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Grey Wolf Optimizer and Cuckoo Search Algorithm for Electric Power System State Estimation with Load Uncertainty and False Data

[1]K. Rajendra, [2]S. Subramanian, [3]N. Karthik, [4]K. Naveenkumar, [5]S. Ganesan
[1]Research Scholar, Department Of Electrical Engineering,
Annamalai University, Annamalai Nagar, Chidambaram ,608002, Tamil Nadu,India
raj207209@gmail.com
[2]Professor, Department Of Electrical Engineering, Annamalai University,
Annamalai Nagar, Chidambaram ,608002, Tamil Nadu,India
dr_smani@yahoo.co.in
[3]Associate Professor, Department Of Electrical and Electronics Engineering,
Bapatla Engineering College, Bapatla, Bapatla (Dt), 522101, Andhra Pradesh ,India.
wizitkarthik@gmail.com
[4]Assistant Professor, Department Of Instrumentation and Control Engineering,
Sri ManakulaVinayagar Engineering College, Madagadipet, Puducherry 605107,
Tamil Nadu, India
naveenk.aueee@gmail.com
[5]Associate Professor, Department Of Electrical and Electronics Engineering,
Government College Of Engineering,Bangalore Highways, Salem, 636 011,Tamil Nadu, India
ganeshshriraj@gmail.com

Abstract:-State estimate serves a crucial purpose in the control centre of a modern power system. Voltage phasor of buses in such configurations is referred to as state variables that should be determined during operation. A precise estimation is needed to define the optimal operation of all components. So many mathematical and heuristic techniques can be used to achieve the aforementioned objective. An enhanced power system state estimator built on the cuck search algorithm is described in this work. Several scenarios, including the influence of load uncertainty and the likelihood of false data injection as significant challenges in electrical energy networks, are proposed to analyse the operation of estimators. The ability to identify and correct false data is also assessed in this regard. Additionally, the performance of the presented estimator is compared to that of the weighted least squares, Cuckoo Search algorithm and grey wolf Optimizer. The findings demonstrate that the grey wolf Optimizer overcomes the primary shortcomings of the conventional approaches, including accuracy and complexity, and is also better able to identify and rectify incorrect data. On IEEE 14-bus and 30-bus test systems, simulations are run to show how well the method works.

I. INTRODUCTION

POWER system state estimation (SE) is a key tool for management systems [1]. In fact, different proceedings such as energy management [2] and network control [3] are not possible without availability of accurate information. Therefore, if SE can predict the unknown data, it will be much simpler for operators to keep tabs on and manage the network. Implementing such a system allows for secure and effective functioning [5]-[7]. As a result, with the proliferation of smart grids and the consequent increase in the flow of data between nodes, it is imperative that SE technologies be developed to ensure the best possible safety, optimization, and management of power systems [8].Active, reactive power injection redundancy and line active, reactive power flows at various nodes provide the basis of the SE's estimation of the bus voltage magnitude and phase angle. [9], [10]. The weighted least square (WLS) method is the most common approach to solve the SE problem. In this procedure, SE is formulated as an optimization problem and solved by an iterative method [11], [12]. This process includes several drawbacks such as ill conditioning of gain matrix, slow detection of false data, and numerical problems in some cases (e.g., simultaneousconnection of short and long line to bus and high weighting coefficients for pseudo measurements) [13]. According to the presented issues, WLS algorithm may provide unacceptable outputs as well as its convergence is not guaranteed [14], [15].

Specifically, a cuckoo search algorithm GWO is suggested in this study to the capacity for detecting inaccurate information and fixing it is also evaluated here. The given estimator is

further evaluated in comparison to the weighted least squares method and the Cuckoo Search technique. These results show that the GWO is superior to traditional methods in spotting

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and fixing inaccurate data, as well as in terms of accuracy and complexity. The CSA approach shines most when used to optimization issues with few tuning knobs. L´evy flights and the likelihood of finding alien eggs in a host bird's nest are the primary processes used in CSA to come up with novel solutions. Findings from applying the suggested CSA method and GWO to the IEEE 14 bus and 30 bus systems and comparing them to results from other methods in the literature are shown and discussed.

II. WLS STATE ESTIMATION

The active and reactive power flows in network nodes, the injections into the bus, and the magnitudes of the bus voltages are all examples of non-synchronized (scanned) z_1 measurements. It is presumed that all potential errors in this collection of measurements have been eliminated using conventional techniques[17]. In order to get the readings, nonlinear functions of the state vector x are used. (a synchronised boost in voltage at the bus stations)

$$z1 = h1(x) + e1 \quad (1)$$

where h_1 is a polar-coordinated nonlinear function of the state vector x and e_1 is a covariance matrix of the dimension errors R_1.

