IUST
Iran University of Science and Technology

Iranian Journal of Electrical and Electronic Engineering

Journal Homepage: ijeee.iust.ac.ir

Optimal PMUs placement considering measurement Redundancy & Zero Injection Bus (ZIB) using multi-objective Harris Hawks optimization algorithm

Masoud Hashemi*, Mohsen Kalantar*(C.A.)

Abstract: The basis of the extensive measurement systems is based on the placement of phasor measurement units (PMUs) in the power grids. With the ever increasing expansion of electric energy consumption and the emergence of the phenomenon of restructuring in power grids and the existence of problems such as extensive blackouts of the power grid has increased the desire of power grid operators to use a wide area monitoring system (WAMS). This paper discusses the problem of optimal placement of phasor measurement units (PMUs) in power grids, which is a critical issue for the reliable and safe operation of power systems. We proposed a multi-objective binary optimization algorithm called the Multi-Objective Binary Harris Hawks Optimization algorithm based on Region selection (MOBHHO/R) to solve this problem. One of the most important innovations of the proposed algorithm is to draw inspiration from feature called a repository or archive to store optimal responses at each stage of the simulation. The algorithm aims to minimize the number of PMUs required while maximizing the observability of the power grids. The proposed algorithm is implemented on the standard IEEE 14 and 30 bus power systems, and the results show its superiority compared to other algorithms.

Keywords: Optimal PMU Placement, Harris Hawks Optimization, multi-objective optimization algorithm, Observability.

Introduction

Now, with the ever-increasing consumption of energy and the emergence of the phenomenon of restructuring in power grids and the problems resulting from them, it has caused the transfer of the power grid from its conventional and usual model to the smart grid, And this model transfer is carried out by a Wide Area Monitoring System (WAMS). The usual model uses a Supervisory Control and Data Acquisition (SCADA) system that cannot properly reflect the current operating conditions of the network due to the lack of synchronization of measurements. On the other hand, the increase in electric energy consumption and the emergence of the electricity market have caused the power grids to be exploited within their limits, in such a way that they have caused problems in the monitoring, control and protection functions of the SCADA system. Therefore, an international desire has been created both in the industrial dimension and in the academic dimension for the exploitation of conventional power grids in the form of smart grid based on WAMS, and on the other hand, one of the requirements of the smart grid is phase measurement, which is measured by the measurement unit. Phasor acquisition, which is a part of the WAMS system is not utilized today. Considering the high cost and budgetary limitations of power companies, installing PMUs in all buses is not cost-effective to ensure grid observability.

Iranian Journal of Electrical & Electronic Engineering, 2025.
Paper first received 10 Jan. 2025 and accepted 15 Feb. 2025.
* The authors are with the Department of Electrical Engineering, Iran University of Science and Technology (IUST), Tehran, Iran.
E-mails: masoudhashemi1997@yahoo.com
kalantar@iust.ac.ir
Corresponding Author: Mohsen Kalantar

Every year, many papers on phasor measurement units are published by prestigious journals in the world on the following topics:

- Optimal placement of PMU or OPP

- State estimation

- Data transmission and cyber security of data transmitted from PMU

The OPP problem has two basic goals in mind:

- Minimizing the number of PMUs

- Finding the best bus in the power grid to position PMUs for maximum observability

Therefore, the problem is an optimization and placement problem.

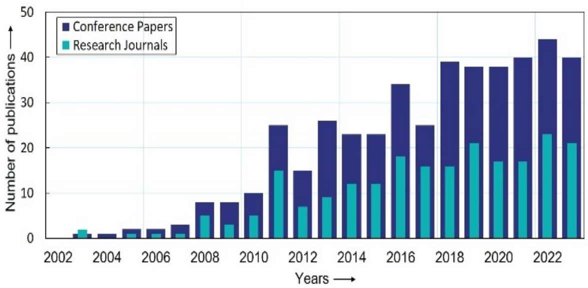


Fig 1. Number of papers published on OPP in important journals like IEEE, ITEES, IET and Elsevier during the years 2003-2023 [1]

Fig. 1 shows the number of papers published in the field of OPP in important journals such as IEEE, ITEES, IET and Elsevier during the years 2003-2023.

In a study, Viglassi et al [2], addressed the problem of optimal placement of PMU in order to maximize observability using a multi-objective evolutionary algorithm. In addition, this paper has investigated the placement problem by considering the effect of measurement redundancy. In the end, the performance of this method on IEEE 14, 30, 57 and 118 bus has been investigated.

Babu et al [3], addressed the problem of optimal placement of PMU using the Modified Branch and Bound Algorithm by considering the redundancy index. In this paper, the grid simulation is done through graph-based methods such as Depth-First Search, and on the other hand, the mentioned algorithm is done in two basic phases, the first phase is called initial search and parametric adjustment, and the second phase is final search. In the end, the performance of this method has been evaluated on IEEE14, 30, 39, 57 and 118 buses.

