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DEVELOPMENT OF AN IMPROVED BINARY CODED GENETIC-RITHM OPTIMAL PMU DEPLOYMENT FOR COMPLETE NETWORK OBSERVABILITY

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ABSTRACT

An Improved Binary Coded Genetic Algorithm for optimal Phasor Measurement Unit (PMU) deployment. A new PMU deployment optimizer was developed, and integrated into the conventional binary coded genetic algorithm (BCGA), to form an improved binary coded genetic algorithm (IBCGA), with high rate of convergence. This is applied for the optimal deployment of the PMUs in systems with different sizes and topologies (both mesh and radial). The Improved algorithm was developed and used to determine the optimal placement of PMU with the objective to minimize the total number of PMU for complete network observability. To ascertain its efficacy, the developed algorithm is applied to IEEE 14-bus mesh system and 33-bus, 69-bus radial systems. The results obtained for IEEE 33-bus and 69-bus system were validated by comparing the results obtained by the available literature, the proposed approach demonstrated effectiveness in the optimal PMU deployment.

1. INTRODUCTION

The imperative of power system observability cannot be overemphasized due to the growing need of reliable, well monitored and adequate power supplies to industries, homes and government institutions etc. A secure operation and control of the power systems requires close monitoring of the system parameters. Hence a power system is observable only if all of its states/parameters can be uniquely determined [1, 3]. Before now, measuring phase angles of the bus voltage in real-time was practically impossible due to the technical difficulties in synchronizing measurements from distant locations.

In an attempt to have a better and a complete power system obeservability, state estimation was evolved. State Estimation (SE) is the process of estimating the state of networks from the telemetry measurements. State estimator has been widely used as an indispensable tool for online monitoring, analysis and control of power systems. With SE, one or several network parameters, whose accuracy is not certain, are obtained. The problem of State estimation is in that the precise state variables cannot be obtained due to the structure complexity and the large-scale nature of the real-life power systems [2]. In solving the problems of SE, several techniques were introduced which includes; Synchro-phasor technology, Remote Terminal Unit (RTU) of Supervisory Control and Data Acquisition (SCADA) systems, Phasor Measurement Unit (PMU), Wide-Area Securement/Monitoring System (WAMS) etc. [3-6].

PMU is more commonly used for state estimation as its Optimal PMU Placement (OPP) strategy achieves a near-optimal resolution for localizing faults for a given number of sensors. However, placing PMU sensors at all buses of the system can be expensive and uneconomical [3,].

This research proposed an Improved Binary Coded Genetic Algorithm (IBCGA) based for the optimal deployment of Phasor Measurement Unit (PMU) for complete power system observability. This approach would reduce cost of deployments of PMU with improved power observability.

2. STATE ESTIMATION OF POWER SYSTEM

Several researches have been carried out on state estimation for online monitoring, analysis and control of power systems. State Estimation (SE) is also exploited to filter redundant data, to eliminate incorrect measurements and to produce reliable state estimates. The need for improving power system network measurement redundancy is improve the accuracy of state estimation. The role of SE in power system network include; monitoring of operation status of a system accurately and provision of reliable data for advanced management software of active power system network such as dynamic control strategy, fault location identification, transient stability and voltage security visualization [8].

Earlier the entire power system measurements were obtained through Remote Terminal Unit (RTU) of Supervisory Control and Data Acquisition (SCADA) systems which have both analogue and logic measurements. This approach was designed to capture only quasi-steady state operating conditions limiting the monitoring of transient phenomenon and difficulty in synchronizing electrical measurement, thus an accurate estimation of electrical variable was impossible [4].

Due to the limitation posed by SCADA, other techniques evolved for SE of power system network, among them is Phasor Measurement Unit which is commonly used. Synchronized Phase Measurement Unit (PMU) is a monitoring device, which was first introduced in mid-1980s. It has the ability to synchronize signals from the global positioning system (GPS) satellites and provide the phasors of voltage and currents measured at a given substation. As the PMUs become more and more affordable, their utilization will increase not only for substation applications but also at the control centers for the EMS applications [9].

