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Voltage Error Decreasing of Power Systems by State Estimation Strategy in the Presence of DG Units Using the Improved Taguchi Method and Phasor Measurement Unit

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Abstract: In recent decades, because of the rapid population growth of the world, considerable changes in climate, the reduction of fossil fuel sources to consume the traditional power plants and their high depreciation, and the increase in fuel prices. Due to the increased penetration of DG units which have a random nature into the power system, the ordinary equations of power flow must be changed. For the power system to operate in a stable condition estimating future demand and calculating the important and operational indexes such as losses of the power system is an important duty that must be done precisely and rapidly. In this paper, the Improved Taguchi method and phasor measurement unit are used to model the uncertainties of DGs and estimate the error of voltage, respectively. The results show that the magnitude error and the angle error of voltage are decreased using PMU. The applied optimal power flow and state estimations are analyzed and verified using standard IEEE 30-bus and 14-bus test power systems by MATLAB, and MINITAB softwares. The Made Strides Taguchi strategy appears to have modeled the DG units precisely and successfully, and using the PMU, the mistake of the point and greatness estimation is exceptionally moot. The values that were evaluated are very close to the values that were done by the Newton-Raphson stack stream.

Keywords: Distributed Generation, Taguchi Method, Orthogonal arrays, Optimal Power Flow, Uncertainty, State Estimation, Phasor Measurement Unit.

Table of symbols			
V_i^{min} , V_i^{max}	The high and low values of voltage	P_i^{min} , P_i^{max}	The high and low values of active and apparent power
T_i^{max}, T_i^{min}	The high and low taps number of transformers	Q_i^{min} , Q_i^{max}	The high and low values of reactive power

1 Introduction

IN recent decades, conventional power systems could not be Responsive to many situations including increasing power demands, increasing losses of transmission power, voltage drop, instability, etc [1]. With the population increase of the world obviously, the amount of power consumption, power losses, and voltage drop will increase since the source of fossil fuels is decreasing and the traditional power plants' efficiency because of their depreciation is reduced [2]. To overcome this issue, renewable energies were entered into power systems because they do not have the disadvantages of conventional power plants and even have many advantages rather to traditional power plants such as non-production of noise and environmental pollution, high efficiency, portable, and no need for fossil fuel [3].

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Using the DG units, the number of power system uncertainties will increase due to their random nature, which changes the normal operation conditions such as optimal power flow, unit commitment, state estimation, and optimization [4, 5]. So it's necessary to transfer uncertainties into certain values using probabilistic assessment technic and uncertainties modeling methods [6, 7]. Uncertainties modeling methods are summarized in six main groups such as probabilistic approaches, possibilistic approach, hybrid possibilistic-probabilistic approaches, Information gap decision theory, robust optimization, and interval analysis, as shown in Figure 1 [8]. In the probabilistic types, the input parameters have a PDF statistical distribution. This types methods are summarizes into numerical and analytical groups such as: Monte Carlo simulation (MCS) [8-10], sequential MCS [11], Markov Chain MCS [12, 13], pseudo sequential MCS [14, 15], and inconsequential MCS methods [16, 17] are a sample from the numerical group and linearization, scenario-based, and PDF approximation are from the analytical group [18, 19]. Also a-cut, and defuzzification methods are categorized in the possibilistic type [20-23].

In the hybrid type, the input variables have the possibilistic and the probabilistic features such as Fuzzy-scenario and fuzzy-MCS methods [24-27]. In the information gap decision type (IGDT), there are two main features such as robustness and opportuneness [28-30]. The robust optimization works according to solving problem with the worst-case scenario [31, 32].

Interval types, are assumes that the input parameters are from a specific interval [33, 34]. Because the power systems are dynamic systems, and the control variables and indexes always are changing so it is necessary to know the future values of variables, the stat estimation technic is useful for this objective [35, 36]. It is necessary to collect the phasor values of voltages and currents at any second for using at state estimation in order to state future values of control variables. Phasor measurement units are useful to collect values of voltages and current at aby buses and lines of power system due to its high speed in transforming real values into phasor values, and is portable. Before Phasor measurement units (PMU)s, another systems such as the SCADA system was useful [37, 38]. In this paper improved Taguchi method, and PMUs are used to model uncerties of DGs, collect and calculate phasors of voltages and currents, respectively.

The notable contributions of this study can be categorized as follows:

1) Solving voltage-error problem considering uncertainties of DG units and Time-varying load using the pmu.
2) Applying the Improved Taguchi method for modeling load, solar irradiance, and wind speed uncertainties.