Yuvaraju and Thangavel [4], addressed the problem of optimal placement of PMU using the optimization algorithm Teaching–Learning Based Optimization (TLBO). In addition, this paper has investigated the problem of placement by considering the effect of zero connection bus. In the end, the performance of this method has been evaluated on IEEE 14, 24, 30, 57 and 118 buses.

Okendo et al [5], the problem of optimal placement of PMU by considering the observability redundancy index in Kenya's power grid. In addition, this paper has used the bee colony algorithm and Mixed Integer Linear Programming (ILP) to solve the problem of optimal placement of PMU. In the end, the performance of this method has been evaluated on IEEE 14 and 30 buses.

Johnson and Moger [6], addressed the problem of optimal placement of PMU by considering replacement indices of observability using the Crow Search Algorithm (CSA). In addition, this paper has investigated the problem of positioning by considering the effect of zero injection bus. In the end, the performance of this method on IEEE 14, 30, 57 and 72 buses has been investigated.

Tshenyego et al [7], addressed the problem of optimal PMU placement by considering observability redundancy indices using the binary firefly algorithm (PFA). In addition, this paper has investigated the positioning problem by considering the influence of the zero injection bus. Finally, the performance of this method has been evaluated on IEEE 14, 30, 39, 57 and 118 buses.

Musadiq et al [8], addressed the problem of optimal placement of PMU by considering observability indices using Integer linear Programming (ILP) algorithm. In addition, this paper has investigated the problem of positioning by considering the effect of zero injection bus. In the end, the performance of this method has been evaluated on IEEE 7, 14, 30, 39, 57 and 118 buses.

Therefore, according to the background and importance of the subject, the proposed method is described in the next section.

Unlike other papers, this paper uses a concept called archive or repository to maintain optimal or non-dominated responses at each stage of the simulation, which prevents the combination of optimal and non-optimal responses at each stage of the simulation.

In the following sections, more details on how to implement this algorithm and its structure will be presented. Also, the effect of using this approach in improving model performance is examined through experimental results.

2. Proposed method

Various methods for optimal placement of PMUs using meta-heuristic algorithms have been presented, but the focus of the proposed method is on the algorithm in which Harris Hawks algorithm is used to select the minimum number of PMUs for complete observation. Power grid considering zero Injection bus has been used. Harris Hawks optimization (HHO) algorithm was presented in 2019 by Heydari et al [9], inspired by the hunting method of a species of Hawk, to solve various optimization problems. Among the features of this algorithm, it can be mentioned that it is efficient, acceptable, simple and easy to implement. This algorithm has only one relationship between the two phases of exploration and exploitation. The adaptation of this model is done during iterations, which is the algorithm that allows to explore most of the search space in the search and then exploits promising areas in the final stages. The main part of the HHO algorithm is inspired by the cooperative behavior and pursuit method of Harris hawks in the wild called surprise attack. In this intelligent strategy, several hawks coordinately surprise a prey (often a rabbit) from different directions to hunt. The Harris's hawk can follow multiple patterns based on the dynamic nature of the scenarios and the prey's escape patterns. This process logically imitates such dynamic patterns and behaviors to develop an optimization algorithm [9]. This algorithm is a population-based and gradient-independent optimization technique. Therefore, it can be used for any optimization problem provided there is a suitable formula. Fig. 2, shows all steps of HHO algorithm [9].

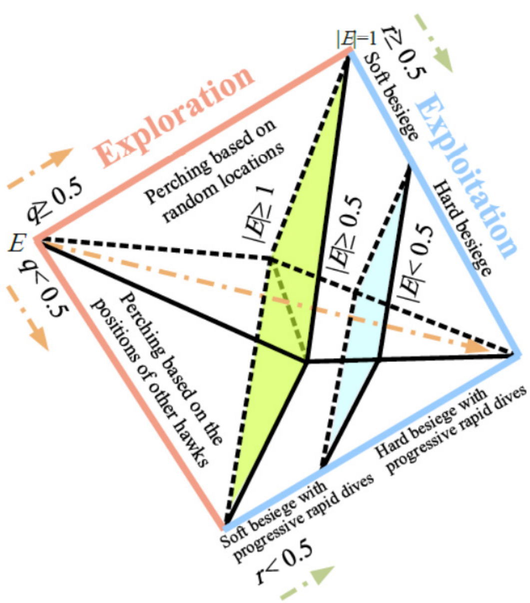


Fig 2. Different stages of the HHO algorithm [9]

In HHO, the Harris hawks perch randomly on some locations and wait to detect a prey based on two strategies [9].

