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Complete Observability Constrained Deployment of PMUs in Power System Network : Using an Upgraded Binary Grey Wolf Optimization Algorithm Approach

[1]M. Ravindra, [2]R. Srinivasa Rao, [3]V. Srinivasa Rao, [4]A. Ramesh

[1,4]Aditya College of Engineering, ADB Road, Surampalem, Kakinada, India.
[2]University College of Engineering, JNTUK, Kakinada, India.
[3]Aditya Engineering College (A), ADB Road, Surampalem, Kakinada, India.
[1]ravieeejntu@gmail.com,[2]srinivas.jntueee@gmail.com,
[3]connectvsr@gmail.com,[4]rameshadireddy@gmail.com.

Abstract

This paper presents an Upgraded Binary Grey Wolf Optimization(UBGWO) for optimal deployment of Phasor Measurement Units (PMU) in power system to obtain complete system observability. The cost increases with increase in allocation of PMUs at every bus, therefore PMUs should be allocated in optimal way so that complete system observability is obtained. The Redundancy of Bus Index (RBI) at every bus is considered to assess performance of every bus connected to the system. Complete System Observability Index (CSOI) is proposed to evaluate the complete performance of the proposed strategy to optimize PMU locations. The proposed UBGWO is programmed in MATLAB software and examined with IEEE 14, 30 and 57 bus networks to obtain complete system observability with optimal allocations. To validate the proposed method, the results are compared with standard methods.

Keywords: *BGWO, Complete Observability, Phasor Measurement Units, Synchrophasor Technology*

1. Introduction

State Estimation (SE) plays an important role protecting power system from blackouts. When compared to data provided by SCADA, Phasor Measurement Units (PMU) provides measurements with accuracy and with the time synchronization provided by Global Positioning Systems (GPS) [1]-[2]. The phasor measurements integrated with conventional measurements provide accurate states of the network. In grid network, it is high economical to place PMUs at every bus, so with optimal locations the Complete System observability is to be attained minimizing the cost of installation. So to minimize cost of PMUs for installation, PMUs should be allocated at optimal places through which network observability is not lost.

Sayedali Mirjallili [3] proposed a latest meta-heuristic grey wolve optimizer inspired by grey wolves. A binary grey wolve optimization is introduced by Emary [4] and is used for optimal feature selection. In recent publications some authors worked on complete network observability. The author [5] proposed the graph theory using vertices of the nodes to obtain complete observability. The author [6] proposed the optimized or reduced version of the exhaustive search to minimize the PMU deployment locations with complete observabiity. The author [7] proposed binary particle swarm optimization (BPSO) for OPP problem and to make the system full observable. The author [8] proposed the teaching- learning approach in which zero injection buses are considered to include and exclude to achieve complete observability of system.

This UBGWO algorithm is proposed with modifying the initialization of the program with initialization similar to Harmony Search Algorithm [13] and GWO [3] for optimal deployment of PMUs in network.

This paper presents Binary Grey Wolf Optimization for optimal PMU deployment in network to obtain complete observability. The channel redundancy at every bus is considered to obtain complete network observability.

2. Problem Formulation

The problem is computed for OPP to attain complete observability. UBGWO method is modeled with observability constraints for OPP in network. The optimum minimization problem is formulated as

$$\boldsymbol{Min} \sum_{j=1}^{N} C_j \boldsymbol{W_j} \tag{1}$$

Subject to $\boldsymbol{AW} \geq \boldsymbol{B}$ (2)

where

$\boldsymbol{C_j}$ is cost weight of PMU measured at bus $\boldsymbol{j}$,

$\boldsymbol{A_1}$ is matrix of order $\boldsymbol{N} \times \boldsymbol{N}$ consisting of buses connectivity,

N is number of buses,

$\boldsymbol{W} = [\boldsymbol{W_1} \quad \boldsymbol{W_2} \quad \boldsymbol{W_3} \quad \ldots \quad \boldsymbol{W_N}]^{\boldsymbol{T}}$ is a binary variable vector,

$\boldsymbol{B}$ is observability constraints which is written as $[1\ 1\ 1\ 1....1]^{\boldsymbol{T}}_{\boldsymbol{N}\times 1}$,