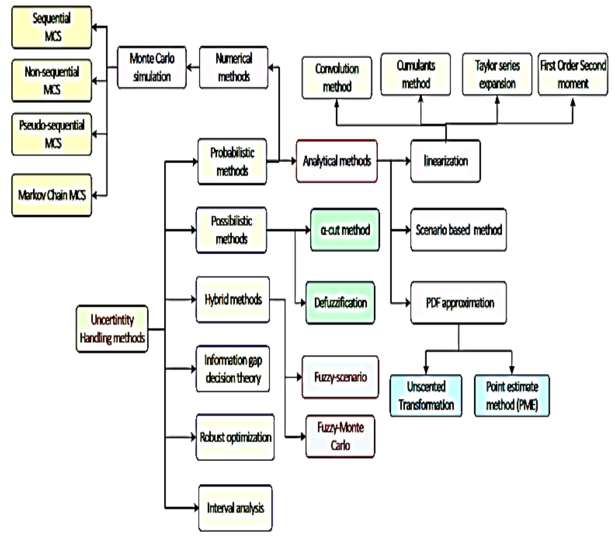

Fig. 1 Uncertainty Modeling Methods [8]

2 Formulation of the Problem

2.1 State Estimation theory

State estimation of the power system means assigning a value to a state variable according to limited measurements from some power system quantities. In the power system, the state variables are (θ, V), and introduced methods by state estimation are based on measurements of some electrical quantities such as V, I, and P. Usual comparative standard aims to be the Sum of squares difference between estimated and measured values being at least. Weighted least squares (WLS) is one of the most common estimation state methods. often, the state estimation algorithm is used in order to correct online measured unit errors in systems. in fact, the state estimation problem is the minimization of a non-linear objective function by considering a set of unequal and non-linear constraints and also is the minimization of measured and real values error from quantities. Assuming a set of measurements can calculate a relationship between measured and real values of quantities as follows (1).

$$Z = h(x) + e \tag{1}$$

Z is the vector of measured values, which could be either real or virtual (initial guess). x is the vector of the state variables. h is a vector of non-linear functions that relate measured values to state variables, and e is the existing error model at every measuring device which has a normal distribution with a mean equal to zero. the vector of state variables is equal to (2),

$$x = (|V_1|, |V_2|, |V_3|, \dots \ \theta_1, \theta_2, \theta_3) \tag{2}$$

the aim of this method is the minimization of the Sum of squared errors between measured and real values which is done according to the weighting of the error of each device. So, the optimization objective function In the WLS method is equal to (3):

$$Min\,J(x) = \sum_{i=1}^{m} w_i\,(z_i - (h_i))^2 = [z - h(x)]^T w[z - h(x)] = [z - h(x)]^T[R]^{-1}[z - h(x)] \tag{3}$$

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

R is the diagonal matrix of the covariance of measurement errors and its elements are the value of the variance of the related measurement errors. By deriving from (3) and then by its Taylor expansion and using the iteration method, the state variables can be estimated using (4), where the matrix H is expressed by (5) and where the matrices P Q, I, V represent active and reactive power, current and voltage, respectively.

$$H = \left[\begin{matrix} \frac{\partial P_{inj}}{\partial \theta} & \frac{\partial P_{flow}}{\partial \theta} & \frac{\partial Q_{inj}}{\partial \theta} & \frac{\partial Q_{flow}}{\partial \theta} & \frac{\partial I_{mag}}{\partial \theta} & \frac{\partial V_{mag}}{\partial \theta} \\ \frac{\partial P_{inj}}{\partial V} & \frac{\partial P_{flow}}{\partial V} & \frac{\partial Q_{inj}}{\partial V} & \frac{\partial Q_{flow}}{\partial V} & \frac{\partial I_{mag}}{\partial V} & \frac{\partial V_{mag}}{\partial V} \end{matrix}\right]^T \tag{5}$$

2.2 Stochastic Assessment

Objective function in this paper is loss minimization of the distribution network as (6). There are many constraints including (7)-(14) [25].

$$P_{Loss} = \sum_{l=1}^{nl} G_{ij}(V_i^2 + V_j^2 - 2V_iV_j\cos\delta_{ij}) \tag{6}$$

$$PG_i - PD_i = V_i \sum_{j=1}^{nb} V_j\left(G_{ij}\cos\delta_{ij} + B_{ij}\sin\delta_{ij}\right) \tag{7}$$

$$QG_i - QD_i = -V_i \sum_{j=1}^{nb} V_j\left(G_{ij}\sin\delta_{ij} - B_{ij}\cos\delta_{ij}\right) \tag{8}$$

$$QG_i^{min} \le QG_i \le QG_i^{max} \tag{9}$$

$$VG_i^{min} \le VG_i \le VG_i^{max} \tag{10}$$

$$T_i^{min} \le T_i \le T_i^{max} \tag{11}$$

$$QC_i^{min} \le QC_i \le QC_i^{max} \tag{12}$$

$$V_i^{min} \le V_i \le V_i^{max} \tag{13}$$

Uncertainty Modeling

In order to model load, the normal distribution is used (14) [39, 40]:

$$f(P_d) = \frac{1}{\sqrt{2\pi}\sigma}\exp\left(-\frac{(P_d - \mu)^2}{2\sigma^2}\right) \tag{14}$$

I) Wind speed modeling: In order to model wind speed, the Weibull distribution is used (15), also for modeling wind produced power equation (16) is used.

$$f(\omega) = \frac{\rho}{\chi}\left(\frac{\omega}{\chi}\right)^{\rho-1}\exp\left(-\left(\frac{\omega}{\chi}\right)^{\rho}\right) \tag{15}$$

$$p = \begin{cases} 0 & \omega_{out}{}^{cut} \le \omega \text{ or } \omega \le \omega_{in}{}^{cut} \\ K_1\omega + K_2 & 0 \le \omega \le \omega_{in}{}^{cut} \\ P_{rated} & \omega_{rated} \le \omega \le \omega_{out}{}^{cut} \end{cases} \tag{16}$$

$K_1 = \frac{P_{rated}}{\omega_{rated} - \omega_{in}{}^{cut}}$, $K_2 = - K_1\omega_{in}{}^{cut}$, χ, and ρ are the shape, and scale factor. Figure.1 explains the equation (16) in details.