The Jacobian matrix, H_1 given by

$$H_1(x) = \frac{\partial h_1(x)}{\partial x} \quad (2)$$

The matrix, $G1(x_k)$ is given by

$$G_1(x^k) = [H_1^T(x_k)R_1^{-1}H_1(x_k)]^{-1} \quad (3)$$

The error covariance matrix of the estimate x is given by

$$\text{cov}([x]) = [H_1^T R_1^{-1} H_1] \quad (4)$$

and the state vector is found from,

$$[x^{k+1}] = [x^k] + [G_1(x^k)]^{-1}[H_1^T R_1^{-1}][z, -h_1(x^k)] \quad (5)$$

The iterative process will continue until one of two conditions is met. Both the rate of change in state variables and the maximum number of allowable iterations must be met.

$$\max|\Delta x^k| \leq \varepsilon \quad (6)$$

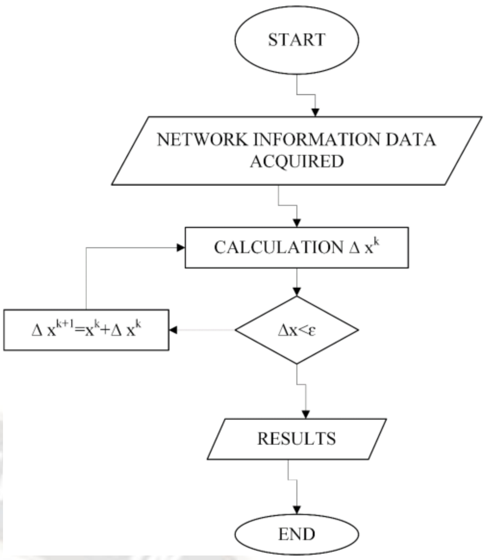

Figure 1 Flowchart of state estimation algorithm

III. OPTIMIZATION ALGORITHMS

3.1. Solution Approach Using CSA

This section discusses the ability to identify and correct false data is also assessed in this regard. Additionally, the performance of the presented estimator is compared to that of the weighted least squares and Cuckoo Search algorithm. The findings demonstrate that the Cuckoo search algorithm overcomes the primary shortcomings of the conventional approaches, including accuracy and complexity, and is also better able to identify and rectify incorrect data. If you're in good condition, that's a bonus. Data such as generator bus voltage magnitudes, tap-changer ratios, shunt MVAr injections, System regulating variables, and power injections at their incident buses, as well as other line data, are updated every cycle. Total real power loss, regular VCPI, and normal voltage deviation index are calculated using the NR power flow explanation to get insight into the global unbiased function described in Eq.

The CSA is developed based on the three rules as follows:

- Each cuckoo lays an egg at a set time in a host nest that it has chosen in advance. - The highest-quality egg will be passed on to the following generation.
- With a constant number of host nests, a cuckoo species has a probability of pa between zero and one of discovering an alien. The host bird will either reject the alien egg or quit the nest in favour of building a new one.
- Applying CSA to this issue yielded the following problem-solution diagram:
- Each egg in a nest represents a different approach to the problem at hand, and the one that is overlooked by the host bird is assumed to be the optimal choice.

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- An objective function plus penalised constraints multiplied by a penalty factor make up the fitness function that will be used to assess the quality of the solutions obtained.
- Lévy flights produce new solutions (eggs) that the host bird is more likely to find, so the poorest solutions are replaced with better ones at each stage.

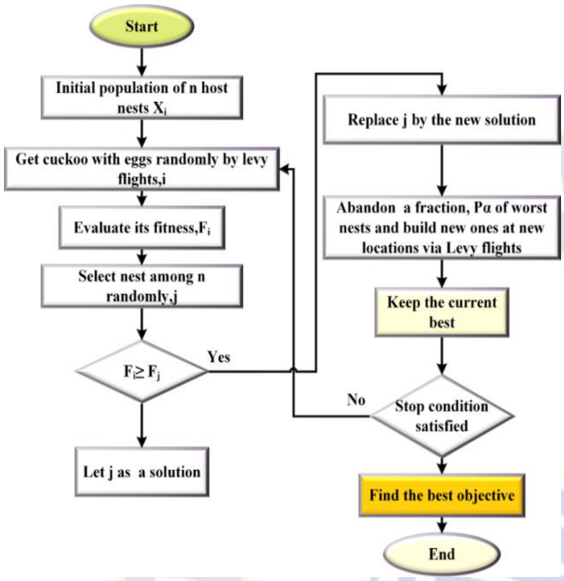

Figure 2. Flowchart for CSA approach for solving OPF problem

An objective function that was constrained was used to formulate the issue. To create the code tree for precise fault diagnosis, three optimization methods were employed to determine the best gas percentage limitations. The diagnostic precision was the fitness function.

3.2. Grey Wolf Optimizer (GWO) Algorithm

To optimise performance, the Grey Wolf Optimizer (GWO) adopts a pack structure and hunting strategies similar to those of wild grey wolves. Grey Wolf Optimization (GWO) is derived from a mathematical model of the feeding technique and social system of grey wolves, which is used to find optimal solutions.

This encircling behaviour can be modelled mathematically using the following expressions:

$$\bar{D}=\left|\bar{C}.\overline{X_p}(iter)-\bar{X}(iter)\right| \qquad (14)$$

$$\overline{X_p}(iter+1)=\overline{Xp}(iter-\bar{A}.\bar{D}) \qquad (15)$$

where $\overline{X_p}(iter)$ is the victim's position vector and iter is the current iteration. As coefficient vectors, $\bar{A}$ and $\bar{C}$ can be written as

$$\begin{cases}\vec{A}=2.\vec{a}.\vec{r_1}-\vec{a}\\ \vec{C}=2.\vec{r_2}\end{cases} \qquad (16)$$

$\vec{r_1}$ and $\vec{r_2}$are random vectors with a range of 0 to 1, where ‘a’ decreases linearly from 2 to 0 over the duration of iterations.