$\boldsymbol{W_j}$ is binary variable and $\boldsymbol{A}$ is incidence matrix which is of order $i \times j$ which is presented as

$$\boldsymbol{W_j} = \begin{cases} 1 & \text{if PMU is located at bus } \boldsymbol{j} \\ 0 & \text{otherwise} \end{cases}$$

$$\boldsymbol{A_{i,j}} = \begin{cases} 1 & \text{if } \boldsymbol{i} = \boldsymbol{j} \text{ or connected to each other} \\ 0 & \text{otherwise} \end{cases}.$$

2. Binary Grey Wolf Optimization

Grey wolf optimization is a swarm intelligent method established by mirjalili et al 2014, which simulates the leadership grading of wolves are well recognized for their cluster hunting. Grey wolves choose to live in pack, they have a firm communal leading hierarchy; the leader is called alpha ($\boldsymbol{\alpha}$).

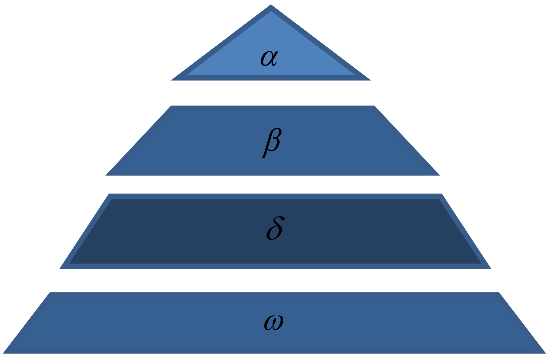
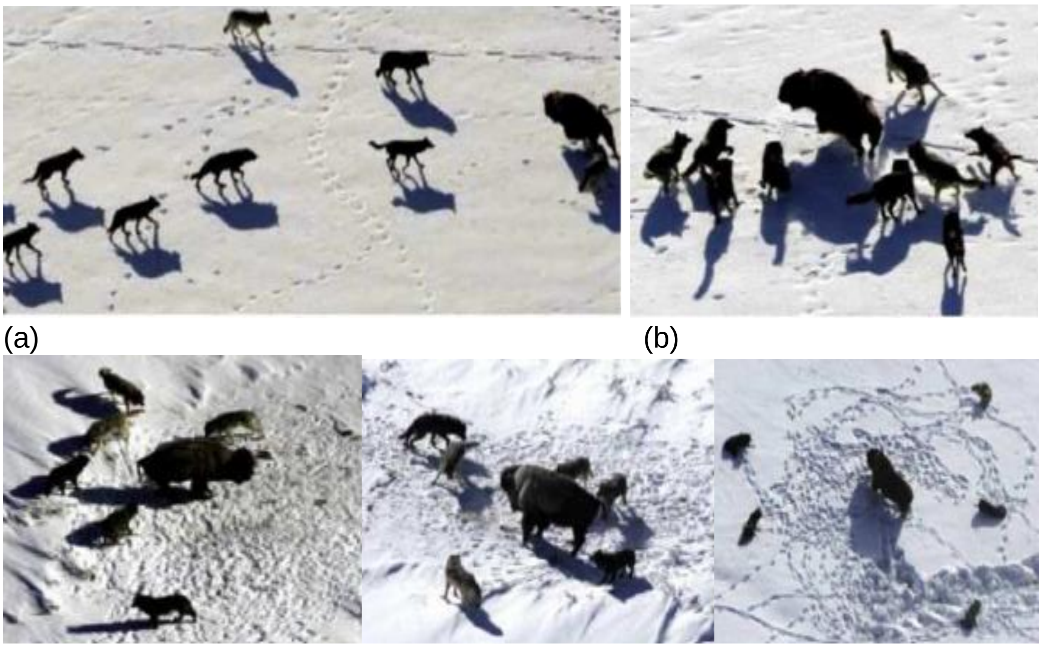


Figure 1. Grading of Grey Wolves



(a) (b) (c) (d) (e)

Figure 2. Hunting Action of Wolves[14]

The alpha is generally responsible for optimal constructing such as hunting, sleeping, wake up time etc. The alpha need not be strong but should be capable of managing pack. The instructions of leading wolf should be followed by pack. The Betas (β) are secondary wolves which aid alpha in decision making. The beta is a mentor to alpha and discipliner for pack. The lowest position in grey wolf is Omega (ω) which has to surrender to all other dominant wolves. The third most leader of pack is called delta. Delta(δ) wolves control omega and present reports to alpha and beta. The grading of grey wolves is shown in Figure 1.