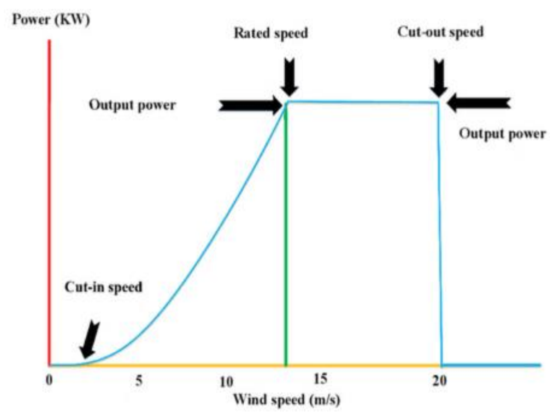

Fig. 2 Characteristic Curve of turbine

In order to model PV, the Beta distribution is used (17-a)

The active produced power from PV is explained using (17-21) [43, 44].

$$F(G) = \frac{1}{G\sigma\sqrt{2\pi}} exp\left[-\frac{\ln(G-\mu)^2}{2\sigma^2}\right] \tag{17-a}$$

$$P_{pv}(sr) = \Gamma * \psi * \zeta(sr) * I(sr) \tag{17}$$

$$\zeta(sr) = \zeta_{oc} - K_{\zeta} * \Delta_C \tag{18}$$

$$\varsigma(sr) = sr * (\varsigma_{SC} + K_{\varsigma} * (\Delta_C - 25)) \tag{19}$$

$$\Delta_C = \Delta_a + sr * \left(\frac{\Gamma_{OT} - 20}{0.8}\right) \tag{20}$$

$$\psi = \frac{\zeta_{MPP} * \varsigma_{MPP}}{\zeta_{OC} * \varsigma_{OC}} \tag{21}$$

Table 1 Orthogonal array $OA_{N_{exp}}\,(N_L)^N$

Experiment number	Level of each variable			
	RV_1	RV_2	…	RV_N
1	L_{11}	L_{12}	…	L_{1N}
2	L_{21}	L_{22}	…	L_{2N}
….	….	….	…	….
N_{exp}	LN_{exp1}	LN_{exp2}	…	LN_{expN}

3 Orthogonal Arrays

An OA is a simple matrix which its rows shows factor levels in each run and its columns shows a specific factor whose levels change in each experiment. An OA is basically a table whose rows are used for experiments and whose columns are used for an RnVr (Table 2) [41, 42].

Table 2 Orthogonal array $OA_4 2^3$

Test N.O	Levels		
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

4 Methodology

The progressed Taguchi method is to extend the precision of the TM as shown in Figure 13. In this strategy, steps 1 to 5 of the TM, and the Progressed TM are exactly rehashed, but within the taking after, other steps are too performed. By comparing sets 1 and 2, likely a few of the same factors will have the same levels. These factors are called certain factors and other factors are called questionable factors. The reason for this naming is that are being gotten the same levels for these factors from two diverse ways, one of the tests and the other of averaging the values gotten from the tests. Certain variables are prohibited from the optimization handle. Within the following area, the 6th step, the arrangement handle is clarified [43,44].

4.1 Placement of uncertain variables in the experiment with the best value

The experiment that has the best result among the experiments performed is one of the possible experiments to examine all combinations of different variables. Therefore, there may be another combination of variables that has a better outcome compared to the current best available test. One of these more suitable combinations may be the combination corresponding to the best experiment, while its uncertain variables are placed according to set 2. Because the averaging of the obtained results was the basis for choosing set 2, the statistical nature of this process increases the probability of choosing the optimal values for the variables. The certain variables determined by the task are removed from the process and only the uncertain variables are re-examined. In order to prevent the interaction of variables, the process of placing uncertain variables from the second set in the best experiment is done individually. If the inserted variable causes a better result than the previous variable, we call this variable definite and fix it in the best test. Other uncertain variables will be placed in the same way.

4.2 Choosing the orthogonal array for the remaining uncertain variables

In this stage, uncertain variables are optimized by using another Taguchi table that is selected for them. If the number of remaining variables is small, we test all possible combinations. The optimization process continues until the optimization completion condition is met.

5 Simulation Results

In this paper, the firstly losses of both type of powers of the network are 22.244 Mvar and 17.59 MW, and also two wind farms are in buses 38, 39 and a PV cell in bus 16, which their nominal capacity is 100 MW [43]. Figures 2 and 3 show voltage angle estimation error with/without PMU and figures 4 and 5 show voltage magnitude estimation error with without PMU in IEEE 14- bus standard network. Figures 6 and 7 show voltage angle estimation error with / without PMU and Figures 8 and 9 show voltage magnitude estimation error with without PMU in IEEE 30- bus standard network. Table 4, and 7 show N-R Load flow for 14, and 30 bus networks respectively. Table 5, and 6 show state estimation without and with PMUs for 14 -bus network. Table 8, and 9 show state estimation without and with PMUs for 30 -bus network. Figure 10, 11, and 12 show IEEE 30-bus Test system, IEEE 14-bus Test system, and Flowchart of improved Taguchi method, respectively. Table 3 shows a result comparison with other methods.

