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State Estimation for Electric Power System with Load Uncertainty and False Data Using Cuckoo Search Algorithm

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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 cuckoo 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 analyses 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 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. On IEEE 14-bus and 30-bus test systems, simulations are run to show how well the method works.

Keywords- State Estimation, Cuckoo Search algorithm, Phasor Measurement Unit, Fake Data Injection and Energy Management Systems.

I. INTRODUCTION

The power system state estimation (SE) is an essential instrument 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].Through hacked meters and sensors, the adversary could provide bogus measurement reports to interfere with the operation of the smart grid. False data injection attacks are those attacks. It may impede the estimate of the grid system's state. It might mess with how electricity is distributed. 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

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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., simultaneous connection 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. In this method, fewer phasor measurement units (PMUs) are required to achieve the same estimation error as well as power flow equations are not embedded into the estimator. By taking packet losses into account, the interconnected optimal filtering problem for distributed dynamic SE based on the mean squared error between the real and estimated states is examine. [14], [15]. Specifically, a cuckoo search algorithm (CSA) 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 [16]. These results show that the Cuckoo search algorithm is superior to traditional methods in spotting 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. Lévy 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 to the IEEE 14 bus and 30 bus systems and comparing them to results from other methods in the literature are shown and discussed. In this paper Section 1 explained Introduction, Section 2 gives the methodology of WLS State estimation, Section 3 introduces the optimization algorithm and Section 4 gives the results and analysis follows conclusion.

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, non-linear purposes 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 purpose of 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.

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

The optimal estimation is obtained by iterations till the value of Δx^{k+1} is within a predefined tolerant range; otherwise, a new iteration process will start from x^{k+1} again. The flowchart which shows the general steps of the WLS process is depicted in Fig. 1.

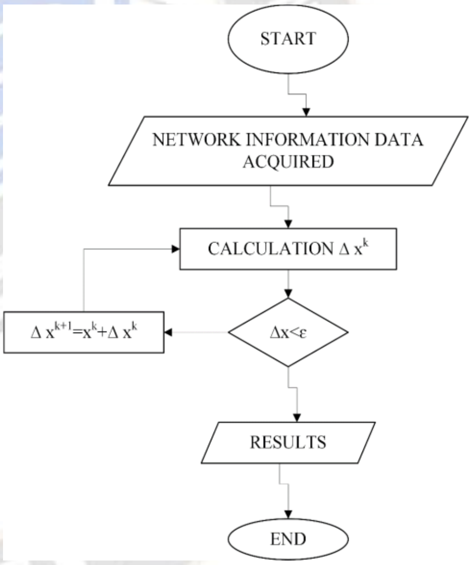

Figure 1: Flowchart of state estimation algorithm

III. OPTIMIZATION ALGORITHMS

3.1 Cuckoo Search Methodology

The Cuckoo Search algorithm has attracted the attention of academics because of its potential for efficiency in practical applications and its ability to tackle a variety of optimal issues. The following three rules [18] outline the standard Cuckoo Search: The nests that have the highest quality eggs are sent on to the next stage, where the bird may find a cuckoo's egg and establish paternity (0, 1). The host bird must then choose whether to abandon the egg or remove it. Figure 1 is a flowchart depiction of the Cuckoo search algorithm, which operates under three predetermined constraints. What sets

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CSA apart from other similar algorithms is its capacity to mix locally and globally random walks in response to a changing variable, which speeds up the time it takes to reach global optimums. The ratio of local to global random walks is determined by the switching parameter pa ε [0, 1], which is related conceptually to Equation.

$$v_i^{t+1} = v_i^t + \alpha s H(P_a - \epsilon) X(v_j^t - v_k^t) \quad (7)$$

$$v_i^{t+1} = v_i^t + \alpha L(m.\lambda) \quad (8)$$

Here v_j^t, v_k^t are the current positions chosen at random; αis the generation of multiple paths in a stepwise fashion; m is the step size; H is the large-side function; Pa is the parameter for transitioning between local and global random walks; and is a random integer chosen from a uniform distribution [19-22]. The Levy distribution L (m, λ) specifies the step size of a random walk. Levy battles, with its casual stages generated by a Levy delivery, effectively allow a random walk for big steps. Using Mantegna's computations with the gamma distributions defined by to find the optimal balance between local and global random walks is the most effective method for generating step weights[20].