The hunting methods and grading of wolves are mathematically considered to develop UBGWO and achieve optimization. The BGWO algorithm is verified with standard test functions that show that it has superior examination and exploitation characteristics than other swarm intelligence techniques.

Furthermore, the BGWO is effectively utilized for solving various applications in engineering. Moreover, most of methods that are used up to the date in optimization problems does not have leader to control over total period. This disadvantage is corrected in GWO in which grey wolves have usual leadership qualities. Further, this algorithm has less parameter only and easy to run program, which makes it superior than earlier ones. The GWO follows hunting actions and communal grading of grey wolves. In addition to communal sorting of grey wolves, pack hunting is another interesting group action of grey wolves.

The main sections of GWO are surrounding hunting and attacking prey as shown in Figure 2. The algorithmic steps of GWO are represented in this section as follows

Initialization: Initialize the BGWO parameters such as search agents (W_s), design variable size (W_d), Vectors A, a, C and Maximum iterations ($iter$).

$$\begin{aligned} \vec{A} &= 2\vec{a}\, rand_1 - \vec{a} \\ \vec{C} &= 2.rand_2 \end{aligned} \tag{3}$$

The value of $\vec{a}$ is reduced linearly from 2 to 0 during course of iterations.

Wolves Memory: The solution vector is assumed as a row vector $[W_1, W_2, W_3 ..... W_n]$ of n-bus generated with 1 random decision variables (0,1). Wolves randomly based on size of the pack. The wolves can be expressed as

$$wolves = \begin{bmatrix} W_1^1 & W_2^1 & W_3^1 & .. & .. & .. & W_{Wd-1}^1 & W_{Wd}^1 \\ W_1^2 & W_2^2 & W_3^3 & .. & .. & .. & W_{wd-1}^2 & W_{Wd}^2 \\ .. & .. & .. & .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. & .. & .. & .. \\ W_1^{Ws} & W_2^{Ws} & W_3^{Ws} & .. & ... & ... & W_{Wd-1}^{Ws} & W_{Wd}^{Ws} \end{bmatrix} \tag{4}$$

Where, W_j^i is the initial value the j^{th} pack of i^{th} wolves

***Fitness value*:** Estimate the fitness value of each agent using equation

$$\vec{D} = \left| \vec{C} . \vec{W}_p(t) - \vec{W}(t) \right| \tag{5}$$

$$\vec{W}(t+1) = \vec{W}_p(t) - \vec{A} . \vec{D} \tag{6}$$

Identifying the best hunt agent (W_α), the second best hunt agent (W_β) and third best hunt agent (W_δ) using equations

$$\vec{D}_\alpha = \left| \vec{C}_1 . \vec{W}_\alpha - \vec{W} \right| \tag{7}$$

$$\vec{D}_\beta = \left| \vec{C}_2 . \vec{W}_\beta - \vec{W} \right| \tag{8}$$

$$\vec{D}_\delta = \left| \vec{C}_3 . \vec{W}_\delta - \vec{W} \right| \tag{9}$$

Crossover: The main updating equation can be formulated as follows

$$W_1^{t+1} = crossover(W_1, W_2, W_3) \tag{10}$$

where W_1, W_2, W_3 are binary vectors signifying the consequence of wolfs transfer towards the α, β, δ grey wolves in order.

$$W_1^d = \begin{cases} 1 \;\; if \;\; (W_\alpha^d + bsp_\alpha^d) \geq 1 \\ 0 \qquad otherwise \end{cases} \tag{11}$$

where W_α^d is position vector of *alpha* (α) wolf in dimension d and bsp_α^d is binary step in dimension d that is formulated as in equation.

$$bsp_\alpha^d = \begin{cases} 1 \;\; if \;\; csp_\alpha^d \geq rand \\ 0 \qquad otherwise \end{cases} \tag{12}$$

where $rand$ is random number obtained from uniform distribution (0,1) and csp_α^d is continuous step computed from sigmoid function as shown in equation.

$$csp_\alpha^d = \frac{1}{1 + e^{-10(A_1^d D_\alpha^d - 0.5)}} \tag{13}$$

where A_1^d and D_α^d are computed in dimension d using equation 3 and 7.