Table 3 Result comparison

losses	I TM	Scenario	LHS	2PEM
μ [MW]	30.5	40.8	52.42	36.3
σ	11.15	26.1	36.22	12.2

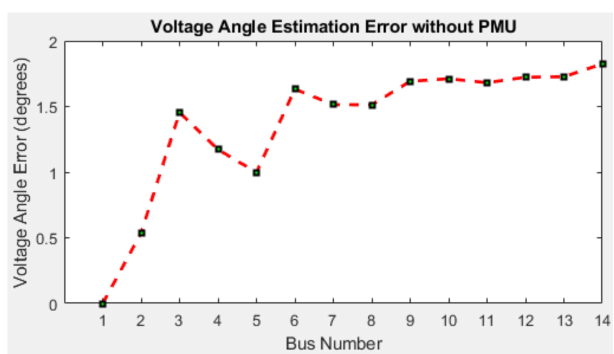

Fig. 3 Voltage Angle Estimation Error without PMU

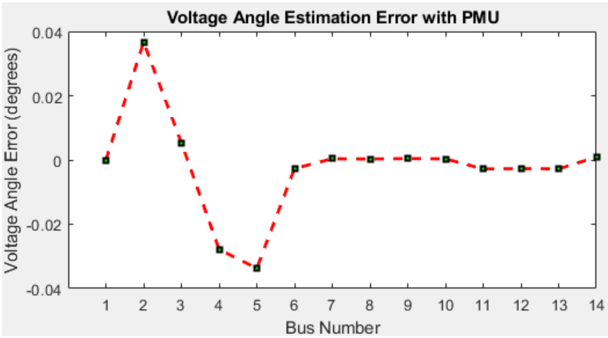

Fig. 4 Voltage Angle Estimation Error without PMU

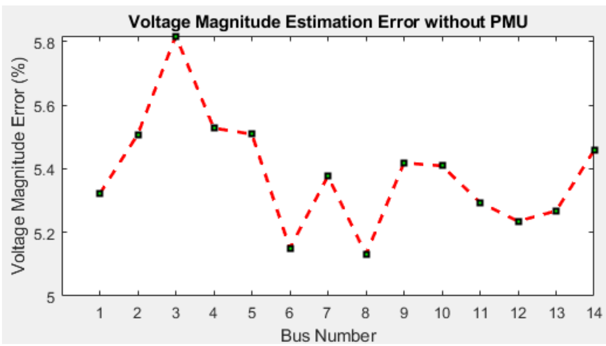

Fig. 5 Voltage Magnitude Estimation Error without PMU

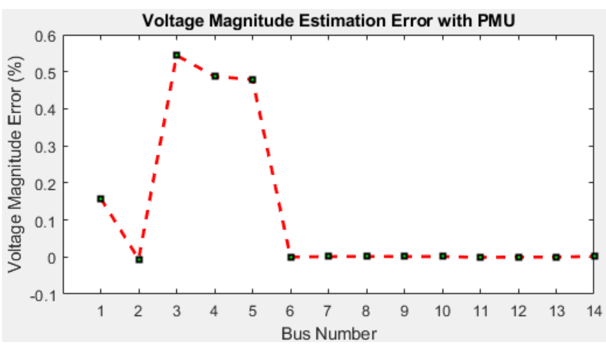

Fig. 6 Voltage Magnitude Estimation Error with PMU

Table 4 N-R Load flow 14 bus network

Bus	Voltage [pu]	Angle [˚]
1	1.0600	0.0000
2	1.0450	-4.9891
3	1.0100	-12.7492
4	1.0132	-10.2420
5	1.0166	-8.7601
6	1.0700	-14.4469
7	1.0457	-13.2368
8	1.0800	-13.2368
9	1.0305	-14.8201
10	1.0299	-15.0360
11	1.0461	-14.8581
12	1.0533	-15.2973
13	1.0466	-15.3313
14	1.0193	-16.0717

Table. 5 State Estimation without PMUs

Bus	Voltage [pu]	Angle [˚]
1	1.0068	0.0000
2	0.9899	-5.5265
3	0.9518	-14.2039
4	0.9579	-11.4146
5	0.9615	-9.7583
6	1.0185	-16.0798
7	0.9919	-14.7510
8	1.0287	-14.7510
9	0.9763	-16.5125
10	0.9758	-16.7476
11	0.9932	-16.5397
12	1.0009	-17.0203
13	0.9940	-17.0583
14	0.9647	-17.8967

Table. 6 State Estimation with PMUs

Bus	Voltage [pu]	Angle [˚]
1	1.0584	0.0000
2	1.0451	-5.0258
3	1.0046	-12.7546
4	1.0083	-10.2142
5	1.0118	-8.7264
6	1.0700	-14.4443
7	1.0457	-13.2372
8	1.0800	-13.2371
9	1.0305	-14.8206
10	1.0299	-15.0364
11	1.0461	-14.8553
12	1.0533	-15.2946
13	1.0466	-15.3285
14	1.0193	-16.0727

30 bus:

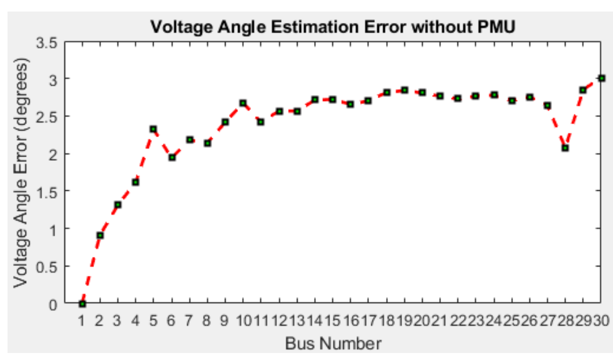

Fig. 7 Voltage Angle Estimation Error without PMU

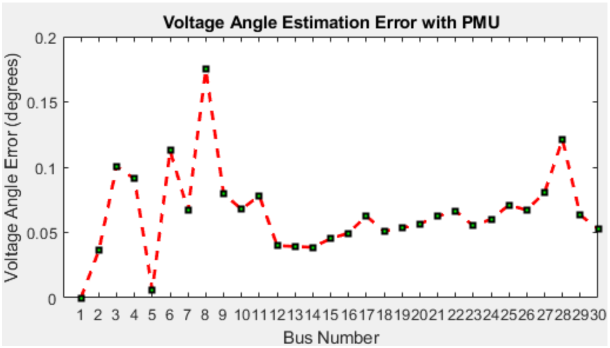

Fig. 8 Voltage Angle Estimation Error with PMU

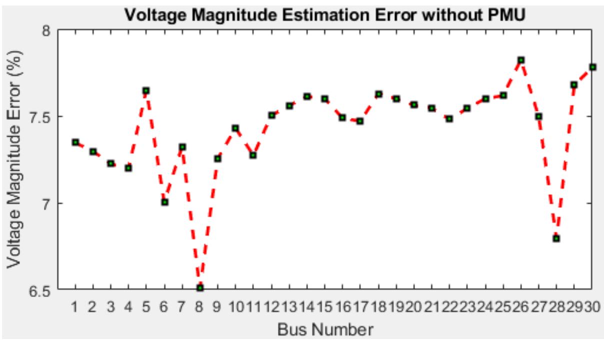

Fig. 9 Voltage Magnitude Estimation Error without PMU

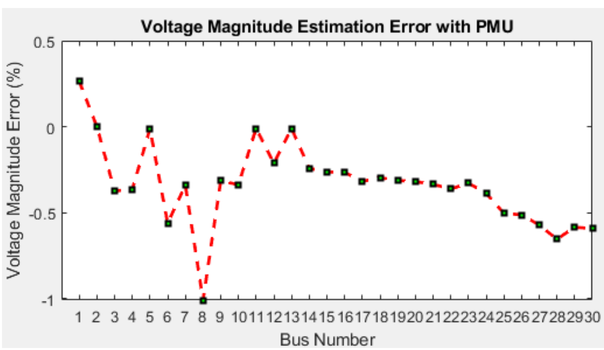

Fig. 10 Voltage Magnitude Estimation Error with PMU

Table 7 N-R Load flow 30 bus network

Bus	Voltage [pu]	Angle [°]
1	1.0600	0.0000
2	1.0430	-5.3543
3	1.0196	-7.5308
4	1.0104	-9.2840
5	1.0100	-14.1738
6	1.0096	-11.0581
7	1.0020	-12.8649
8	1.0100	-11.8193
9	1.0392	-14.0644
10	1.0215	-15.6706
11	1.0820	-14.0644
12	1.0496	-15.1245
13	1.0710	-15.1245
14	1.0320	-16.0018
15	1.0251	-16.0084
16	1.0304	-15.6251
17	1.0188	-15.8687
18	1.0114	-16.6067
19	1.0066	-16.7658
20	1.0095	-16.5502
21	1.0082	-16.2178
22	1.0120	-15.9811
23	1.0085	-16.2294
24	0.9991	-16.3007
25	1.0032	-16.0720
26	0.9852	-16.5038
27	1.0145	-15.6559
28	1.0078	-11.7163
29	0.9944	-16.9077
30	0.9828	17.8067

Table 8 State Estimation without PMUs

Bus	Voltage [pu]	Angle [°]
1	0.9865	0.0000
2	0.9700	-6.2635
3	0.9474	-8.8420
4	0.9384	-10.902
5	0.9335	-16.494
6	0.9395	-12.997
7	0.9287	-15.044
8	0.9449	-13.960
9	0.9667	-16.481
10	0.9472	-18.344
11	1.0093	-16.481
12	0.9746	-17.691
13	0.9954	-17.691
14	0.9559	-18.713
15	0.9491	-18.729
16	0.9555	-18.280
17	0.9441	-18.571
18	0.9352	-19.419
19	0.9306	-19.606
20	0.9339	-19.358
21	0.9328	-18.982
22	0.9372	-18.711
23	0.9331	-18.995
24	0.9231	-19.078
25	0.9270	-18.778
26	0.9070	-19.259
27	0.9395	-18.296
28	0.9398	-13.791
29	0.9177	-19.760
30	0.9051	-20.817

Table 9 State Estimation with PMUs

Bus	Voltage [pu]	Angle [°]
1	1.0574	0.0000
2	1.0430	-5.3904
3	1.0234	-7.6313
4	1.0141	-9.3750
5	1.0101	-14.179