The top three results are saved in GWO, and the other search agents are forced to adjust their places accordingly. The GWO algorithm begins by classifying the wolf population into four levels, or packs: alpha (α), beta (β), delta (δ), and omega (ω). Over iterations, the top three optimal solutions are indicated by, and. Changes to the coordinates and in a two-dimensional space are shown in Figure 2.

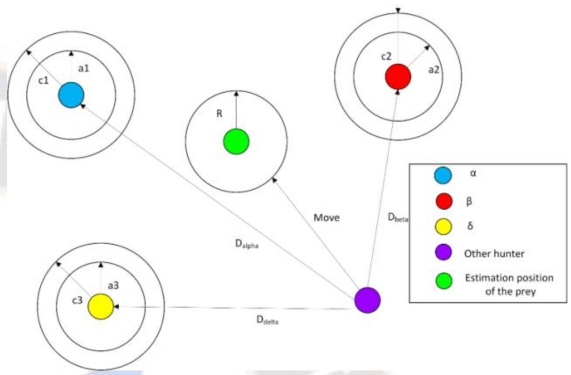

Figure 3: Position updating in GWO

We'll refer to the remaining options as. This algorithm's searching and optimization are governed by by α, β, δ and ω. The pack of wolves must close in for superior solutions, and.

Incorporate the best three results so far and make the remaining search agents, including the omegas, realign their locations to match the best one's. The following expressions are proposed in this regard.

$$\overrightarrow{D_\alpha}=\left|\overrightarrow{C_1}.\overrightarrow{X_\alpha}-\vec{X}\right| \qquad (17)$$

$$\overrightarrow{D_\beta}=\left|\overrightarrow{C_2}.\overrightarrow{X_\beta}-\vec{X}\right| \qquad (18)$$

$$\overrightarrow{D_\delta}=\left|\overrightarrow{C_3}.\overrightarrow{X_\delta}-\vec{X}\right| \qquad (19)$$

$$\overrightarrow{X_1}=\overrightarrow{X_\alpha}-\overrightarrow{A_1}(\overrightarrow{D_\alpha}) \qquad (20)$$

$$\overrightarrow{X_2}=\overrightarrow{X_\beta}-\overrightarrow{A_2}(\overrightarrow{D_\beta}) \qquad (21)$$

$$\overrightarrow{X_3}=\overrightarrow{X_\delta}-\overrightarrow{A_1}(\overrightarrow{D_\delta}) \qquad (22)$$

$$\vec{X}(iter+1)=\frac{\overrightarrow{X_1}+\overrightarrow{X_2}+\overrightarrow{X_3}}{3} \qquad (23)$$

Using these equations, a search agent can adjust its location in a dimensional search space according to α, β, δ Vectors $\vec{A}$ and $\vec{C}$. These equations leverage the A and C vectors to encourage the GWO algorithm to actively seek for and take advantage of search space. As a decrease in A occurs, we devote 50% of each iteration to exploration and 50% to exploitation..

The range of $\vec{C}$ is $2 \leq \vec{C} \leq 0$, and when $\vec{C}> 1$., the vector $\vec{C}$ also facilitates exploration. When $\vec{C}< 1$ and $\vec{A}$ decreases linearly over the duration of repetitions [35] exploitation is highlighted. To promote exploration and exploitation at any

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level and to avoid local optima, $\vec{C}$, on the other hand, is created at random.

Where the simulation repeatedly settled at a local minimum solution, the basic GWO failed to capture the ideal solution. In order to improve GWO's capacity to arrive at the ideal answer, the algorithm was changed. The performance of the GWO's convergence has been enhanced using a variety of techniques. Changes were made to enhance GWO's capacity to find the search area and arrive at the best solution.