PMU can be employed in measurement of voltage phasor of the bus and associated branch current phasor (measurements) at high frequency. If PMU is installed on each bus, the network is said to be completely/fully observable. However, the cost implication is high to install PMU in all buses of the power network. For Optimal Phasor Measurement Unit Placement (OPP), an algorithm is needed to optimal place the PMU in a power networks in order to reduce the number of PMU needed for complete network observability [9]. The conventional binary coded genetic algorithm (BCGA), involves the minimization of a given objective function, subject to certain constraints, using three main optimization stages (reproduction, cross-over, and mutation). However, only two of these (cross-over, and mutation), are involved in the BCGA iterative optimization procedure. In general, the conventional BCGA if not improved, will result in slower rate of convergence (when applied to a multi-objective PMU deployment optimization), and can hardly converge to a global optimum solution. To avoid such case, alternative method called Improved Binary Coded Genetic Algorithm (IBCGA) has been proposed, which ensure optimality by filtering the infeasible solution. This filtration narrows the solution search space while still guiding the solution search procedure. Since complete network observability is one of the main objectives of this work, the conventional BCGA, being random in selection, may fail to achieve that especially for highly meshed networks.

3. PMU DEPLOYMENT PROBLEM FOMULATION FOR COMPLETE OBSERVABLITY

PMU deployment is aimed at measuring the states (voltage magnitude and angles) at the network buses/nodes. These states, if accurately known, can be used to evaluate the complete network power flow conditions, which comprises of the line/branch forward and reverse power flow; the bus injected power and the voltage magnitude itself. Therefore, the branch power flow; the bus injected power; and the voltage magnitude are usually termed as network measurements. Effective network monitoring and coordination is only possible if the network states and measurements can be accurately known or estimated at any given time. Optimum deployment of PMUs can simplify the measurement/estimation of complete network states, while still minimizing a set of predefined objectives. In this regard, a multi-objective improved binary coded genetic algorithm (IBCGA) is developed for optimum deployment of PMUs, in the presence/absence of supervisory control and data acquisition (SCADA) systems based measurement and/or zero injection buses (ZIBs), for complete network observability. In general, the complexity of PMU deployment problem is of the order $\left(2^{B}-1\right)$, where B represents the number of network buses. This implies that, for a 5-bus network, a total of 31 solutions are possible, most of which have the same number of PMUs. However, the locations differ. This necessitates the development of a suitable set of objective function that could minimize the number of PMUs while optimizing both redundancy and observability.

4. OPTIMAL PLACEMENT OF PMU

PMU placement is not required to place in all the buses of the power system to make it completely observable. PMU Observability may be classified as Numerical Observability, Topological Observability and Hybrid Observability [10]. In this paper topological observability is taking into account. When PMU is placed at a bus, the voltage and current phsaor is known for that particular. If Voltage and current phasor of one end of the branch is known, then the other side may be computed easily by using Ohms' law. This shows if a PMU is placed at one bus, then the busses incident to PMU installed bus also become observable. When there is no current injection at a bus, the power flow in any one of the incident lines can theoretically be calculated by using Kirchhoff's current law (KCL), when the power flow in the remaining of the connected lines are known [11]. Conventionally, for an n-bus system, the PMU placement problem can be formulated using Equation (1)

$$\min \sum_{i}^{n} w_i * x_i \qquad s.t.\dots f(X) \geq \hat{I} \tag{1}$$

Where X is a binary decision variable column vector, whose entries are defined using Equation (2):

$$x_i = \begin{cases} 1 & if \quad a \quad PMU \quad is \quad installed \quad at \quad bus i \\ 0 & otherwise \end{cases} \tag{2}$$

w_i is the cost of the PMU installed at bus i.