$$\lambda = \{|[\Gamma(1+\beta)sin(\Pi\beta/2)]/[\gamma(1+\beta)/2)\beta.2^{\alpha-1/2}]|\}^{1/\beta} \quad (9)$$

where γ [] is distribution function and β=3/2

A. Solution Approach Using CSA

The capacity to spot and fix erroneous information is also evaluated here. The given estimator is evaluated alongside the weighted least squares and Cuckoo Search algorithms. The results show that the Cuckoo search algorithm is superior to traditional methods in spotting and fixing inaccurate data, as well as in terms of accuracy and complexity [23]. It's a plus if you're in good shape. Every cycle, new information is added to the line database, including readings from the generator buses, tap-changer ratios, shunt MVAR injections, System regulating factors, and power injections at the incident buses. Using the NR power flow explanation, one may get the global unbiased function indicated by Eq. by calculating total real power loss, regular VCPI [24-25], and normal voltage deviation index.

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 favor 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.
- An objective function plus penalized constraints multiplied by a penalty factor makes 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.

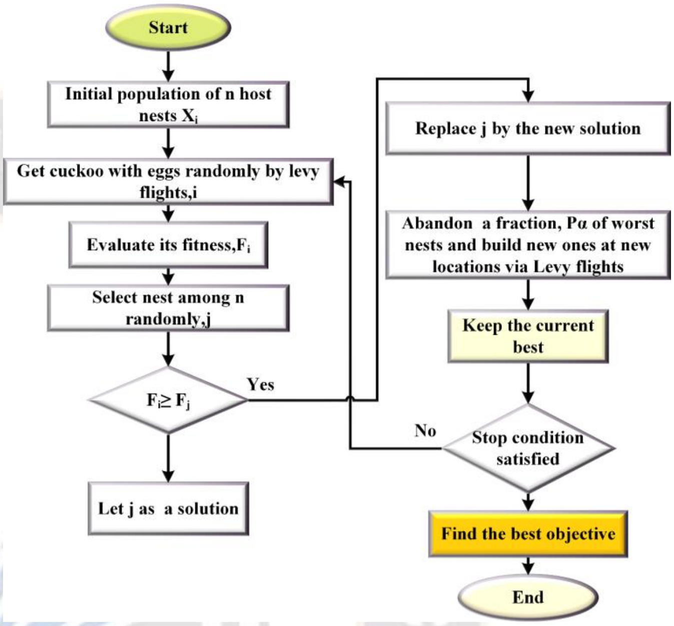

Figure 2: Flowchart for CSA approach for solving OPF problem

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 utilize 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 00 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. it shows the variation and reducing the errors of Voltage magnitude

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error and phase angle error using WLS and CSA compared to WLS, CSA reduced the error margin of voltage magnitude and phase angle error.

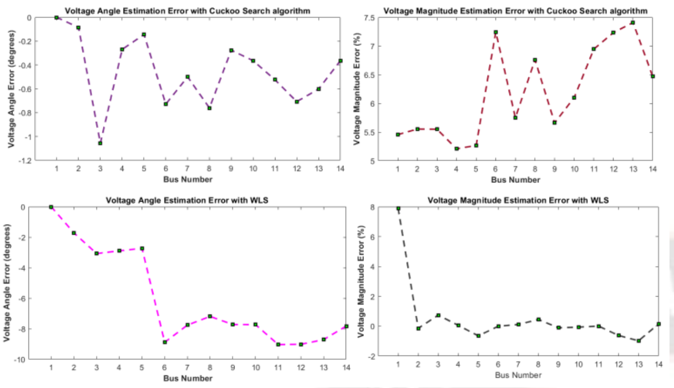

Figure 3: Voltage magnitude and angle estimation errors with WLS and CSA

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

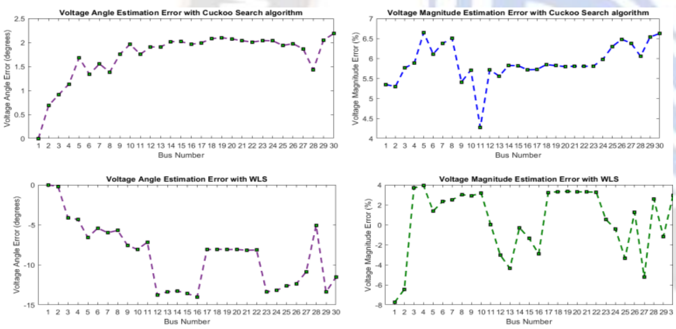

Figure 4: Voltage magnitude estimation errors with WLS and with CSA

Table1: Voltage magnitude estimation errors and angle error with WLS and with CSA for IEEE-14 bus system.