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$$W_2^d = \begin{cases} 1 \ \ if \ \ (W_\beta^d + bsp_\beta^d) \geq 1 \\ 0 \qquad otherwise \end{cases} \tag{14}$$

where W_β^d is position vector of $beta(\beta)$ wolf in dimension d and bsp_α^d is binary step in dimension d that can be formulated as in equation.

$$bsp_\beta^d = \begin{cases} 1 \ \ if \ \ csp_\beta^d \geq rand \\ 0 \qquad otherwise \end{cases} \tag{15}$$

csp_β^d is continuous step computed from sigmoid function as shown in equation.

$$csp_\beta^d = \frac{1}{1 + e^{-10(A_1^d D_\beta^d - 0.5)}} \tag{16}$$

where A_1^d and D_β^d are computed in dimension d using equation 3 and 6.

$$W_3^d = \begin{cases} 1 \ \ if \ \ (W_\delta^d + bsp_\delta^d) \geq 1 \\ 0 \qquad otherwise \end{cases} \tag{17}$$

where W_δ^d is position vector of ***delta*** wolf in dimension d and bsp_α^d is binary step in dimension d that can be formulated as in equation,

$$bsp_\delta^d = \begin{cases} 1 \ \ if \ \ csp_\delta^d \geq rand \\ 0 \qquad otherwise \end{cases} \tag{18}$$

csp_δ^d is continuous step computed from sigmoid function as shown in equation

$$csp_\delta^d = \frac{1}{1 + e^{-10(A_1^d D_\delta^d - 0.5)}} \tag{19}$$

where A_1^d and D_δ^d are calculated in dimension d using equation 1 and 4.
location of current hunt agent using

$$\vec{W}(t+1) = \frac{\vec{W}_1 + \vec{W}_2 + \vec{W}_3}{3} \tag{20}$$

In this strategy of binary grey wolf, position vector is enforced to be binary

$$W_d^{t+1} = \begin{cases} 1 \ \ if \ \ sigmoid\left(\frac{W_1 + W_2 + W_3}{3}\right) \geq rand \\ 0 \qquad otherwise \end{cases} \tag{21}$$

The objective task is described as fitness value that satisfies constraints. The weight vector is used to define cost value depending on factor of installation and manufacture criteria.

$$Fitness(W) = \sum_{j=1}^{n} C_j W_j \tag{22}$$

where C_j is weight matrix in the form of a diagonal matrix, normally considered as a diagonal unit vector or weight can be increased or decreased i.e., range between 0 and 2.

Updating: update the values of $W_\alpha, W_\beta, W_\delta$ and updating of parameter a that controls tradeoff between exploration and exploitation. The parameter a is linearly updated in every iteration to range from 2 to zero.

$$a = 2 - t\frac{2}{Iter_{\max}} \tag{23}$$

Where t is iteration number and $Iter_{\max}$ is total number of iterations

Stopping criterion: check for stopping condition whether iteration reaches maximum, if it reaches maximum, print best value of solution.

3. Complete Observability constrained UBGWO for optimal deployment

The initial requirements for OPP are bus incidence matrix which defines the connectivity of buses in network considered,[B] as observability constraints. Solution [W], considered as row vector for allocation of PMUs. Binary Grey wolf memory is organized with 'P' Pack row vectors of n-bus system. Observability is checked at the stage of initializing size of Grey wolves (W) and at the end of the algorithm to obtain complete observability of system network. In initialization of problem, every row in matrix is measured as one pack, in which each row is considered as decision variable matrix to place PMUs. For cost analysis in problem the weight C_j considered is 1p.u and is presented as diagonal matrix.

The binary grey wolf optimization is programmed for optimal PMU deployment is presented in Fig 4. The parameters considered for 14-bus system is presented in Table 2.