$f(X)$ is a column vector function, whose entries are non-zero if the corresponding bus voltage is solvable using the given measurement set and zero otherwise. $\hat{I}$ is a column vector whose entries are all ones [12].

5. PMU DEPLOYMENT MULTI-OBJECTIVE FUNCTION

Conventionally, the objective function of PMU deployment is to minimize the number PMUs deployed subject to the observability constraints. It is possible to minimize the number of PMU deployed while still improving the redundancy in observability, which in turn increase the network reliability. In this work, a multi-objective optimization is developed for optimal PMU deployment, for complete network observability. The objective function comprised of four separate objective functions as represented using equation (3). The constraints of the optimization problem are also modeled as one of the four separate objective functions.

$$\underset{X^{PMU}, X^{ZIB}, X^{SCADA}}{Minimize:} F_{Obj} = \frac{1}{N^2} \cdot \left(f_{PMU}\left(X^{PMU}\right) + f_{WLSSE}\left(X^{PMU}\right) + f_{Consts}\left(X^{PMU}\right)\right) + F_{\mathrm{Alg-1}}^{X^{PMU}}$$

(3)

Where N represents the total number of network buses, and $X^{PMU}, X^{ZIB}, X^{SCADA}$ are binary column vectors (with N elements) which are used to represent the presence/absence of PMU, ZIB, and/or SCADA information at a given bus in a network. $f_{PMU}(X^{PMU})$ represents the PMU deployment objective function defined by equation (4), $f_{WLSSE}(X^{PMU})$ represents the weighted least square state estimator (WLSSE) error objective function, $f_{Consts}(X^{PMU})$ represents the constraints objective function, $F_{\mathrm{Alg-1}}^{C_k^0}$ represent an optimization correction function defined for Algorithm-1, and F_{Obj} represents the overall multi-objective optimization objective function of the proposed optimal PMU deployment algorithm.

5.1. PMU Deployment Objective Function

In equation (4), the total number of PMU deployed can be minimized by optimizing the three functions $f_1^{PMU}(X^{PMU})$, $f_2^{PMU}(X^{PMU})$, and $f_3^{PMU}(X^{PMU})$. Furthermore, $f_1^{PMU}(X^{PMU})$ attempt to directly optimize the total number PMUs deployed. $f_2^{PMU}(X^{PMU})$ attempt to optimize the number of PMUs by minimizing the redundancy in observability (the number of times a network bus can be observed). Finally, $f_3^{PMU}(X^{PMU})$ attempt to optimize the number of PMUs by minimizing the standard deviation of the observability matrix.

$$f_{PMU}\left(X^{PMU}\right)= f_1^{PMU}\left(X^{PMU}\right)+ f_2^{PMU}\left(X^{PMU}\right)+ f_3^{PMU}\left(X^{PMU}\right)$$
(4)

where

$$f_1^{PMU}\left(X^{PMU}\right)=\left(\sum_{b=1}^{N} X_b^{PMU}\right)^2 \quad (5)$$

Where

$$X_b^{PMU}=\begin{cases}1 & if \quad a \quad PMU \quad is \quad placed \quad at \quad bus \quad b\\ 0 & otherwise\end{cases} \quad (6)$$

Where X_b^{PMU} is the ***b***th element in X^{PMU}

$$f_2^{PMU}\left(X^{PMU}\right)=\sum_{\substack{b=1\\ j=1}}^{N} A_{b,j}.X_b^{PMU} \quad (7)$$

where

$$A_{b,j}=\begin{cases}1 & if \quad bus \quad b \quad and \quad j \quad are \quad connected\\ 0 & otherwise\end{cases} \quad (8)$$

and

$$f_3^{PMU}\left(X^{PMU}\right)=\sqrt{\frac{1}{N^3}.\sum_{b=1}^{N}\left(N.\sum_{k=1}^{N}A_{b,k}.X_k^{PMU}-f_2^{PMU}\left(X^{PMU}\right)\right)^2} \quad (9)$$