$$X(t+1) = \begin{cases} X_{rand}(t) - r_1|X_{rand}(t) - 2r_2X(t)| & q \geq 0.5 \\ (X_{rabbit}(t) - X_m(t)) - r_3(LB + r_4(UB - LB)) & q < 0.5 \end{cases} \quad (1)$$

Where $X(t+1)$ is the position vector of hawks in the next iteration $t, X_{rabbit}(t)$ is the position of rabbit, $X(t)$ is the current position vector of hawks, r_1, r_2, r_3, r_4, and q are random numbers inside $(0,1)$, which are updated in each iteration, LB and UB show the upper and lower bounds of variables, $X_{rand}(t)$ is a randomly selected hawk from the current population, and X_m is the average position of the current population of hawks. The average position of hawks is attained using Eq. (2):

$$X_m(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t) \quad (2)$$

Where $X_i(t)$ indicates the location of each hawk in iteration t and N denotes the total number of hawks. Transition from exploration to exploitation, to model this step, the energy of a rabbit is modeled as:

$$E = 2E_0\left(1 - \frac{t}{T}\right) \quad (3)$$

Where E indicates the escaping energy of the prey, T is the maximum number of iterations, and E_0 is the initial state of its energy.
Exploitation phase:
- Soft besiege
This behavior is modeled by the following rules:

$$X(t+1) = \Delta X(t) - E|JX_{rabbit}(t) - X(t)| \quad (4)$$
$$\Delta X(t) = X_{rabbit}(t) - X(t) \quad (5)$$

Where $\Delta X(t)$ is the difference between the position vector of the rabbit and the current location in iteration t, r_5 is a random number inside $(0,1)$, and $J = 2(1 - r_5)$ represents the random jump strength of the rabbit throughout the escaping procedure. The J value changes randomly in each iteration to simulate the nature of rabbit motions.

- Hard besiege
In this situation, the current positions are updated using Eq. (6):

$$X(t+1) = X_{rabbit}(t) - E|\Delta X(t)| \quad (6)$$

- Soft besiege with progressive rapid dives
To perform a soft besiege, we supposed that the hawks can evaluate (decide) their next move based on the following rule in Eq. (7):

$$Y = X_{rabbit}(t) - E|JX_{rabbit}(t) - X(t)| \quad (7)$$

We supposed that they will dive based on the LF-based patterns using the following rule:

$$Z = Y + S \times LF(D) \quad (8)$$

Where D is the dimension of problem and S is a random vector by size $1 \times D$ and LF is the levy flight function, which is calculated using Eq. (9):

$$LF(x) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{\frac{1}{\beta}} \quad (9)$$

Where u, v are random values inside $(0,1)$, β is a default constant set to 1.5. hence, the final strategy for updating the positions of hawks in the soft besiege phase can be performed by Eq. (10):

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & ifF\ (Z) < F(X(t)) \end{cases} \quad (10)$$

Where Y and Z are obtained using Eqs.(7) and (8).

- Hard besiege with progressive rapid dives
The following rule is performed in hard besiege condition:

$$X(t+1) = \begin{cases} Y & if\ F(Y) < F(X(t)) \\ Z & if\ F(Z) < F(X(t)) \end{cases} \quad (11)$$

Where Y and Z are obtained using new rules in Eqs. (12) and (13).

$$Y = X_{rabbit}(t) - E|JX_{rabbit}(t) - X_m(t)| \quad (12)$$
$$Z = Y + S \times LF(D) \quad (13)$$

Where $X_m(t)$ is obtained using Eq. (2).

The proposed method works in three steps. In the first step, by reading the bus data information, the adjacency matrix of the bus grid is built. In the second step, using the Harris hawks algorithm, the cost function that will calculate the number of PMUs will be called, and the algorithm will evaluate the cost function based on the position of the hawks, which are binary. In the third step, the optimal placement of the PMU will be given as the output of the algorithm. The main player in the problem of optimal placement of PMUs is Harris Hawks algorithm. This algorithm should work in such a way as to provide the highest observability with the least number of PMUs.

Among the innovations of the proposed method are:

1- Despite other multi-objective algorithms that benefit from the idea used in the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) algorithm, this algorithm uses a concept called a repository or archive.

2- Keeping a separate place for non-dominant answers and not combining dominant and non-dominant answers.

3- Not losing non-dominant answers when the population changes and transforms.

A repository or archive is an infinite set of populations (responses) that have been obtained. that no operation is performed on it and they only use it as an archive. In fact, it is an advanced model of two-dimensional array in MATLAB software, which is maintained in each step of the simulation of non-dominant responses.