BUS No.	With NR-method		With WLS		With CSA	
	V (pu)	Angle (Degree)	V (pu)	Angle (Degree)	V (pu)	Angle (Degree)
1	1.05	0	0.99	0	0.97	0
2	1.03	-5.09	0.97	-5.00	1.03	-3.38
3	1.00	-13.06	0.94	-12.01	0.99	-10.00
4	1.00	-10.45	0.95	-10.19	1.00	-7.57
5	1.00	-8.94	0.95	-8.80	1.01	-6.21
6	1.06	-14.73	0.98	-14.01	1.05	-5.84
7	1.03	-13.51	0.97	-13.01	1.03	-5.75
8	1.07	-13.51	1.00	-12.75	1.06	-6.32
9	1.02	-15.12	0.96	-14.85	1.02	-7.406
10	1.01	-15.34	0.95	-14.98	1.02	-7.61
11	1.03	-15.16	0.96	-14.63	1.03	-6.12
12	1.04	-15.60	0.97	-14.89	1.04	-6.58
13	1.03	-15.64	0.96	-15.03	1.04	-6.92
14	1.00	-16.40	0.94	-16.03	1.00	-8.57

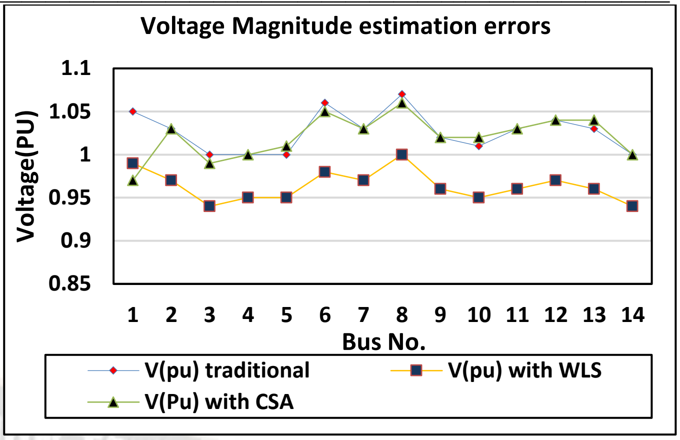

Figure 5: Comparisons results of Voltage Magnitude estimation errors with Traditional, with WLS and with CSA for IEEE-14 bus system

Fig.5 depicts the comparison of voltage variation in per unit with Traditional ,WLS and CSA. The results reveal that voltage magnitude can significantly improve the state estimation algorithm's performance.

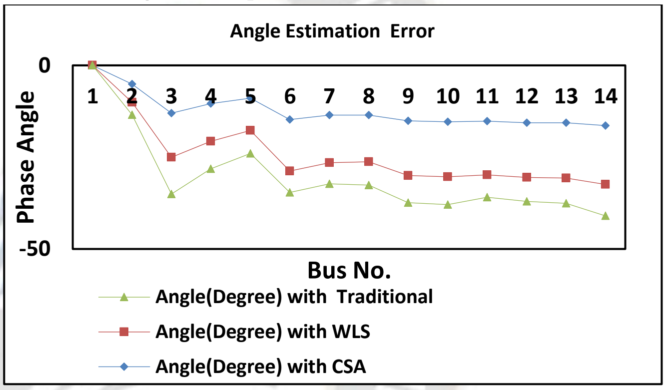

Figure 6: Comparisons results of Angle estimation errors with Traditional, with WLS and with CSA for IEEE-14 bus system

Fig.6 depicts the comparison of angle Estimation Error for IEEE 14 bus with Traditional, WLS and CSA. The results reveal that angle measurements can significantly improve the state estimation algorithm's performance

Table2: Voltage magnitude estimation errors and angle error with WLS and with CSA for IEEE-30 bus system

Bus. No	With NR-method		With WLS		With CSA	
	V (pu)	Angle (Degree)	V (pu)	Angle (Degree)	V (pu)	Angle (Degree)
1	1.04	0.00	1.11	0.00	0.9	0.000
2	1.02	-5.58	1.08	-6.26	0.9	-5.363
3	1.01	-7.93	0.96	-8.84	0.94	-3.784
4	1.00	-9.77	0.95	-10.90	0.93	-5.449
5	1.00	-14.81	0.98	-16.49	0.93	-8.235
6	1.00	-11.66	0.97	-13.00	0.93	-6.254
7	0.99	-13.49	0.96	-15.04	0.92	-7.513
8	1.01	-12.58	0.97	-13.96	0.94	-6.883
9	1.02	-14.73	0.99	-16.48	0.966	-7.168
10	1.00	-16.38	0.97	-18.34	0.94	-8.308
11	1.05	-14.73	1.05	-16.48	1.00	-7.566
12	1.03	-15.79	1.06	-17.69	0.97	-2.010