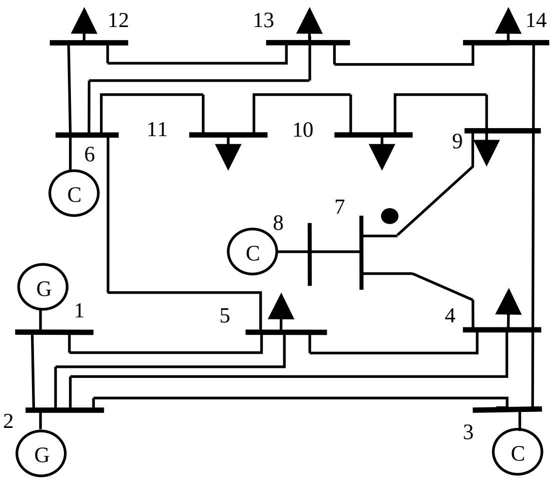

Figure 3. Single line diagram of 14-bus network

Table 1. Bus Network Data

Test Case	No of Branches	ZI Buses		Radial Buses	
		Total Buses	Bus No	Total Buses	Bus No
14-Bus system	20	1	7	1	8
30-Bus system	41	15	4,7,11,21,22,24,26, 34,36,37,39,40,45,46,48	3	11,13,26
57-Bus system	81	6	6,9,22,25,27,28	No radial buses	No radial buses

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Table 2. Parameters for UBGWO

Search Agents	14
No of Iterations	100
Dimensions	81
Search Domain	[0 1]