2.1 Binary HHO (BHHO)

Preparing the binary version of this algorithm is very simple, the following method is used to convert the Harris Hawks continuous algorithm to binary space:

Let X_{rabbit} (t) and X(t) be the current target point (rabbit position) and the current position of the hawk in the population, respectively. The next position of the Hawk X(t+1) is calculated according to the following Eq. (14):

$$S(X(t+1)) = X(t) - E(X_{rabbit}(t) - X(t)) \quad (14)$$

In order for the new position to be suitable for the binary space, the sigmoid function has been used for the simplicity of the concept and convenient implementation to map X(t+1) to the range [0,1] [10].

$$S(X(t+1)) = \frac{1}{1 + exp(-X(t+1))} \quad (15)$$

if $S \geq rand\ then\ X(t+1) = 1$ (16)
if $S < rand\ then\ X(t+1) = 0$ (17)

Where rand is a random number uniformly distributed in the interval [0,1]. In this paper, the sigmoid function makes it easier to call and takes less memory by binarizing a continuous algorithm, thus increasing the speed of simulation.

2.2 Multi Objective HHO algorithm based on Region selection(MOHHO/R)

This algorithm is the latest version of Harris Hawks algorithm, which was presented for the first time in this paper. In fact, this algorithm, or MOHHO/R for short, is a generalization of the PESA-II algorithm, which is used for multi-objective problems. Apart from standard parameters such as crossover and mutation rates, PESA has two parameters concerning population size, and one parameter concerning the hyper-grid crowding strategy.

In the proposed algorithm of PESA-II algorithm, a concept called archive or reservoir is added compared to the normal HHO algorithm, which is also known as the hall of fame. This archive represents the Pareto front and all the non-dominated solutions, which is known as the non-dominated set. When the hawks want to make a move, they choose a member of the solutions in the reservoir as the leader and They move towards it.

The leader selection process in the PESA-II algorithm is based on a region-based approach instead of an individual-based one. The solution space is divided into grids or cells, with the size and number of these grids being flexible. Each cell contains archive members, and cells with fewer members are given higher priority for leader selection. The selection process utilizes a discrete probability distribution, where sampling is performed using a roulette-wheel mechanism. The Boltzmann probability distribution is identified as the most suitable distribution for this purpose. Probabilities are assigned to each cell based on the defined method, and one cell is sampled using the roulette-wheel mechanism. Finally, one member from the selected cell is randomly chosen as the leader. As highlighted, the PESA-II algorithm organizes the solution space based on the Pareto front. The benefit of partitioning the Pareto space is that it shifts the focus from individual solutions to cells or regions. Each cell can accommodate multiple members of the population. Fig. 3, illustrates this concept in a bi-objective minimization space. When the archive population exceeds its predefined limit, cells with a higher number of members (e.g., Cell A in Fig. 3) are prioritized for deletion to maintain the diversity of the Pareto front. However, for crossover or mutation operations, cells with fewer members (e.g., Cell B in Fig. 3) are preferred. This ensures representation across various points of the Pareto front, enhancing diversity and orderliness in the solutions [11].

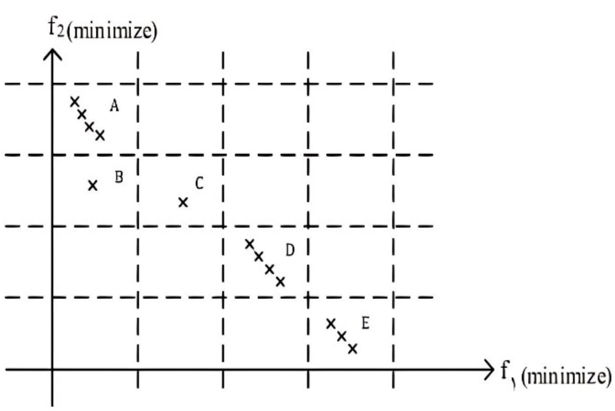


Fig 3. tabulation of the multi-objective Pareto space in the selected region [11]

In Fig. 4 and Fig. 5 the performance of the MOHHO/R algorithm for the objective functions of MOP2 and MOP4 with dual objectives is presented (Table 1).

Table 1. Dual objective functions MOP2 and MOP4 [12]

Fun	$F = (f_1(x), f_2(x))$	x_i
MOP2	$f_1(x) = 1 - exp\left(-\sum_{i=1}^{n}\left(x_i - \frac{1}{\sqrt{n}}\right)^2\right)$ $f_2(x) = 1 - exp\left(-\sum_{i+1}^{n}\left(x_i + \frac{1}{\sqrt{n}}\right)^2\right)$	$-4 \leq x_i \leq 4$; $i = 1,2,3$
MOP4	$f_1(x) = \sum_{i=1}^{n-1}\left(-10e^{(-0.2)*\sqrt{x_i^2+x_{i+1}^2}}\right)$ $f_2(x) = \sum_{i=1}^{n}\left(\lvert x_i\rvert^a + 5sin\ (x_i)^b\right)$	$-5 \leq x_i \leq 5$ $i = 1,2,3$ $a = 0.8$ $b = 3$