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13	1.05	-15.79	1.09	-17.69	0.99	-2.407
14	1.01	-16.70	1.0	-18.71	0.95	-3.433
15	1.01	-16.71	1.02	-18.73	0.94	-3.153
16	1.01	-16.32	1.04	-18.28	0.95	-2.269
17	1.00	-16.58	0.96	-18.57	0.944	-8.487
18	0.99	-17.34	0.96	-19.42	0.93	-9.288
19	0.99	-17.51	0.95	-19.61	0.93	-9.421
20	0.99	-17.29	0.95	-19.36	0.93	-9.212
21	0.99	-16.95	0.95	-18.98	0.93	-8.772
22	1.00	-16.70	0.96	-18.71	0.93	-8.560
23	0.99	-16.96	0.98	-19.00	0.93	-3.583
24	0.98	-17.04	0.98	-19.08	0.92	-3.851
25	0.99	-16.84	1.02	-18.78	0.927	-4.201
26	0.97	-17.29	0.95	-19.26	0.907	-4.913
27	1.00	-16.43	1.05	-18.30	0.93	-5.551
28	1.00	-12.36	0.97	-13.79	0.93	-7.302
29	0.98	-17.71	0.99	-19.76	0.917	-4.319
30	0.97	-18.63	0.94	-20.82	0.90	-7.089

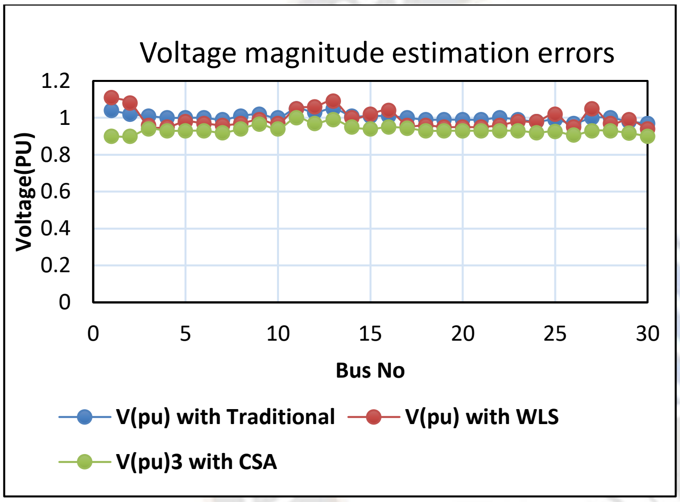

Figure 7 Comparisons results of voltage magnitude estimation errors with Traditional, with WLS and with CSA for IEEE-30 bus system

Fig.7 depicts the comparison of voltage variation in per unit with Traditional, WLS and CSA. The results reveal that voltage magnitude can significantly improve the state estimation algorithm's performance.

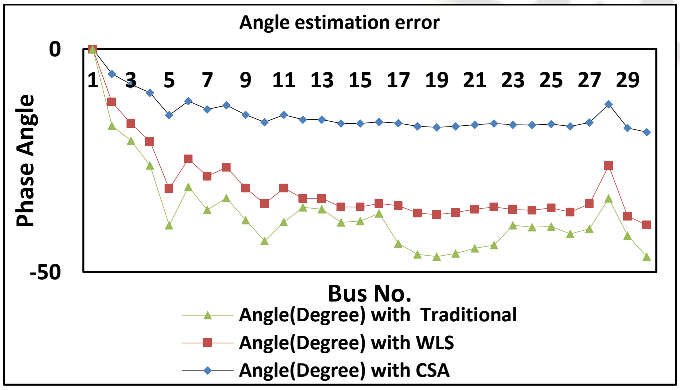

Figure 8 Comparisons results of Angle estimation errors with Traditional, with WLS and with CSA for IEEE-30 bus system

Fig.8 depicts the comparison of angle Estimation Error for IEEE 30bus with Traditional, WLS and CSA. The results reveal that angle measurements can significantly improve the state estimation algorithm's performance

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. 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. Due to the fact that the measurement vector in classical state estimation is a non-linear function of the state vector, it suggested to be 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.

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