5.2. Weighted Least Square State Estimation (WLSSE) Objective Function: The second part of the overall objective function is designed to optimize the number of PMU deployed by minimizing the error in the state estimates obtained using the conventional WLSSE. This is described using equation (10). In this work, a WLS state estimation is proposed to ensure flexibility in PMU deployment optimization. State estimation requires network measurements as previously described in this chapter. This measurement can be obtained either through the PMUs deployed or the SCADA systems installed within the network.

$$f_{WLSSE}\left(X^{PMU}\right)=\left(\frac{100}{N}.\sum_{b}^{N}\left(\left|V_b^{True}\right|-\left|V_b^{Est}\right|\right)\right)^2+\left(\frac{100}{N}.\sum_{b}^{N}\left(\delta_b^{True}-\delta_b^{Est}\right)\right)^2 \quad (10)$$

where $\left|V_b^{True}\right|$ and δ_b^{True} represents the true values of voltage magnitude and angle at ***bus b*** respectively, whereas, $\left|V_b^{Est}\right|$ and δ_b^{Est} represents the estimated values of voltage magnitude and angle respectively. Equation (3.8) ensures good penalization of the overall objective function due to error in state estimation.

5.3. Constraint cost function: This function must be minimized to 0, to ensure total constraints satisfaction. It also ensures that every bus in the network is observable (i.e. every of the $2N$ states can be known). $f_{Consts}\left(X^{PMU}\right)$ can be evaluated using equation (11).

$$f_{Consts}\left(X^{PMU}\right)=\mu_{Const}.\sum_{b=1}^{N}\left(1-\min\left(f_{Const,b}^{Observ}\left(X_b^{PMU}\right),\ 1\right)\right) \quad (11)$$

where,

$$\mu_{Const}=\left(\sum_{\substack{b=1\\ j=1}}^{N}A_{b,j}\right)^2 \quad (12)$$

And,

$$f_{Const,b}^{Observ}\left(X_b^{PMU}\right)=\sum_{k=1}^{N}\left(A_{b,k}.X_k^{PMU}\right)+X_b^{ZIB}+X_{Inj,b}^{SCADA}+X_{Flo,b}^{SCADA}$$

where,

$$X_b^{ZIB}=\begin{cases}O_b^{ZIB} & if \quad b\in\left\{M^{ZIB}\cup\left[A_{b,j}=1\right]\right\}\\ 0 & otherwise\end{cases} \quad (13)$$

where $\left[A_{b,j}=1\right]$ contains all the neighbour of bus ***b*** (all the busses connected to ***b***).

$$O_b^{ZIB}=\min\left(\left(\prod_{\substack{j=1\\ j\neq b}}^{N}\left(\sum_{k=1}^{N}\left(A_{j,k}.X_k^{PMU}\right)\right)\right),\ 1\right) \quad (14)$$

Also $X_{Inj,b}^{SCADA}=\begin{cases}O_{Inj,b}^{SCADA} & if \quad b\in\left\{M_{Inj}^{SCADA}\cup\left[A_{b,j}=1\right]\right\}\\ 0 & otherwise\end{cases}$

(15)

where,

$$O_{Inj,b}^{SCADA} = O_b^{ZIB}$$

(16)

Finally,

$$X_{Flo,b}^{SCADA} = \begin{cases} \left(1 - O_{Flo,b}^{SCADA}\right) O_{Flo,j}^{SCADA} & if \quad [b,j] \in M_{Flo}^{SCADA} \\ 0 & otherwise \end{cases} \tag{17}$$

where,

$$O_{Flo,b}^{SCADA} = \min\left(\left(\left(\sum_{k=1}^{N} A_{b,k}.X_k^{PMU}\right) + X_b^{ZIB}\right) \ , \ 1\right) \tag{18}$$