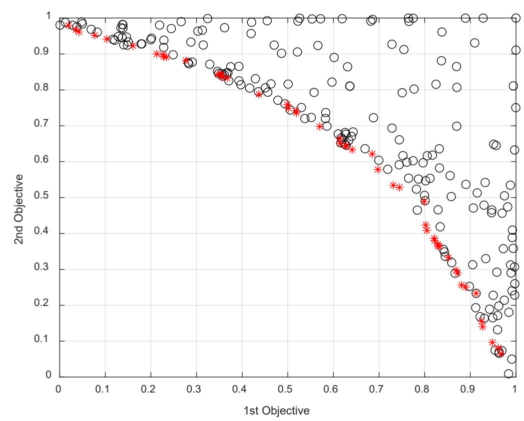


Fig 4. Pareto optimal MOHHO/Rfor MOP 2dual objective function

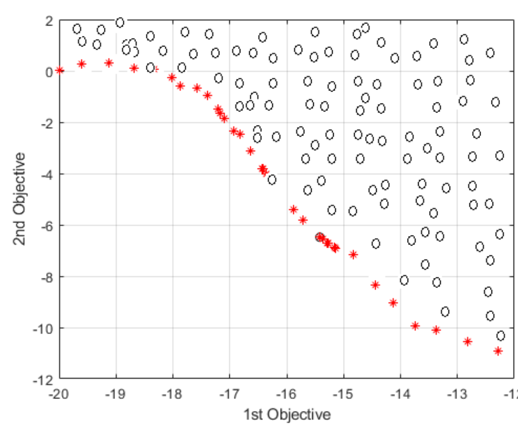


Fig 5. Pareto optimal MOHHORfor MOP 4dual objective function

2.3 Modeling the OPP problem

In this work, the goal of PMU placement is to minimize the number of PMUs and maximize the number of buses with measurement redundancy. This problem is solved by considering full observability for the system. According to the explanations provided, the multi-objective optimization of the optimal PMU placement for an N-bus system can be expressed as the following relationship [13]:

$$Min\, \Sigma_{i=1}^{N} x_i \qquad s.t.\, A \times X \geq b \tag{18}$$

$$x_i = \begin{cases} 1 = \text{ if PMU installed in bus } i \\ 0 = \text{ otherwise} \end{cases} \tag{19}$$

$$A_{ij} = \begin{cases} 1 = if\ i == j \\ 1 = \text{ if the bus } i \text{ is connected to bus } j \\ 0 = \text{ otherwise} \end{cases} \tag{20}$$

$$b = [1\ 1\ 1\ \dots\ 1] \tag{21}$$

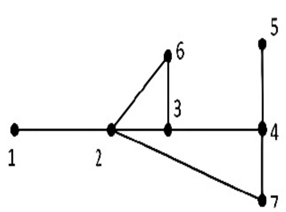
In the above relationships, x is a binary variable vector and i is equal to the bus number. Also, x_i is equal to 1 if it has a PMU in bus number i, x_i is zero if there is no PMU on the i bus. Also, A is equal to the system adjacency matrix, which is obtained from the system bus information. Its main diameter is one and the other dimensions are set in such a way that if bus i is connected to bus j, it takes the value of one, otherwise it takes the value of zero. In addition, vector b is a vector that considers the value of all buses to be equal to one. Since the objective function of the problem is a minimization function, the objective function becomes a cost function, and the cost function of the problem in question must have the following two conditions:

Obtaining the minimum number of PMUs as well as the most optimal proposed location for PMUs

$$\text{Stage1: cost function } Min\Sigma_{n=1}^{Nbus} S(n) \tag{22}$$

$$\text{Stage2: cost function } Max(Measurment\ Redundancy) \tag{23}$$

So, for example, for system 7 buses:



$$A = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

Fig 6. Proximity matrix from the ۷-bus testsystem [14]

Two indicators bus observability index (BOI) and system observability redundancy index (SORI) corresponding to 7 buses:

Bus	1	2	3	4	5	6	7	BOI
1	1	1	0	0	0	0	0	2
2	1	1	1	0	0	1	1	5
3	0	1	1	1	0	1	0	4
4	0	0	1	1	1	0	1	4
5	0	0	0	1	1	0	0	2
6	0	1	1	0	0	1	0	3
7	0	1	0	1	0	0	1	3

Fig 7. Proximity matrix of the7- bus testsystem

$$SORI = \Sigma BOI(i) \tag{24}$$

For example:

$$\text{SORI}(1) = \text{BOI}(2) + \text{BOI}(3) = 5 + 4 = 9$$
$$\text{SORI}(2) = \text{BOI}(1) + \text{BOI}(5) = 2 + 2 = 4$$

The rows of this matrix include the values zero and one: zero means that the bus is not observable by the PMU and one means that the bus is observable by the PMU. In Harris Hawks Algorithm, each hawk should be modeled as follows: the length of a Hawk is considered equal to an array of zero and one bits. In addition, the length of each Hawk is equal to the number of buses. In the following example, the number one indicates the presence of PMU in that bus and the number zero indicates the absence of PMU in that bus.