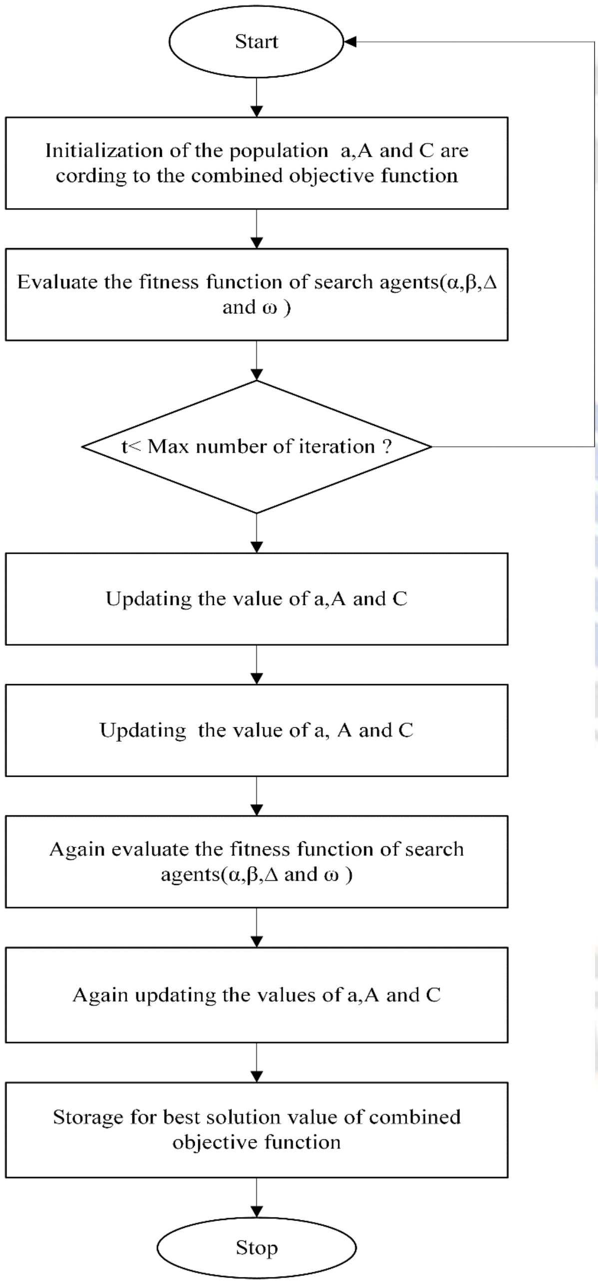

Figure 4. Flow chart for GWO) Algorithm

Start

- Establish the GW population from scratch.
- Start with the combined objective function in Xi (i=1, 2,..., n) to determine the values for A and C.
- Find out how fit each search agent is, and give them a score based on that. (Xα denotes the search agent's top result, Xβ the search agent's second-best result, and Xδ the search agent's third-best result.) When t = 0
- While (t < maximum number of iterations)
- In each case, a search agent Update the current search's location in accordance with the equation.
- End for
- All search agents' fitness values should be recalculated and re-graded.
- Recalculate the location of Xα, Xβ, and Xδ t = t+1
- Update the value of a, A, and C in accordance with the combined objective function
- Store the best solution value.
- While Ending

End

IV. SIMULATION RESULTS

The provided state estimate method was put through its paces in a simulation on IEEE-14 and IEEE-30 bus systems. We expect the load flow solution to be the basis for generating measurements with adequate measurement errors, and we utilise the load flow for the basic case as our point of departure. Estimation of the classical state makes use of the magnitudes of voltages, currents, and flows of active and reactive power, as well as the injections of active and reactive power. One type of phasor is the measurement of voltage and current, both of which are called "voltage" and "current" respectively. The system-wide distribution of measurements is constant. Errors in the observed values were introduced using a normal random number generator with a sufficient standard deviation, and the load flow solution is supposed to represent the true value of the state vector. All of the lines that connect to a given bus should have their voltage and current measured by a single PMU. It is now compliant with the standard, which calls for a phasor angle of 0^0 degrees on the swing bus. Figure 3 displays voltage angle and magnitude estimate errors on the IEEE-14 bus system using post-processed phasor measurements and conventional state estimation data.

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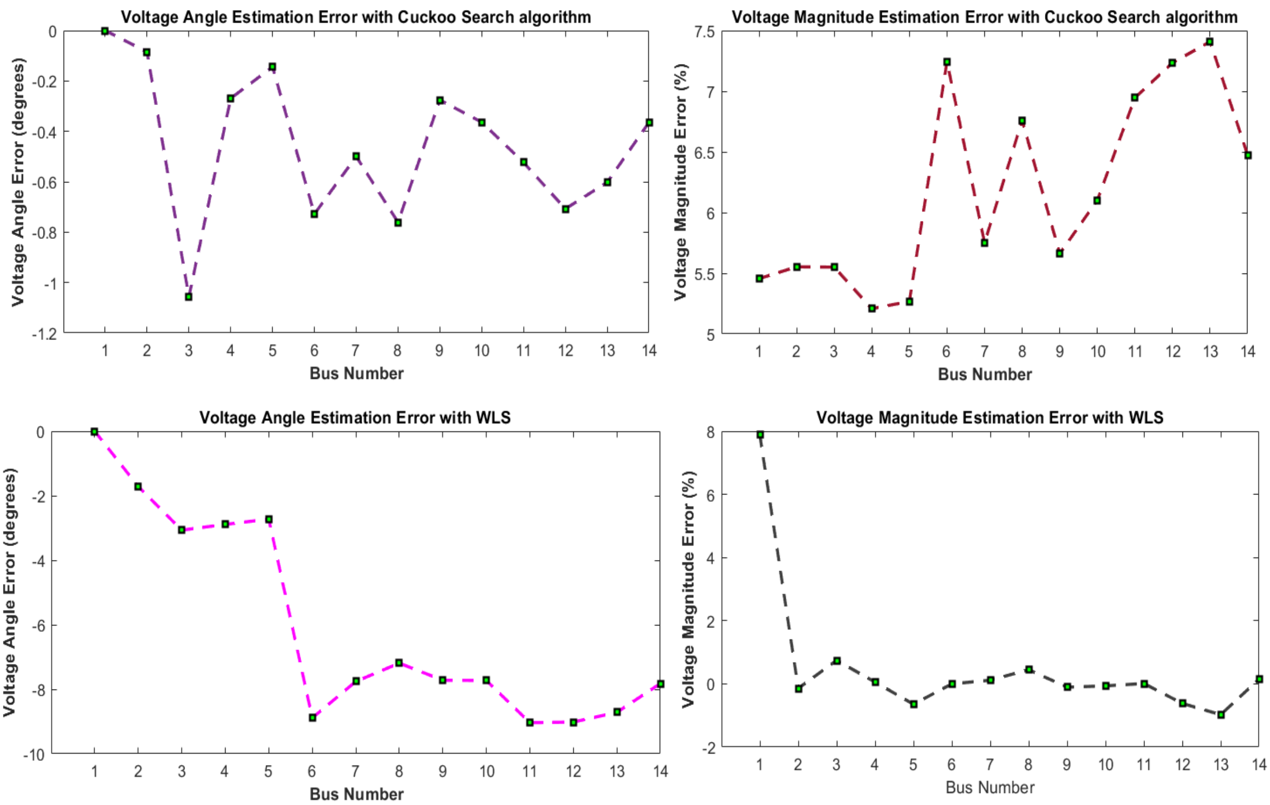