In general, the PMU deployment cost function $f_{PMU}\left(X^{PMU}\right)$, the state estimation error cost function $f_{WLSSE}\left(X^{PMU}\right)$, and the constraints cost function $f_{Consts}\left(X^{PMU}\right)$, all directly/indirectly depends on X_b^{PMU}, X_b^{ZIB}, $X_{Inj,b}^{SCADA}$ and/or $X_{Flo,b}^{SCADA}$ which are all binary variables

6. DEVELOPED IMPROVED BINARY CODED GENETIC ALGORITHM (IBCGA)

The conventional binary coded genetic algorithm (BCGA), involves the minimization of a given objective function, subject to certain constraints, using three main optimization stages (reproduction, cross-over, and mutation). However, only two of these (cross-over, and mutation), are involved in the BCGA iterative optimization procedure. In general, the conventional BCGA if not improved, will result in slower rate of convergence (when applied to a multi-objective PMU deployment optimization), and can hardly converge to a global optimum solution. Narrowing the solution search space, and guiding the solution search procedure, could go a long way in improving its performance, while still guaranteeing its rate of convergence. In this regard, the conventional BCGA is improved to form an IBCGA, by modifying the reproduction stage and integrating it into the iterative procedure of the conventional BCGA, in order to guarantee and improve the rate of convergence to a true optimum solution. Let $\Re^{[1,N]}$ represent a random integer bounded by $1 \le \Re^{[1,N]} \le N$; Let N_C represents the number of chromosomes (candidate locations of PMUs) at each generation/Iteration; Let $a \to B$ denotes the addition of element *a*, to set *B and T* denote transpose. Note that X^0, is initialized as a row vector, with all its elements equals 1. Then the proposed reproduction stage can be achieved using Algorithm-1, which is designed to enforce constraints satisfaction while still optimizing both the total number of PMUs and redundancy, require for complete network observability. Algorithm-1 achieves this, by logically generating multiple solutions that minimizes equation (19).

$$F_{\mathrm{Alg}-1}^{C_k^0} = \frac{1}{N} \cdot \left(\frac{\sum_{b=1}^{N} C_{k,b}^0}{\sum_{b=1}^{N} f_{Const,b}^{Observ}\left(C_k^0\right)} \right) + f_{Consts}\left(C_k^0\right) \tag{19}$$

where $C_{k,b}^0$ represents an element at the *k*th row of the *b*th column in the candidate solution matrix (C^0). Figure 1 represents the flowchart of the improved binary coded genetic algorithm (IBCGA). Finally, Figure 3.2 can be used to illustrate the IBCGA based approach for optimal PMU deployment to achieve complete network observability.

Algorithm-1: Reproduction

1. ***Input:*** X^0, ***N and*** N_C
2. | $C = \{\ \}$
3. ***While1 the number of rows in C is less than*** $(N * N_C)$
4. | $C^0 = \{\ \}$
5. ***While2 the number of rows in*** C^0 ***is less than*** N_C
6. | $B = \{\ \}$
7. | $X_b^{PMU} = X^0$
8. | ***While3 the number of elements in B is less than N***
9. | | $b = \Re^{[1,N]}$
10. | | ***If1*** $b \notin B$
11. | | | $a \rightarrow B$
12. | | | $X_b^{PMU} = 0$
13. | | | ***If2*** $f_{Consts}\left(X^{PMU}\right) > 0$
14. | | | | $X_b^{PMU} = 1$
15. | | | ***EndIf2***
16. | | ***EndIf1***
17. | ***EndWhile3***
18. | ***If3*** $\left[X^{PMU}\right]^T \notin C^0$
19. | | $\left[X^{PMU}\right]^T \rightarrow C^0$
20. | ***EndIf3***
21. ***EndWhile2***
22. | ***Determine the best solution*** (C_{Best}^0) ***In*** C^0 ***that minimizes equation (3.28)***
23. | $C_{Best}^0 \rightarrow C$
24. ***EndWhile1***
25. | ***Select the best*** N_C ***solutions from C and store them in*** C_{Best}
26. ***Output:*** C_{Best}