Harris hawk	Bus_1	Bus_2	Bus_3	Bus_4	Bus_5	Bus_6	Bus_7
Harris Hawk	0	1	0	1	0	1	0

In power grids, a bus is called a Zero Injection Bus (ZIB) that has no connection with the load and generator. If all the buses in the side of the ZIB are observable, the ZIB is also observable. Therefore, the ZIB merges with one of its side buses in a way.

The simulations are run using MATLAB ۲۰24b software :on a computer with the following specifications

- CPU Intel(R) Core i7-6700K CPU @ 4.20GHz;
- Memory: 16.0 GB DDR4;
- Hard Disk:2TB SSD;
- Run time: 9 to 11 seconds;

2.4 Summary of the proposed method

All the contents mentioned in this section can be summarized in the following flowchart:

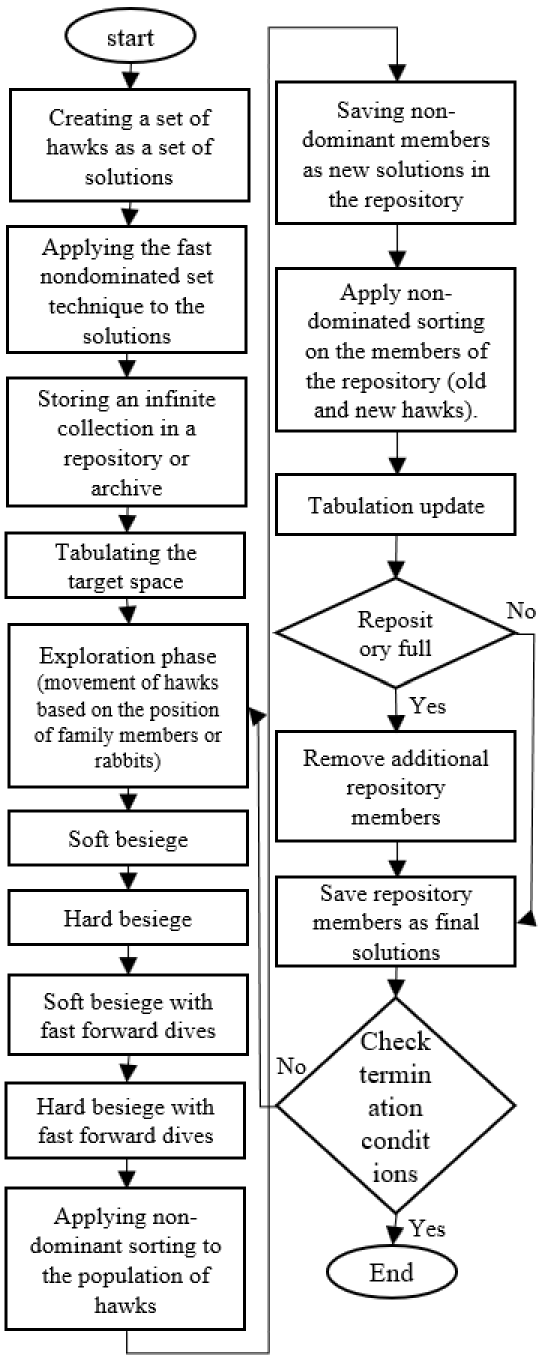


Fig 8. Flowchart of the proposed method

3. Experiments and Comparison

To evaluate the performance of BHHO and MOBHHO/R algorithms in solving the problem of optimal placement of PMU, this problem has been solved for two standard IEEE 14 Bus and IEEE 30 Bus systems. Therefore, in two different scenarios, measurement redundancy criteria and zero Injection bus effect have been used. In the following section, the mentioned scenarios are presented in the form of experiments.