Figure 5. Voltage magnitude and angle estimation errors with WLS and CSA

On the IEEE-30 bus system, Fig.4 exhibits voltage angle estimate and magnitude errors using traditional state estimation data and phasor measurements in the post-processing stage, respectively.

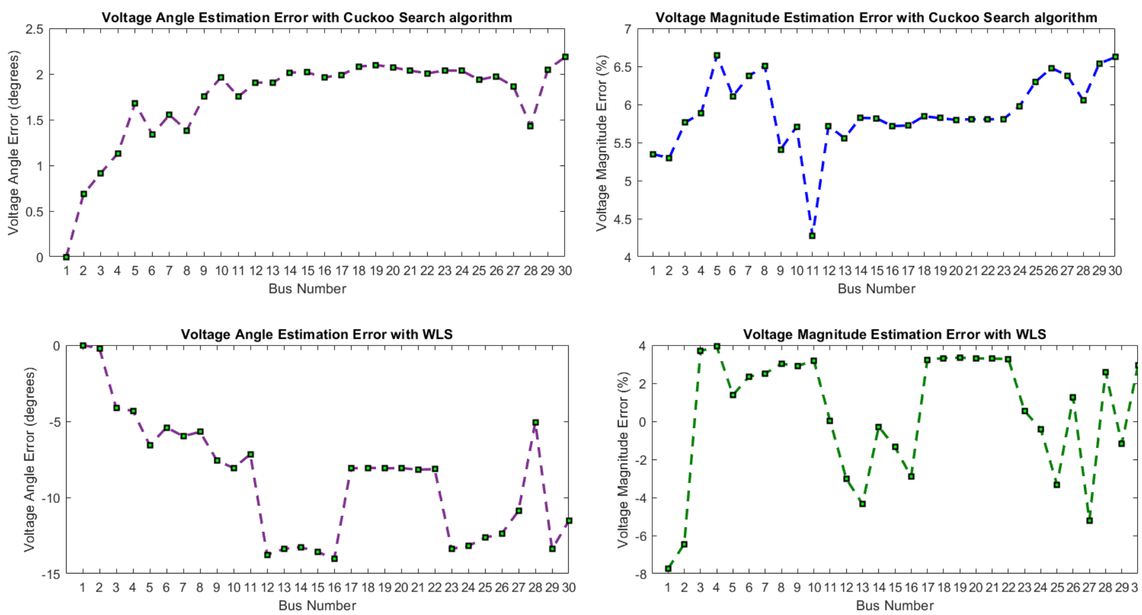

Figure6. Voltage magnitude estimation errors with WLS and with CSA

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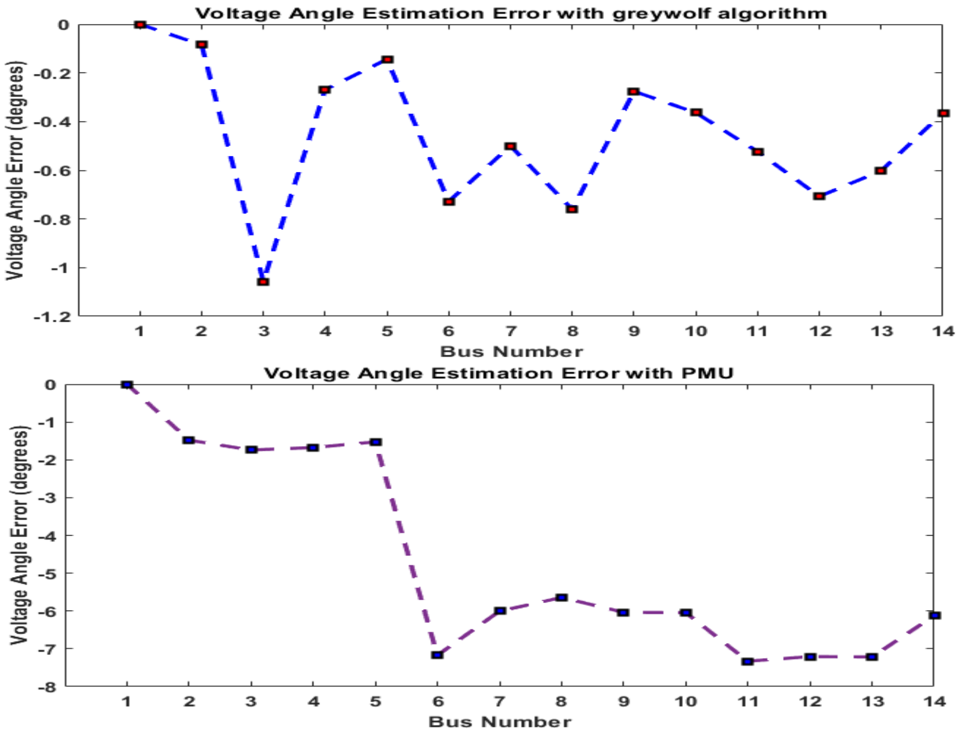

