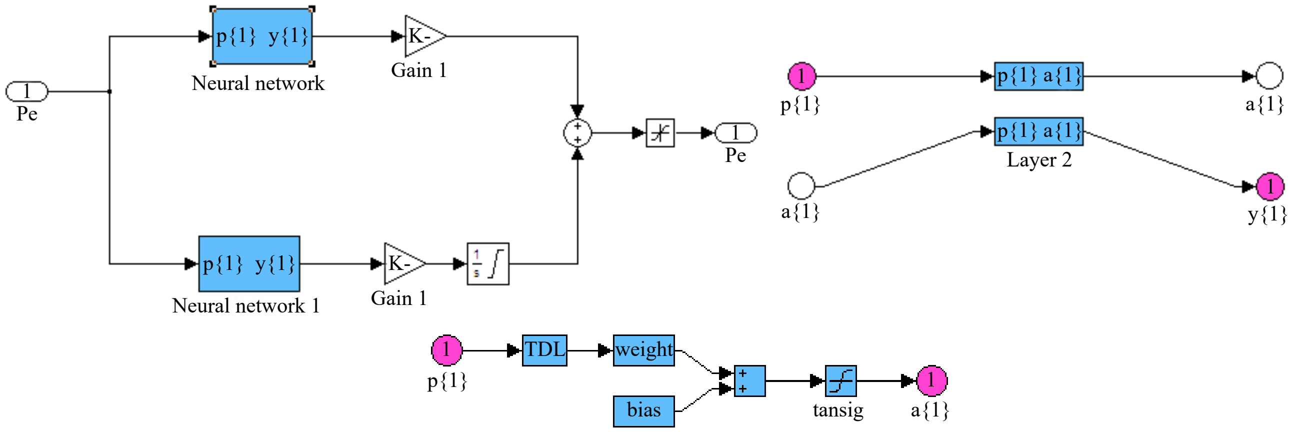

Figure 8. Subsystem of back propagation algorithm - feedforward (ANN)

M-file program for linking ANN:

```
function [baseMVA, bus, gen, branch, areas, gencost] = case14
%%system MVA base
baseMVA = 100;
%%bus data
% bus_i type Pd Qd Gs Bs area Vm Va baseKV zone Vmax Vmin
bus = [
 1 3 0 0 0 0 1 1.06 0 0 1 1.06 0.94;
 2 2 21.7 12.7 0 0 1 1.045 -4.98 0 1 1.06 0.94;
 3 2 94.2 19 0 0 1 1.01 -12.72 0 1 1.06 0.94;
 4 1 47.8 -3.9 0 0 1 1.019 -10.33 0 1 1.06 0.94;
 5 1 7.6 1.6 0 0 1 1.02 -8.78 0 1 1.06 0.94;
 6 2 11.2 7.5 0 0 1 1.07 -14.22 0 1 1.06 0.94;
 7 1 0 0 0 0 1 1.062 -13.37 0 1 1.06 0.94;
 8 2 0 0 0 0 1 1.09 -13.36 0 1 1.06 0.94;
 9 1 29.5 16.6 0 19 1 1.056 -14.94 0 1 1.06 0.94;
 10 1 9 5.8 0 0 1 1.051 -15.1 0 1 1.06 0.94;
 11 1 3.5 1.8 0 0 1 1.057 -14.79 0 1 1.06 0.94;
 12 1 6.1 1.6 0 0 1 1.055 -15.07 0 1 1.06 0.94;];
save baseMVA baseMVA;
save bus bus;
%%generator data
% bus Pg Qg Qmax Qmin Vg mBase status Pmax Pmin
gen = [
 1 232.4 -16.9 10 0 1.06 100 1 332.4 0;
 2 40 42.4 50 -40 1.045 100 1 140 0;
 3 0 23.4 40 0 1.01 100 1 100 0;
 6 0 12.2 24 -6 1.07 100 1 100 0;
 8 0 17.4 24 -6 1.09 100 1 100 0;];
 save gen gen;
%%branch data
% fbus tbus r x b rateA rateB rateC ratio angle status
branch = [
 1 2 0.01938 0.05917 0.0528 9900 0 0 0 0 1;
 1 5 0.05403 0.22304 0.0492 9900 0 0 0 0 1;
```

```
 2  3  0.04699  0.19797  0.0438  9900  0  0  0  0  1;
 2  4  0.05811  0.17632  0.034  9900  0  0  0  0  1;
 2  5  0.05695  0.17388  0.0346  9900  0  0  0  0  1;
 3  4  0.06701  0.17103  0.0128  9900  0  0  0  0  1;
 4  5  0.01335  0.04211  0  9900  0  0  0  0  1;
 4  7  0  0.20912  0  9900  0  0  0.978  0  1;
 4  9  0  0.55618  0  9900  0  0  0.969  0  1;
 5  6  0  0.25202  0  9900  0  0  0.932  0  1;
 6  11  0.09498  0.1989  0  9900  0  0  0  0  1;
 6  12  0.12291  0.25581  0  9900  0  0  0  0  1;
 6  13  0.06615  0.13027  0  9900  0  0  0  0  1;
 7  8  0  0.17615  0  9900  0  0  0  0  1;
 7  9  0  0.11001  0  9900  0  0  0  0  1;
 9  10  0.03181  0.0845  0  9900  0  0  0  0  1;
 9  14  0.12711  0.27038  0  9900  0  0  0  0  1;
 10  11  0.08205  0.19207  0  9900  0  0  0  0  1;
 11  12 0.22092  0.19988  0  9900  0  0  0  0  1;];
save branch branch;
%%-----  OPF Data  -----%%
%%area data
areas = [  1  1;];
%%generator cost data
%  1  startup  shutdown  n  x1  y1  ...  xn  yn
%  2  startup  shutdown  n  c(n-1)  ...  c0
gencost = [
 2  0  0  3  0.0430293  20  0;
 2  0  0  3  0.25  20  0;
 2  0  0  3  0.01  40  0;
 2  0  0  3  0.01  40  0;
 2  0  0  3  0.01  40  0;];
return;
```