The developed IBCGA as shown in Figure 1 ensure optimality by filtering the infeasible solution using Algorithm 1. This filtration narrows the solution search space while still guiding the solution search procedure. Since complete network observability is one of the main objectives of this work, the conventional BCGA, being random in selection, may fail to achieve that especially for highly meshed networks

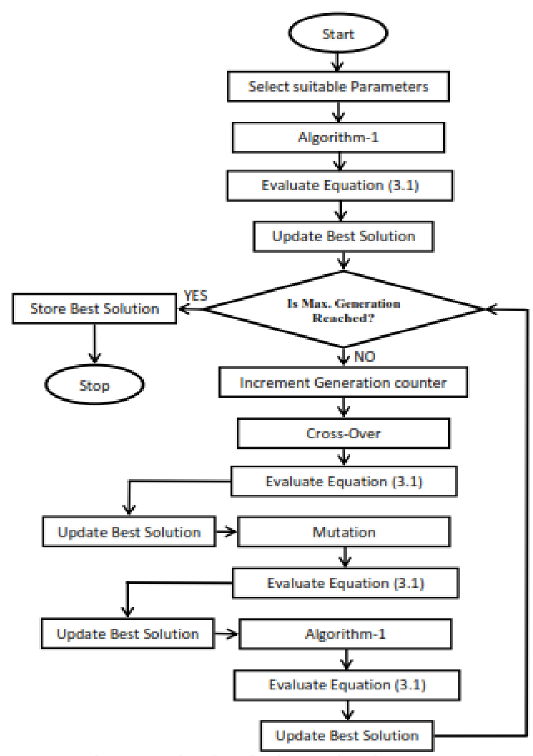

Fig.1: Flowchart for the Developed IBCGA.

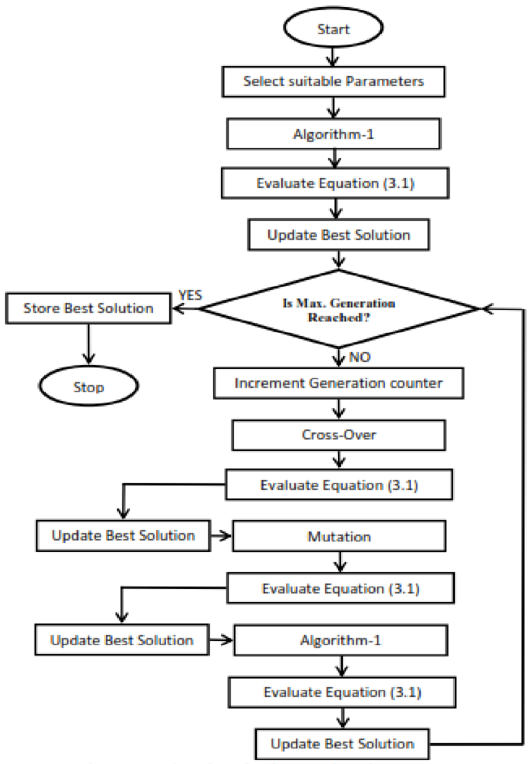

Fig. 2: Flow Chart for The IBCGA Based Multi-Objective Optimum PMU Deployment Algorithm.

7.0 RESULT ANALYSIS

The performance of the proposed IBCGA based PMU with other existing scheme was simulated, analyzed and compared. The simulation parameters for IBCGA Based PMU are shown in table 1 below;

Table 1: Simulation parameter for IBCGA based PMU

S/N	Parameters	Values
1	Software	MATLAB
2	IEEE BUS	33, 69
3	Optimal PMU placement (OPP)	0-31
4	Number of generation/iteration	100
5	Population of chromosomes	10
6	Mutation rate	25%
	Max no of iteration of WLSEE Algorithm	3
7	Selection probability	50%
8	Performance metrics	i. Number of PMU ii. Number of UOB iii. Objective constraint iv. Converge objective function v. Weighted Least Square