Figure.7. Voltage angle estimation errors with PMU and Greywolf algorithm

On the IEEE-14 bus system, Fig.6 exhibits voltage magnitude estimate errors using just conventional state estimation data and utilizing phasor measurements with traditional measurements in the post-processing stage.

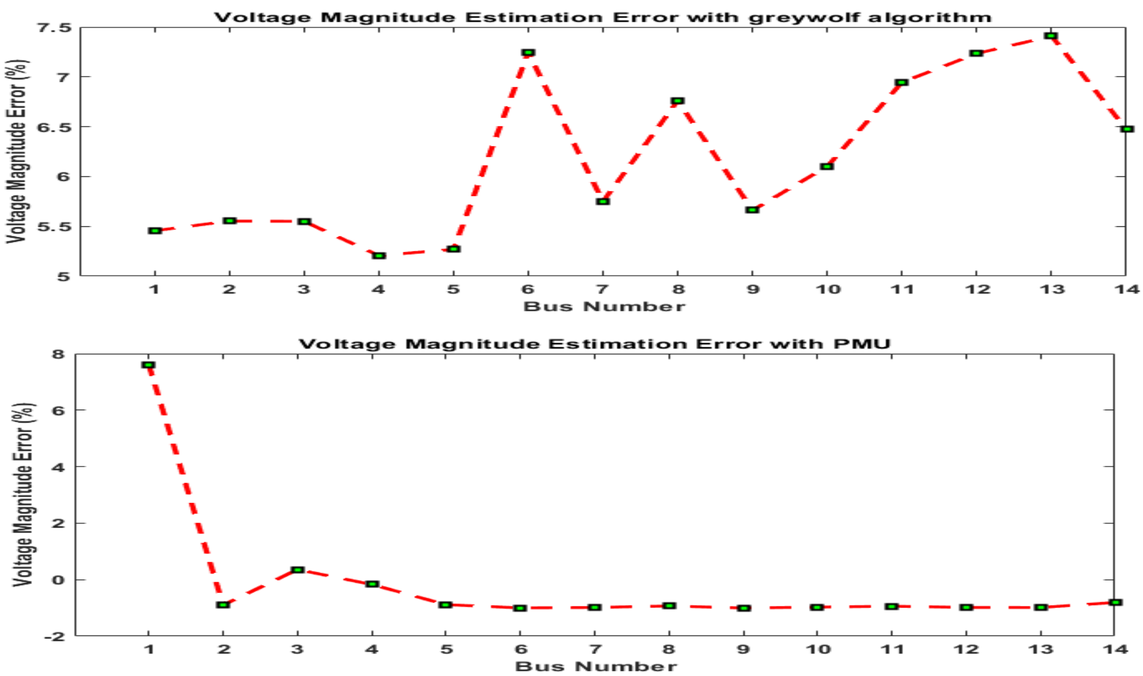

Figure 8 Voltage magnitude estimation errors without and with Grey wolf algorithm

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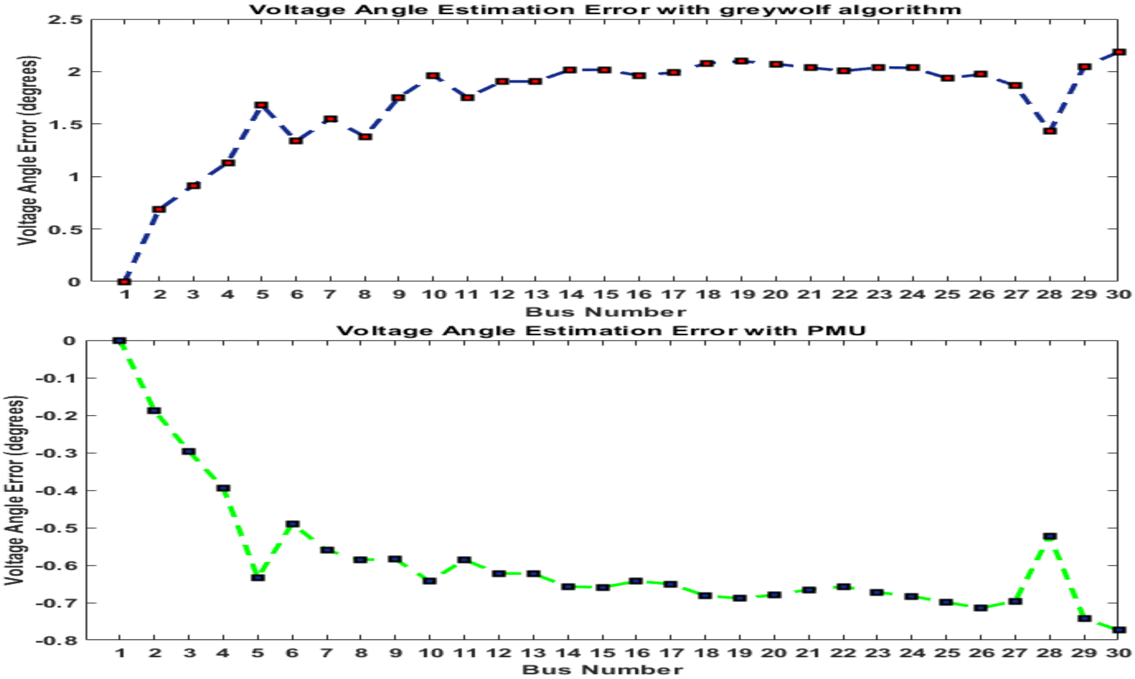