6	1.0152	-11.170
7	1.0054	-12.931
8	1.0201	-11.994
9	1.0424	-14.144
10	1.0248	-15.738
11	1.0821	-14.142
12	1.0517	-15.164
13	1.0711	-15.163
14	1.0344	-16.040
15	1.0277	-16.053
16	1.0331	-15.674
17	1.0219	-15.931
18	1.0144	-16.657
19	1.0097	-16.819
20	1.0127	-16.606
21	1.0115	-16.280
22	1.0156	-16.047
23	1.0118	-16.284
24	1.0030	-16.360
25	1.0082	-16.142
26	0.9904	-16.570
27	1.0202	-15.736
28	1.0143	-11.837
29	1.0003	-16.971
30	0.9888	-17.859

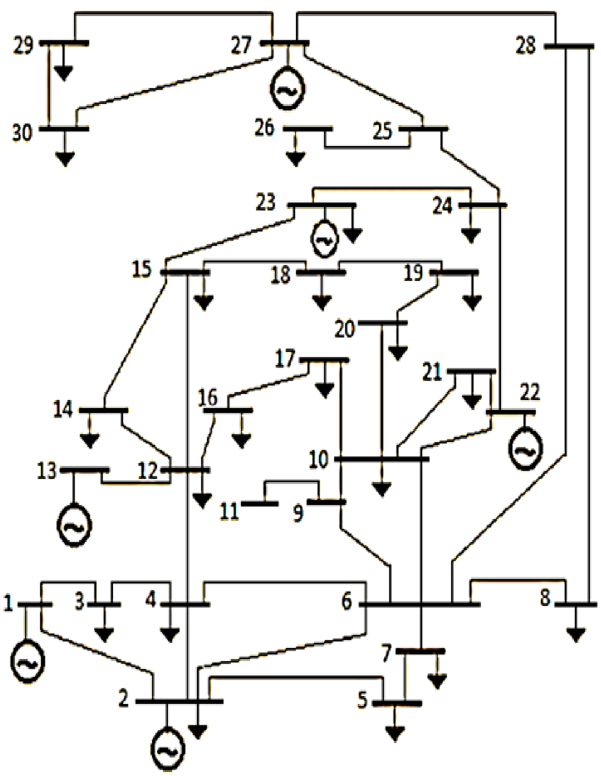

Fig. 11 IEEE 30-bus Test system [41]

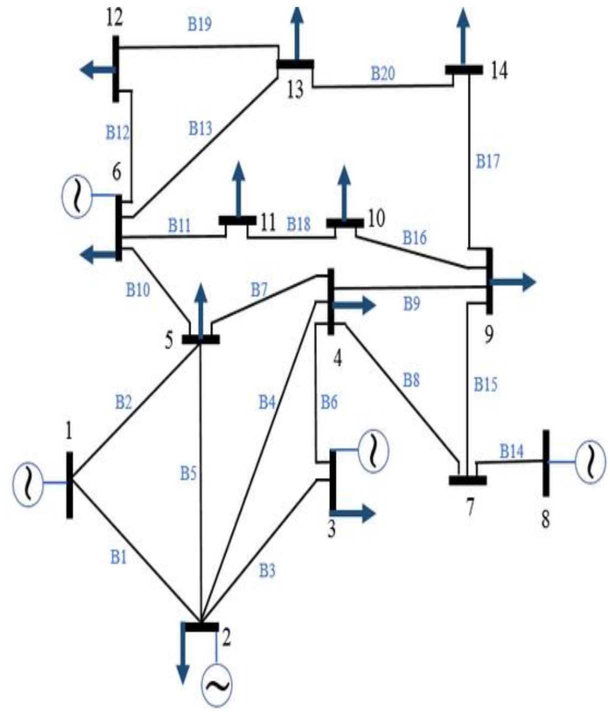

Fig. 12 IEEE 14-bus Test system [44]

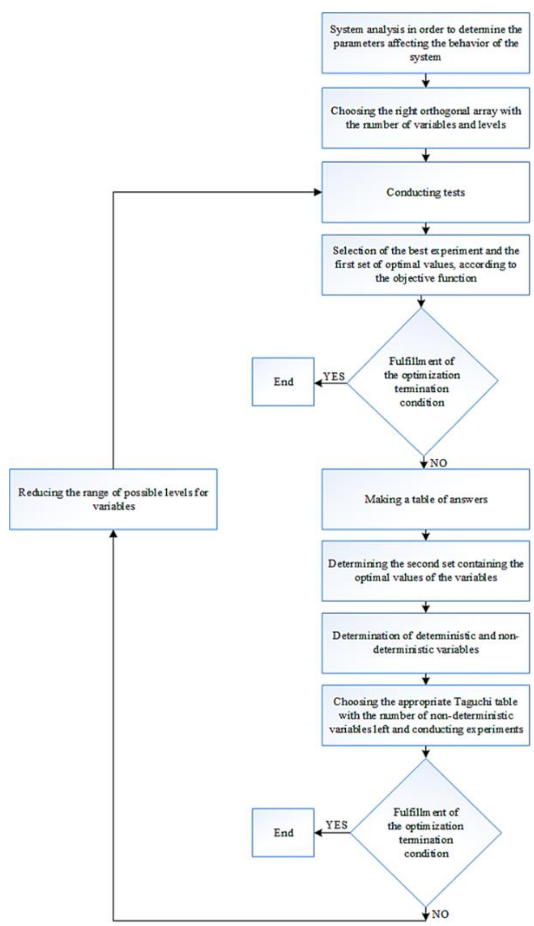

Fig. 13 Improved TM [45]

6 Conclusion

State estimation has a key role in power system operation and controlling, which estimates the values of state variables of power systems, by increasing the DGs in power systems, it is necessary to analyze this concept in the presence of DG units. In this paper, the improved Taguchi method is utilized to model the DG units in state estimation problems using PMU for collecting the voltage and current phasors. The results show that the Improved Taguchi method has modeled the DG units accurately and effectively, and using the PMU the error of the angle and magnitude estimation is very low. Estimated values are very near to real values which were done by Newton-Raphson load flow.