7.1. Case-Study/Test Systems

In this work, three test systems were employed to investigate and demonstrated the performance of the proposed IBCGA based optimal PMU deployment approach

7.2. Case: The 14-Bus Mesh System

Here, three scenarios were also simulated, and the results are presented in Table 2. At first, the condition for convergence was set to $f_{WLSSE} \le 1$, or that the Mean Absolute Deviation (MAD) in state estimates given by $MAD = 0.01\sqrt{f_{WLSSE}} \le 0.01pu$. The first solution was obtained by enforcing a convergence criteria of $MAD \le 0.01$, whereas, the second and third solutions were only limited by the maximum number of generations/iterations. It can be observed that the least number of PMUs required for complete network observability is 4, whereas, an additional PMU is required at bus 5, if the ZIB is ignored. Furthermore, a total of 7 PMUs are required to satisfy both the complete observability criteria and highly accurate state estimate. The SCADA branch power flow and bus power injections were not considered

Table 2: Optimal PMU Deployment Results for 14-Bus Meshed Network

PMU-Buses	F_{Obj}	f_{PMU}	f_{WLSSE}	f_{Const}	$F_{Alg-1}^{C_k^0}$	*MAD*	ZIBs
3 4 5 6 7 9 14	0.6359	121	0.0307	0	0.0153	0.0018	1
4 6 7 9	0.4749	83	6.9071	0	0.0139	0.0263	1
4 5 6 7 9	0.4761	83	6.9071	0	0.0152	0.0263	Non

Table 3. Results for 33-bus Radial Network

Method /Reference	Number of PMUs	PMU-Buses	UOB without ZIB & SCADA	F_{Obj}	f_{PMU}	f_{WLSSE}	f_{Con}	$F_{Alg-1}^{C_k^0}$	*MAD*
IBCGA Solution-1	11	2 6 9 12 15 17 21 24 28 29 32	4	0.6629	181	534	0	0.0056	0.2312
IBCGA Solution-2	12	2 3 6 9 11 14 17 21 24 26 29 32	Non	9.8358	181	10524	0	0.0056	1
[8] Economy	10	2 8 11 15 17 20 24 26 30 32	4 5 13 22 28	9420	155	2120	9409	9409	0.4604
[8] Compromise	11	2 4 8 11 15 17 20 24 26 30 32	13 22 28	1.8209	181	1796	0	0.0056	0.4238
[13]	12	2 6 8 11 15 17 21 24 28 29 32	4 13	0.5885	181	453	0	0.0057	0.2129
[14]	14	2 4 6 8 11 13 15 17 21 23 24 27 29 32	Non	2.1878	181	2195	0	0.0057	0.4685
[15]	11	2 5 8 11 14 17 21 24 27 30 32	Non	1.6707	180	1633	0	0.0055	0.4041

7.3 COMPARATIVE ANALYSIS OF THE IBCGA BASED OPTIMAL PMU DEPLOYMENT

In order to compare the performance of the developed IBCGA based optimal PMU deployment strategy, with other similar algorithms, 3 of the most recent similar literatures with the best performing PMU deployment strategies, were considered for comparison, based on the PMU deployment solutions of the standard IEEE 33, and 69-Bus networks. These literatures include [8],[13],[14] and [15].To achieve this, 5 performance metrics which includes number of PMUs, number of unobserved buses (UOB) without ZIB and SCADA data, the converged value of objective function, observability constraints cost function, and the mean absolute deviation (MAD) in state estimate can be considered

It can be observed in Table 3 above that a minimum of 11 PMUs are required for complete observability of the 33-Bus network. This is because the 10-PMUs solution reported in [8] does not satisfy the complete network observability criteria ($f_{Const} = 9409 > 0$). Despite the unobserved bus (bus 4) in the absence of both ZIBs and SCADA data, the IBCGA Solution-1 represents the best solution for the 33-Bus network. This is because, it uses 11-PMUs to achieve relative lower values of F_{Obj}, MAD, while still ensuring that $f_{Const} = 0$. However, the solution having the least value of F_{Obj}, presented by [13], made use of 12-PMUs and has 2 unobservable buses (4, and 13).