Figure 9 Voltage angle estimationerrors with PMU and with Grey wolf algorithm

On the IEEE-30 bus system, Fig.9 exhibits voltage angle estimate errors using traditional state estimation data and phasor measurements in the post-processing stage, respectively..

On the IEEE-30 bus system, Fig.10. displays voltage magnitude prediction errors using just conventional state estimation data and utilizing phasor measurements with traditional measurements in the post-processing stage.

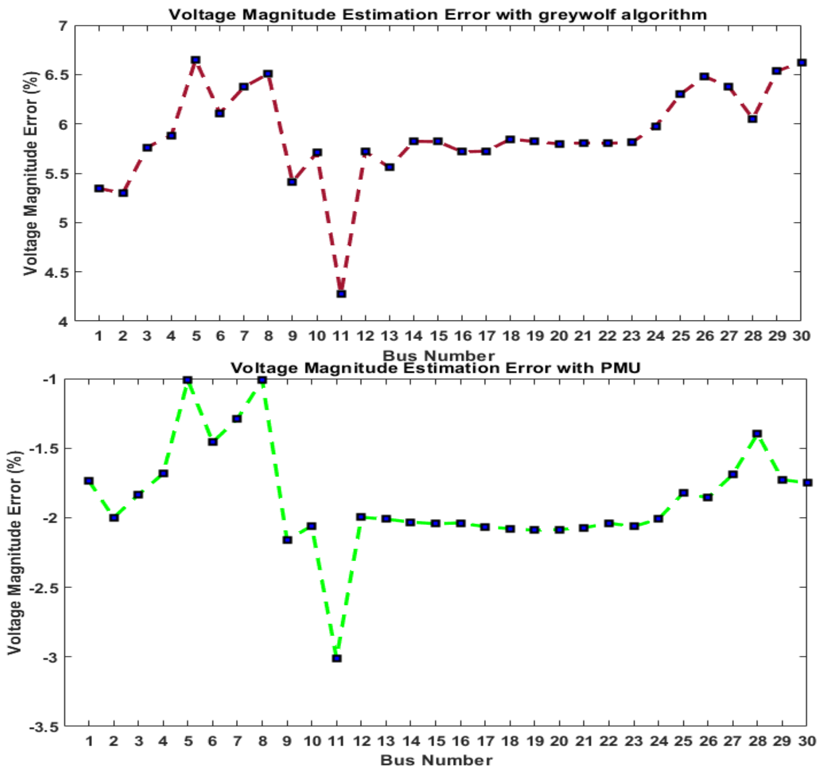

Figure 10. Voltage magnitude estimation errors with WLS and with Grey wolf algorithm

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TABLE.1: VOLTAGE MAGNITUDE ESTIMATION ERRORS AND ANGLE ERROR WITH WLS, WITH GREY WOLF ALGORITHM AND CSA FOR IEEE-14 BUS SYSTEM

	With NR-method		With WLS		With grey wolf algorithm		With CSA	
BUS No.	V(pu)	Angle(Degree)	V(pu)	V(pu)	V(pu)	Angle(Degree)	V(pu)	Angle(Degree)
1	1.06	0	1.0584	0	0.9954	0	0.97	0
2	1.045	-4.9891	1.0451	-5.5265	0.9795	-5.0097	1.03	-3.38
3	1.01	-12.7492	1.0046	-14.2039	0.9495	-12.0124	0.99	-10.00
4	1.0132	-10.242	1.0083	-11.4146	0.9521	-10.1909	1.00	-7.57
5	1.0166	-8.7601	1.0118	-9.7583	0.9544	-8.8006	1.01	-6.21
6	1.07	-14.4469	1.07	-16.0798	0.9875	-14.0111	1.05	-5.84
7	1.0457	-13.2368	1.0457	-14.751	0.9783	-13.0116	1.03	-5.75
8	1.08	-13.2368	1.08	-14.75	1.0024	-12.7507	1.06	-6.32
9	1.0305	-14.8201	1.0305	-16.5125	0.9639	-14.8504	1.02	-7.406
10	1.0299	-15.036	1.0299	-16.7476	0.9588	-14.9817	1.02	-7.61
11	1.0461	-14.8581	1.0461	-16.5397	0.9666	-14.6378	1.03	-6.12
12	1.0533	-15.2973	1.0533	-17.0203	0.9708	-14.8987	1.04	-6.58
13	1.0466	-15.3313	1.0466	-17.0583	0.9624	-15.0397	1.04	-6.92
14	1.0193	-16.0717	1.0193	-17.8967	0.9443	-16.036	1.00	-8.57