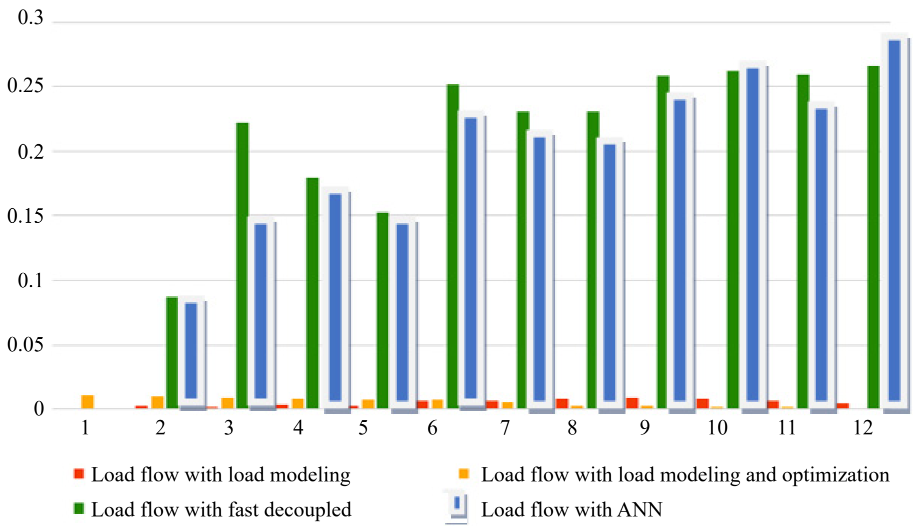

Figure 9. Comparison of three different algorithms (x-axis is the bus number and y-axis voltage states)

Table 12. Comparison of load flow algorithms combined error (%) for three load modeling

Bus no.	Error %			
	Load flow with load modeling	Load flow with load modeling and optimization	Load flow with fast decoupled	Load flow with ANN
1	0	0.0113	0	0.001123
2	0.002594	0.0103	0.0870	0.06251
3	0.001755	0.0094	0.2223	0.13254
4	0.003394	0.0082	0.1790	0.15422
5	0.002082	0.0075	0.1529	0.14558
6	0.005857	0.0069	0.2516	0.23145
7	0.005872	0.0049	0.2312	0.2111
8	0.007941	0.0029	0.2312	0.2089
9	0.008906	0.0023	0.2588	0.2499
10	0.007971	0.0016	0.2625	0.2588
11	0.006566	0.0012	0.2591	0.2448
12	0.004732	0.0006	0.2664	0.2768

The challenging solutions to real-life problems are to find out the dimensions in the exact form of the problems, which are significant. A multi-threading inventory model is tested in this 12-bus system through an ANN when experiencing an uncertain environment. Whenever faults are present in power systems with sudden loading, a neural network with multi-threading is one of the optimization procedures to find the best optimal solution with an inflation and time value of money [29, 30].

4. Conclusion

This paper discusses an analysis of distribution system SE. The concept of DSE estimation methods and their applications to the 12-bus radial distribution system are discussed in detail. According to the study, the majority of the authors mostly focused on modified SE methods to improve efficiency. The mathematical analysis of SE and ANN has been presented. The WLS method was found to be more efficient when compared to other methods in terms of various factors such as robustness, accuracy, and time of computation. The scope of this review is to set up a wide range of platforms for future studies to realize the vision of smarter grids. A SE with an optimization method is considered in this paper to improve the distribution network, which includes a minimum number of measurements. The implemented DSE includes modeling of composite loads. The modeled load model with different loads in distribution networks and their estimation methods and results are considered to be accurate. The 12-bus distribution network is considered by improving the voltage profiles rapidly by 0.5047% and 1.4972%. The results that are tested are considered to improve the robustness of this proposed method and solve problems like DSE with different measurements that are selectively considered.

5. Further extensions

Distribution network SE is an algorithm that is mainly based on data processing and converts measurement data and other exiting data into different radial distribution network state estimates, which can quickly and mainly determine the real-time operating state of the system. It plays an important role in the management system. With the development of distribution networks and the emergence of renewable energy and distributed generation (DG), the scale of distribution networks is larger and the topology is more complex, posing significant challenges in computing the performance of the traditional centralized SE (CSE) of distribution networks. By dividing the distribution networks into several sub-regions, DSE can reduce the computational complexity and meet the performance requirements of the active distribution network for the SE method, which can be implemented in larger power distribution systems [31, 32]. The linear and nonlinear extended fast-decoupled state estimator algorithms, referred to as XDC-SE and XFD-SE, respectively, are applied in distinct power systems, and the scenarios for the chosen networks are the IEEE 14- and 118-bus systems.

Conflict of interest

There is no conflict of interest in this study.

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