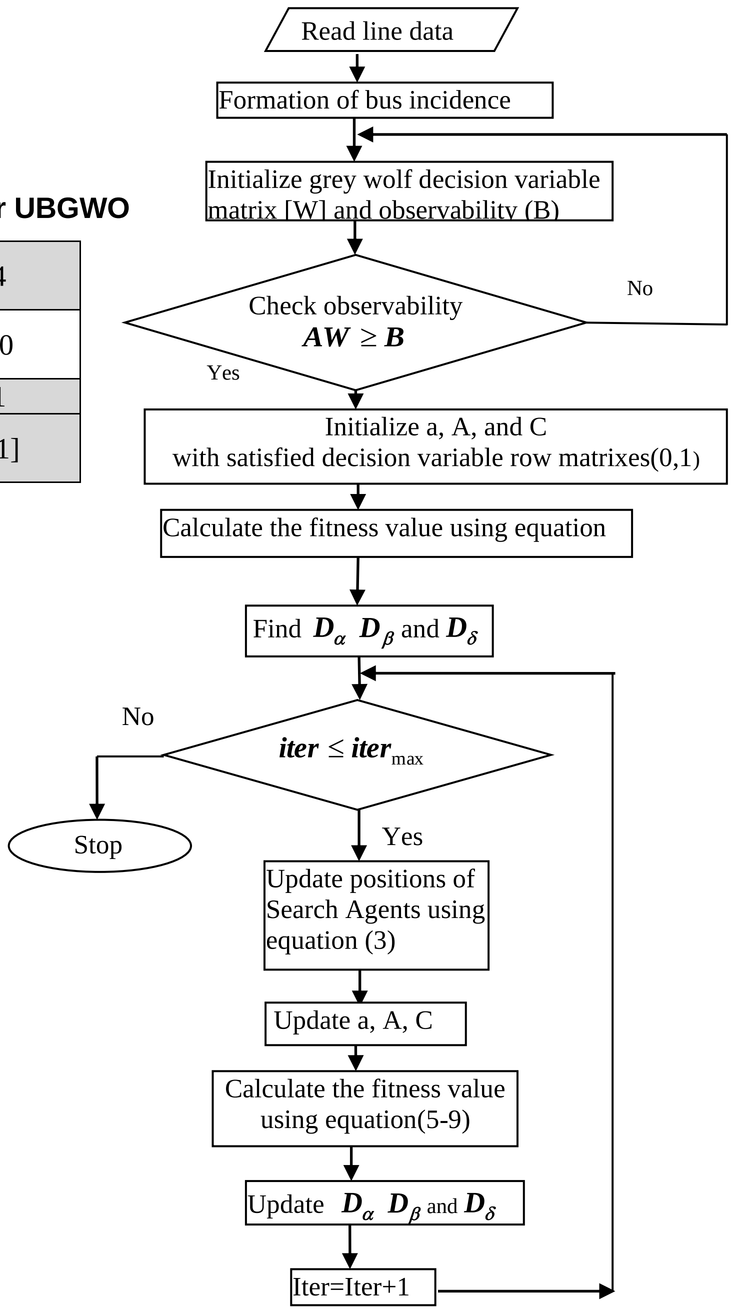

Figure 4. Flowchart of UBGWO for optimal PMU deployment

4. Results and Analysis

To allocate PMUs and check complete observability, three different large scale power system IEEE test cases such as 14, 30 and 57-bus test systems are considered to analyze applicability of suggested UBGWO. The optimal PMU deployment problem with UBGWO is programmed in MATLAB. UBGWO is modeled for deployment of PMUs in optimal locations to obtain redundant measurements. The bus network data of different bus systems is shown in Table 1. The single line diagram of 14-bus network is shown in Figure. 3.

Consider 14-bus IEEE network, for which convergence characteristics for 100 iterations with the alpha score obtained is shown in Fig 5. The alpha positions obtained for alpha score is shown in Table 3. Table 4 shows, minimum PMUs to obtain complete network observability.

Table 3. Alpha position in 14 bus network

Bus No	1	2	3	4	5	6	7	8	9	10	11	12	13	14
PMU Locations	0	1	0	0	0	1	0	1	1	0	0	0	0	0

Table 4. PMU deployment with UBGWO

Test Case	No .of PMUs	PMU Locations
14-Bus system	4	2,6,8,9
30-Bus system	9	1,7,9,12,19,24,25,27,29
57Bus system	16	1,4,6,13,19,22,25,29,32,36,39,41, 45,47,51,54

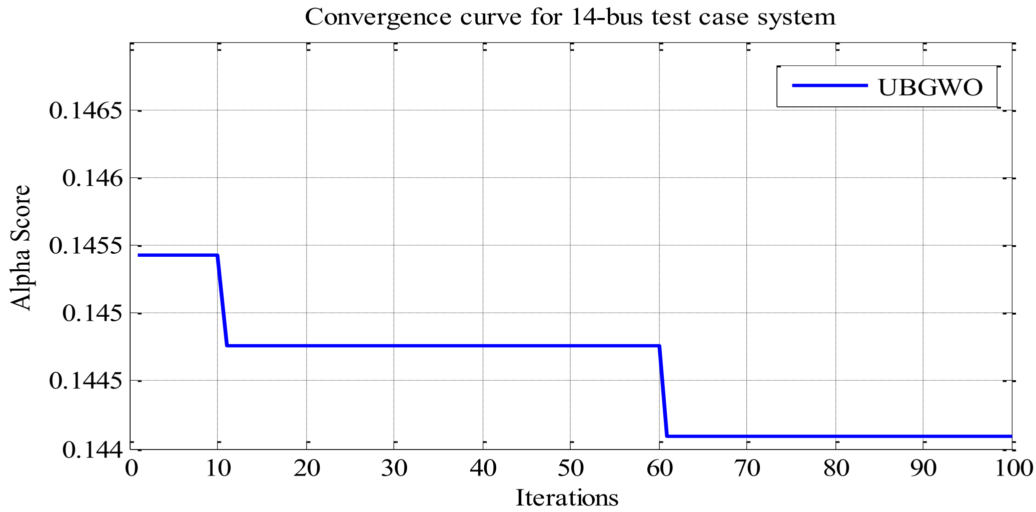

Figure 5. Convergence Characteristics of 14-bus system

RBI is computed at every bus to estimate number of times bus is observed by PMU to achieve complete network observability of bus network. RBI of network can be formulated as

$$\boldsymbol{RBI} = \sum_{j=1}^{N} [A]_{N\times N} * [W]_{N\times 1} \tag{22}$$

Performance of UBGWO approach for optimal deployment of PMUs can be computed with RBI for IEEE test case system is as follows. Table 5 presents RBI at every bus of 14-network. The power network is completely observable if every bus of network is observed by PMU by least one time.