TABLE.2: VOLTAGE MAGNITUDE ESTIMATION ERRORS AND ANGLE ERROR WITH WLS, WITH GREY WOLF ALGORITHM AND CSA FOR IEEE-30 BUS SYSTEM

	With NR-method		With PMU		With grey wolf algorithm		With CSA	
Bus.No	V(pu)	Angle(Degree)	V(pu)	Angle(Degree)	V(pu)	Angle(Degree)	0.9	0.000
1	1.06	0	1.057355	0	0.9868	0	0.9	-5.363
2	1.043	-5.35430751	1.042999	-5.39041268	0.97	-6.2635	0.94	-3.784
3	1.019644	-7.5308155	1.02338	-7.63134855	0.9474	-8.842	0.93	-5.449
4	1.010412	-9.28396954	1.014075	-9.37502199	0.9384	-10.9021	0.93	-8.235
5	1.01	-14.1737784	1.010119	-14.179506	0.9335	-16.4941	0.93	-6.254
6	1.009576	-11.0580891	1.015186	-11.1707616	0.9395	-12.9975	0.92	-7.513
7	1.001971	-12.864867	1.005376	-12.9316008	0.9287	-15.0443	0.94	-6.883
8	1.01	-11.819268	1.020088	-11.9941309	0.9449	-13.9608	0.966	-7.168
9	1.039247	-14.0643995	1.042396	-14.144075	0.9667	-16.4813	0.94	-8.308
10	1.021471	-15.6705834	1.024848	-15.7383872	0.9472	-18.3445	1.00	-7.566
11	1.082	-14.0643995	1.082103	-14.142468	1.0093	-16.4813	0.97	-2.010
12	1.049586	-15.124513	1.051713	-15.1644662	0.9746	-17.6918	0.99	-2.407
13	1.071	-15.124513	1.071103	-15.1637676	0.9954	-17.6918	0.95	-3.433
14	1.032019	-16.0017996	1.034434	-16.0404276	0.9559	-18.7137	0.94	-3.153
15	1.025081	-16.0084462	1.027715	-16.0537189	0.9491	-18.7299	0.95	-2.269
16	1.03042	-15.6251032	1.033082	-15.6746218	0.9555	-18.28	0.944	-8.487
17	1.018756	-15.8686901	1.021943	-15.9313114	0.9441	-18.5714	0.93	-9.288
18	1.011447	-16.6066892	1.014414	-16.6575341	0.9352	-19.4195	0.93	-9.421
19	1.006565	-16.7658328	1.00969	-16.8193011	0.9306	-19.6063	0.93	-9.212
20	1.009498	-16.5502256	1.01269	-16.6067776	0.9339	-19.3581	0.93	-8.772
21	1.008194	-16.2177504	1.011547	-16.2801428	0.9328	-18.9821	0.93	-8.560
22	1.011956	-15.9810835	1.015582	-16.0477055	0.9372	-18.7111	0.93	-3.583
23	1.008549	-16.2294051	1.011838	-16.284519	0.9331	-18.9957	0.92	-3.851
24	0.999085	-16.3006777	1.002966	-16.3608574	0.9231	-19.0788	0.927	-4.201
25	1.003182	-16.0719602	1.008218	-16.1428936	0.927	-18.7784	0.907	-4.913
26	0.985245	-16.5037665	0.990373	-16.5709447	0.907	-19.2593	0.93	-5.551
27	1.014454	-15.6558669	1.020172	-15.7364827	0.9395	-18.2962	0.93	-7.302
28	1.007787	-11.7163327	1.014339	-11.8374387	0.9398	-13.791	0.917	-4.319
29	0.994424	-16.9076742	1.00027	-16.9710178	0.9177	-19.7604	0.90	-7.089
30	0.98284	-17.8067089	0.988771	-17.8592266	0.9051	-20.8172	0.9	0.000

V. CONCLUSION

This paper explains how to use the grey wolf algorithm approach to estimate the status of a power system using PMU readings. This work observes false data injection attacks on a hybrid state estimator and develops a mechanism for injecting false data based on CSA method. It has been demonstrated that tainted data may bypass conventional bad data detection methods. Corrective steps are conducted when the system operator determines that the system is performing abnormally. With the use of supporting theory and simulations on IEEE-14 and IEEE-30 bus systems, when estimating using grey wolf algorithm, the error is shown to be much lower (more accurate) than WLS. The results reveal that angle measurements can significantly improve the state estimation algorithm's performance. Due to the fact that the measurement vector in classical state estimation is a non-linear function of the state vector, iterative techniques are required to solve for the state vector, which increases solution time. Phasor measurements are found at a post-processing stage, which allows for faster computations. WLS and CSA (voltage and current phasors) are two methods of traditional state estimation that produce a set of measures that are linear functions of the state vector.

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