3.1 Experiments

In this section, the results are:

- First scenario: simulation using BHHO algorithm:
  - For a 14-bus system (Fig. 9) with / without considering the ZIB (Table 2)
  - For a 30-bus system (Fig. 10) with / without considering the ZIB (Table 3)
- Second scenario: simulation using MOBHHO/R algorithm:
  - For a 14-bus system (Fig. 9) with / without considering the ZIB (Table 4)
  - For a 30-bus system (Fig. 10) with / without considering the ZIB (Table 5)

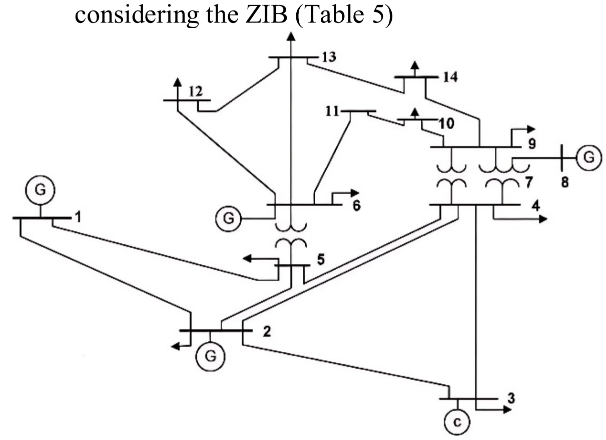


Fig 9. IEEE14 bus test system-[15]

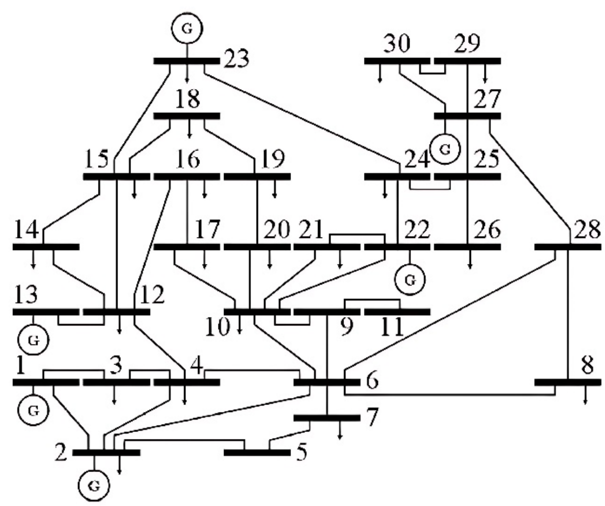


Fig 10. IEEE 30-bus test system [16]

In this section, the optimization results for each system are presented in the five runs. The aims to minimize the number of PMUs required while maximizing the redundancy of the power grids. The optimal state in each scenario is highlighted in bold.

Scenario 1: simulation results using the BHHO algorithm:

Table 2. 14-bus system with / without considering the ZIB in the Scenario 1. "The optimal state is highlighted in bold."

No	ZIB	Number of PMUs	Redundancy	PMU Location
1	without considering the ZIB	4	16	2,7,11,13
2		4	14	2,8,10,13
3		6	22	1,4,6,8,10,14
4		**4**	**17**	**2,6,8,9**
5		**4**	**17**	**2,6,8,9**
1	with considering the ZIB	4	19	2,6,9,12
2		4	17	1,4,10,13
3		4	19	2,6,9,12
4		**3**	**16**	**2,6,9**
5		**3**	**16**	**2,6,9**

In Table 2, the most optimal solution in the five runs using the BHHO algorithm (scenario 1) for a 14-bus system without considering the ZIB is equal to 4 PMUs and the redundancy index is equal to 17. Also, the most optimal solution in the five runs using the BHHO algorithm (scenario 1) for a 14-bus system with considering the ZIB is equal to 3 PMUs and the redundancy index is equal to 16.

In Table 4, the most optimal solution in the five runs using the MOBHHO/R algorithm (scenario 2) for a 14-bus system without considering the ZIB is equal to 4 PMUs and the redundancy index is equal to 19. Also, the most optimal solution in the five runs using the MOBHHO/R algorithm (scenario 2) for a 14-bus system with considering the ZIB is equal to 3 PMUs and the redundancy index is equal to 16.

In Table 5, the most optimal solution in the five runs using the MOBHHO/R algorithm (scenario 2) for a 30-bus system without considering the ZIB is equal to 10 PMUs and the redundancy index is equal to 52. Also, the most optimal solution in the five runs using the MOBHHO/R algorithm (scenario 2) for a 30-bus system with considering the ZIB is equal to 7 PMUs and the redundancy index is equal to 32.

In Table 2 to Table 5 showed the results in the five runs for both scenarios as well as for both systems 14 and 30 buses.

Table 3. 30-bus system with / without considering the ZIB in the Scenario 1. "The optimal state is highlighted in bold."