Whereas, the solution presented by [15] can be observed to have both a higher F_{Obj}, and poor state estimation accuracy. Furthermore, the IBCGA Solution-2 can be seen to have no unobserved bus in the absence of ZIBs and SCADA data using only 12-buses. The two 33-Bus network PMU deployment solutions presented in Table 4.6, has demonstrated a relatively better performance of the proposed IBCGA based PMU deployment strategy over the existing similar algorithms. Finally, for the 33-Bus network case, the order of performance of the methods/approached is: IBCGA > [15]>[8] > [13] > [14]

Table 4. Results for 69-Bus Radial Network

Method /Reference	Number of PMUs	PMU-Buses	UOB without ZIB & SCADA	F_{Obj}	f_{PMU}	f_{WLSSE}	f_{Const}	$F_{Alg-1}^{C_k^0}$	*MAD*
IBCGA Solution-3	22	3 4 8 11 12 15 18 22 26 30 34 38 42 45 48 51 53 55 57 62 64 68	1 6 20 24 32 60 66	0.2178	654	111	0	0.0026	0.1053
[8] Economy	22	2, 3, 8, 11, 14, 17, 22, 26, 28, 33, 34, 37, 41, 45, 49, 51, 56, 59, 62, 64, 66, 68	5 6 19 20 24 30 31 39 43 47 53 54 57 58	504406	601	371	504300	504300	0.1925
[8] Compromise	23	2, 3, 8, 11, 12, 14, 17, 22, 26, 28, 33, 34, 37, 41, 45, 49, 51, 56, 59, 62, 64, 66, 68	5 6 19 20 24 30 31 39 43 47 53 54 58	462372	652	47	462275	462275	0.0684
[13]	26	1, 4, 8, 14, 17, 19, 21, 24, 27, 28, 31, 34, 37, 39, 42, 45, 49, 51, 54, 56, 59, 61, 64, 66, 68, 69	6 10 11 12 47 57 58	210169	807	89	210125	210125	0.0941
[14]	27	1, 4, 5, 8, 9, 12, 15, 18, 20, 23, 26, 29, 32, 34, 37, 40, 42, 45, 49, 52, 53, 55, 58, 61, 64, 66, 69	39 47 59	42034	869	228	42025	42025	0.1510
[15]	25	2, 4, 7, 9, 14, 17, 20, 23, 26, 29, 32, 34, 37, 40, 43, 45, 49, 51, 54, 57, 58, 61, 64, 66, 68	11 39 47 55 56 59	168137	753	8980	168100	168100	0.9476

In the case of the 69-bus network, the entire solutions presented in Table 4 were achieved in the presence of ZIBs data. It can be observed in Table 4 that a minimum of 22 PMUs are required for complete observability of the 69-Bus network. Despite the 7 unobserved buses in the absence of ZIBs data, the IBCGA Solution-3 represents the best solution for the 69-Bus network. It also represents the only solution that satisfies complete network observability in the absence of both SCADA power injection measurements (PIM), and power flow measurements (PFM) data. Furthermore, it has the least values of F_{Obj}, f_{Const}, and f_{WLSSE}. In general, the developed approach has demonstrated superiority over the existing most recent similar algorithms. Finally, for the 69-Bus network case, the order of performance of the methods/approached is also: IBCGA > [8] >[15]> [13] > [14]

CONCLUSION

The proposed technique has been implemented using MATLAB as a programming tool. The optimal placement of PMU is performed in this paper using Improved Binary Coded Genetic algorithm has been used which shows reduction in number of PMU for complete network observability. A comparative study has been made with different optimization algorithm, and the proposed approach shows effectiveness in PMU deployment using standard IEEE bus 33 and 69 as shown in table 3 and 4. The test result indicates improved power system observability.

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