References

[1] P. S. Kundur and O. P. Malik, Power system stability and control. McGraw-Hill Education, 2022.

[2] Z. Huang, B. Fang, and J. Deng, "Multi-objective optimization strategy for distribution network considering V2G-enabled electric vehicles in building integrated energy system," Protection and Control of Modern Power Systems, vol. 5, pp. 1-8, 2020.

[3] A. García-Olivares, J. Solé, and O. Osychenko, "Transportation in a 100% renewable energy system," Energy Conversion and Management, vol. 158, pp. 266-285, 2018.

[4] H. M. Hasanien, "Whale optimisation algorithm for automatic generation control of interconnected modern power systems including renewable energy sources," IET Generation, Transmission & Distribution, vol. 12, no. 3, pp. 607-614, 2018.

[5] V. Singh, T. Moger, and D. Jena, "Uncertainty handling techniques in power systems: A critical review," Electric Power Systems Research, vol. 203, p. 107633, 2022.

[6] X. Tang et al., "Prediction-uncertainty-aware decision-making for autonomous vehicles," IEEE Transactions on Intelligent Vehicles, vol. 7, no. 4, pp. 849-862, 2022.

[7] K. N. Hasan, R. Preece, and J. V. Milanović, "Existing approaches and trends in uncertainty modelling and probabilistic stability analysis of power systems with renewable generation," Renewable and Sustainable Energy Reviews, vol. 101, pp. 168-180, 2019.

[8] M. Ebeed and S. H. A. Aleem, "Overview of uncertainties in modern power systems: Uncertainty models and methods," in Uncertainties in Modern Power Systems: Elsevier, 2021, pp. 1-34.

[9] W. Zhan, Z. Wang, L. Zhang, P. Liu, D. Cui, and D. G. Dorrell, "A review of siting, sizing, optimal scheduling, and cost-benefit analysis for battery swapping stations," Energy, p. 124723, 2022.

[10] Y. Li and W. Li, "Do fodder import and credit loans lead to climate resiliency in the pastoral social-ecological system of Inner Mongolia?," Ecology & Society, vol. 26, no. 1, 2021.

[11] J. Zhang, "Modern Monte Carlo methods for efficient uncertainty quantification and propagation: A survey," Wiley Interdisciplinary Reviews: Computational Statistics, vol. 13, no. 5, p. e1539, 2021.

[12] W. K. Hastings, "Monte Carlo sampling methods using Markov chains and their applications," 1970.

[13] L. Tierney, "Markov chains for exploring posterior distributions," the Annals of Statistics, pp. 1701-1728, 1994.

[14] J. Mello, M. Pereira, and A. L. Da Silva, "Evaluation of reliability worth in composite systems based on pseudo-sequential Monte Carlo simulation," IEEE Transactions on Power Systems, vol. 9, no. 3, pp. 1318-1326, 1994.

[15] A. L. Da Silva, L. D. F. Manso, J. D. O. Mello, and R. Billinton, "Pseudo-chronological simulation for composite reliability analysis with time varying loads," IEEE Transactions on Power Systems, vol. 15, no. 1, pp. 73-80, 2000.

[16] F. Vallée, C. Versèle, J. Lobry, and F. Moiny, "Non-sequential Monte Carlo simulation tool in order to minimize gaseous pollutants emissions in presence of fluctuating wind power," Renewable energy, vol. 50, pp. 317-324, 2013.

[17] T. S. Amaral, C. L. Borges, and A. M. Rei, "Composite system well-being evaluation based on non-sequential Monte Carlo simulation," Electric power systems research, vol. 80, no. 1, pp. 37-45, 2010.

[18] T. Amraee, A. Soroudi, and A. Ranjbar, "Probabilistic determination of pilot points for zonal voltage control," IET Generation, transmission & distribution, vol. 6, no. 1, pp. 1-10, 2012.

[19] S. Kamel, S. Abdel-Fatah, M. Ebeed, J. Yu, K. Xie, and C. Zhao, "Solving optimal reactive power dispatch problem considering load uncertainty," in 2019 IEEE innovative smart grid technologies-Asia (ISGT Asia), 2019: IEEE, pp. 1335-1340.

[20] M. Aien, M. Rashidinejad, and M. Fotuhi-Firuzabad, "On possibilistic and probabilistic uncertainty assessment of power flow problem: A review and a new approach," Renewable and Sustainable energy reviews, vol. 37, pp. 883-895, 2014.