Table 5. RBI for 14 Bus network

Bus No	1	2	3	4	5	6	7	8	9	10	11	12	13	14
RBI	1	1	1	2	2	1	2	1	1	1	1	1	1	1

4.1. Complete Observability Analysis

For large power networks, Complete System observability is obtained by two methods, one is through finding Jacobian matrix rank in SE process and other one is through network topology. Here in this work, the network topology is considered. Through this method every bus of network is checked with RBI to find the network whether it is optimal redundant. The limitation of RBI is measured as maximum number of channels or branches connected plus one [16].

$$\Re_j \leq \chi_j + 1 \tag{23}$$

For bus-*j*, *BOI* ($\Re$) gives number of PMUs placed to measure bus. Sum of $\Re$ at all buses of network gives Complete System Observability Index (CSOI) and is given as

$$\boldsymbol{CSOI} = \sum_{j=1}^{N} \Re_j \tag{24}$$

Maximum redundancy of bus can be presented as

$$\boldsymbol{Max} \sum_{j=1}^{N} \boldsymbol{B}^T \boldsymbol{A} \boldsymbol{W}_j \tag{25}$$

Subjected to following constraints

$$\sum_{l=1}^{N} \boldsymbol{W}_j = \partial_0 \tag{26}$$

where ∂_0 is minimum number of PMUs required for complete observability

Table 6. Complete System Observability

IEEE bus networks	Complete System Observability Index
14-bus	17
30-bus	50
57-bus	79

Table 7. Comparison of Proposed UBGWO with other methods for complete Observability

Method	14-bus system	30-bus system	57-bus System
Graph Theory[5]	4	10	-
Exhaustive Search[6]	4	10	-
BPSO[7]	4	10	-
Teaching Learning method[8]	4	10	17
Semi-definite programming[9]	4	10	-
Binary Cuckoo Search[10]	4	10	-
BIP[15]	5	10	20
Proposed	4	9	16

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RBI shows number of times every bus is measured by PMU. From RBI table, it is observed that bus with more number of branches connected is measured more times than bus with less number of branches connected. Table 6 shows CSOI of IEEE 14-bus, 30 and 57 bus networks. Table 7 shows the comparison of proposed UBGWO with other methods shown in literature that obtained optimal PMU locations with complete observability. With application of UBGWO method deployment, it is able to minimize number of PMUs in IEEE standard power networks obtaining complete observability.

5. Conclusion

This paper presented an Upgraded Binary Grey Wolf Optimization method, formulated considering redundancy and observability constraints for optimal PMU deployment. UBGWO approach is utilized to obtain Complete System observability with redundant number of measurements through deployment of PMUs at optimal places. The bus observability is performed at every bus through proposed Redundancy of Bus (RBI).The performance of complete bus network is evaluated through proposed Complete System Observability Index (CSOI). Power system networks such as IEEE 14-bus, 30-bus, and 57-bus networks are examined with proposed UBGWO method through which optimal locations are obtained for PMU deployment. This proposed method when compared with standard methods to show its effectiveness.

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Authors

Dr. M. Ravindra is an Assistant Professor in the Department of Electrical and Electronics Engineering at Aditya College of Engineering, ADB Road, Surampalem, Kakinada, A.P. India. His areas of interest include power system state estimation, power systems operation and control and electric power distribution systems.

Dr. R. Srinivasa Rao is a Professor in the Department of Electrical and Electronics Engineering at Jawaharlal Nehru Technological University, Kakinada, India. His areas of interest include electric power distribution systems and power systems operation and control and state estimation.

Dr. V. Srinivasa Rao received his B.Tech degree in Electrical and Electronics engineering from Kakatiya University, Andhra Pradesh, India in 2000. M.Tech in High Voltage Engineering (HVE) from JNTU College of Engineering, Kakinada, Andhra Pradesh, India in 2002. He received his Ph.D in power systems from JNTUK, Kakinada, India in 2016. Currently he is working as a Professor and HOD in the department of Electrical and Electronics Engineering, Aditya Engineering College (A), Surampalem, A.P. India. He is a life member of the Indian Society for Technical Education (ISTE). His areas of interest include power systems, control systems and energy systems.

Dr. A. Ramesh received his B. Tech in Electrical &Electronics Engineering and M.Tech in High Voltage Engineering from JNTU College of Engineering, Kakinada, Andhra Pradesh, India. He obtained his Ph. D from K.L. University India. His research interests are power electronics and electrical drives. Currently he is working as a Professor in the Department of Electrical and Electronics Engineering, Aditya College of Engineering, Surampalem, A.P. India. He is a life member of the Indian Society for Technical Education.