[21] H. R. Baghaee, M. Mirsalim, G. B. Gharehpetian, and H. A. Talebi, "Fuzzy unscented transform for uncertainty quantification of correlated wind/PV

microgrids: possibilistic–probabilistic power flow based on RBFNNs," IET Renewable Power Generation, vol. 11, no. 6, pp. 867-877, 2017.
[22] H. Wu, P. Dong, and M. Liu, "Random fuzzy power flow of distribution network with uncertain wind turbine, PV generation, and load based on random fuzzy theory," IET Renewable Power Generation, vol. 12, no. 10, pp. 1180-1188, 2018.
[23] A. Soroudi and M. Ehsan, "A possibilistic–probabilistic tool for evaluating the impact of stochastic renewable and controllable power generation on energy losses in distribution networks—A case study," Renewable and Sustainable Energy Reviews, vol. 15, no. 1, pp. 794-800, 2011.
[24] M. Aien, A. Hajebrahimi, and M. Fotuhi-Firuzabad, "A comprehensive review on uncertainty modeling techniques in power system studies," Renewable and Sustainable Energy Reviews, vol. 57, pp. 1077-1089, 2016.
[25] H. Yao et al., "Possibilistic evaluation of photovoltaic hosting capacity on distribution networks under uncertain environment," Applied Energy, vol. 324, p. 119681, 2022.
[26] A. R. Jordehi, "How to deal with uncertainties in electric power systems? A review," Renewable and sustainable energy reviews, vol. 96, pp. 145-155, 2018.
[27] S. Pineda and A. Conejo, "Scenario reduction for risk-averse electricity trading," IET generation, transmission & distribution, vol. 4, no. 6, pp. 694-705, 2010.
[28] A. Soroudi and M. Afrasiab, "Binary PSO-based dynamic multi-objective model for distributed generation planning under uncertainty," IET renewable power generation, vol. 6, no. 2, pp. 67-78, 2012.
[29] Y. Ben-Haim, Info-gap decision theory: decisions under severe uncertainty. Elsevier, 2006.
[30] A. Rabiee, A. Soroudi, and A. Keane, "Information gap decision theory based OPF with HVDC connected wind farms," IEEE Transactions on Power Systems, vol. 30, no. 6, pp. 3396-3406, 2014.
[31] M. Nazari-Heris and B. Mohammadi-Ivatloo, "Application of robust optimization method to power system problems. Classical and recent aspects of power system optimization," Academic Press, Cambridge, US, vol. 2, pp. 19-32, 2018.
[32] A. Ben-Tal, L. El Ghaoui, and A. Nemirovski, Robust optimization. Princeton university press, 2009.
[33] R. E. Moore, R. B. Kearfott, and M. J. Cloud, Introduction to interval analysis. SIAM, 2009.
[34] P. Zhang, W. Li, and S. Wang, "Reliability-oriented distribution network reconfiguration considering uncertainties of data by interval analysis," International Journal of Electrical Power & Energy Systems, vol. 34, no. 1, pp. 138-144, 2012.
[35] J. Zhao et al., "Power system dynamic state estimation: Motivations, definitions, methodologies, and future work," IEEE Transactions on Power Systems, vol. 34, no. 4, pp. 3188-3198, 2019.
[36] A. H. Abolmasoumi, A. Farahani, and L. Mili, "Robust Particle Filter Design with an Application to Power System State Estimation," IEEE Transactions on Power Systems, 2023.
[37] G. Cheng, Y. Lin, A. Abur, A. Gómez-Expósito, and W. Wu, "A Survey of Power System State Estimation Using Multiple Data Sources: PMUs, SCADA, AMI, and Beyond," IEEE Transactions on Smart Grid, 2023.
[38] R. Khalili and A. Abur, "PMU-based decoupled state estimation for unsymmetrical power systems," IEEE Transactions on Power Systems, vol. 36, no. 6, pp. 5359-5368, 2021.
[39] M. Gholami and M. J. Sanjari, "Optimal Operation of Multi-Microgrid System Considering Uncertainty of Electric Vehicles," International Journal of Engineering, vol. 36, no. 8, 2023.
[40] M. Peiravi and D. Domiri Ganji, "Generating electrical power using movement of various vehicles in new lighting base," International Journal of Engineering, vol. 35, no. 2, pp. 387-396, 2022.
[41] M. Najjarpour, B. Tousi, and S. Jamali, "Loss Reduction in Distribution Networks With DG Units by Correlating Taguchi Method and Genetic Algorithm," Iranian Journal of Electrical and Electronic Engineering, vol. 18, no. 4, p. 1, 2022.
[42] M. Najjarpour and B. Tousi, "Loss Reduction of Distribution Network by Optimal Reconfiguration and Capacitor Placement Using Cuckoo and Cultural Algorithms," in 2023 8th International Conference on Technology and Energy Management (ICTEM), 2023: IEEE, pp. 1-5.
[43] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in MHS'95. Proceedings of the sixth international symposium on micro machine and human science, 1995: Ieee, pp. 39-43.
[44] L. M. Leon, A. S. Bretas, and S. Rivera, "Quadratically constrained quadratic programming formulation of contingency constrained optimal power flow with photovoltaic generation," Energies, vol. 13, no. 13, p. 3310, 2020.
[45] M. Najjarpour and B. Tousi, "Probabilistic Reactive Power Flow Optimization of The Distribution System in The Presence of Distributed Units Uncertainty Using the Combination of Improved

Taguchi Method and Dandelion Algorithm," International Journal of Engineering, 2023.

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