No	ZIB	Number of PMUs	Redundancy	PMU Location
1	without considering the ZIB	12	45	3,5,6,11,12,17, 18,20,21,24,26, 27
2		11	45	1,5,8,10,11,12, 15,19,24,25,27
3		**10**	**48**	**2,4,6,10,11,12, 15,19,25,29**
4		**10**	**48**	**2,4,6,10,11,12, 15,19,25,29**
5		**10**	**48**	**2,4,6,10,11,12, 15,19,25,29**
1	with considering the ZIB	7	29	1,7,10,12,18,24 ,29
2		**7**	**31**	**2,3,10,12,18,24 ,29**
3		7	30	3,7,10,12,15,20 ,29
4		7	30	3,7,10,12,15,20 ,29
5		**7**	**31**	**2,3,10,12,18,24 ,29**

Scenario 2: simulation results using the MOBHHO/R algorithm:

Table 4. 14-bus system with / without considering the ZIB in the Scenario 2. "The optimal state is highlighted in bold."

No	ZIB	Number of PMUs	Redundancy	PMU Location
1	without considering the ZIB	4	17	2,6,8,9
2		**4**	**19**	**2,6,7,9**
3		4	16	2,7,11,13
4		**4**	**19**	**2,6,7,9**
5		**4**	**19**	**2,6,7,9**
1	with considering the ZIB	**3**	**16**	**2,6,9**
2		**3**	**16**	**2,6,9**
3		**3**	**16**	**2,6,9**
4		**3**	**16**	**2,6,9**
5		**3**	**16**	**2,6,9**

Table 5. 30-bus system with / without considering the ZIB in the Scenario 2. "The optimal state is highlighted in bold."

No	ZIB	Number of PMUs	Redundancy	PMU Location
1	without considering the ZIB	**10**	**52**	**2,4,6,9,10,12,15, 18,25,27**
2		10	48	2,4,6,10,11,12,15, 19,25,29
3		**10**	**52**	**2,4,6,9,10,12,15, 18,25,27**
4		**10**	**52**	**2,4,6,9,10,12,15, 18,25,27**
5		**10**	**52**	**2,4,6,9,10,12,15, 18,25,27**
1	with considering the ZIB	**7**	**32**	**1,2,10,12,15,18, 29**
2		7	31	2,3,10,12,18,24, 29
3		**7**	**32**	**1,2,10,12,15,18, 29**
4		**7**	**32**	**1,2,10,12,15,18, 29**
5		**7**	**32**	**1,2,10,12,15,18, 29**

Based on these results, it is clear that the performance of the MOBHHO/R algorithm is more favorable and the output responses are more redundancy with a lower number of PMU. Also, the position of each PMU in the respective system is specified. And the optimal state in each scenario is highlighted in bold.

3.2 Comparison

Comparison of the proposed method in two different scenarios with the proposed methods of other papers. In this section, the superiority of the proposed algorithm is demonstrated in terms of the minimum number of PMUs and maximum redundancy. Furthermore, the convergence of the optimal solution is evident in both proposed algorithms, BHHO and MOBHHO/R.

In Table 6, for a 14-bus system, with out considering the ZIB, the redundancy index of 17 and 19 has been reached in two algorithms, BHHO and MOBHHO/R, respectively, which is a competitive performance compared to other algorithms.

In Table 7, for a 14-bus system, considering ZIB, the redundancy index of 16 is obtained for both BHHO and MOBHHO/R algorithms, which is a competitive performance compared to other algorithms.

Table 6. 14-bus system without considering the ZIB

No	Year	Method	Number of PMUs	Redundancy
1	2016	MICA [16]	4	17
2	2018	MOBPSO [17]	4	19
3	2020	FPA [18]	4	19
4	2021	DFS [5]	6	22
5	2022	CSA [6]	4	19
6	2023	PFA [7]	4	19
7	2024	ILP [8]	4	19
8	-	Proposed BHHO	4	17
9	**-**	**Proposed MOBHHO/R**	**4**	**19**

Table 7. 14-bus system with considering the ZIB

No	Year	Method	Number of PMUs	Redundancy
1	2016	MICA [16]	3	16
2	2018	MOBPSO [17]	3	15
3	2020	FPA [18]	3	15
4	2021	DFS [5]	3	15
5	2022	CSA [6]	3	15
6	2023	PFA [7]	3	15
7	2024	ILP [8]	3	16
8	-	Proposed BHHO	3	16
9	**-**	**Proposed MOBHHO/R**	**3**	**16**

Table 8. 30-bus system without considering the ZIB

No	Year	Method	Number of PMUs	Redundancy
1	2016	MICA [16]	10	43
2	2018	MOBPSO [17]	10	48
3	2020	FPA [18]	10	50
4	2021	DFS [5]	12	45
5	2022	CSA [6]	10	50
6	2023	PFA [7]	10	51
7	2024	ILP [8]	10	50
8	-	Proposed BHHO	10	48
9	**-**	**Proposed MOBHHO/R**	**10**	**52**

In Table 8, for a 30-bus system, with out considering the ZIB, the redundancy index of 48 and 52 has been reached in two algorithms, BHHO and MOBHHO/R, respectively, which is a competitive performance compared to other algorithms.

Table 9. 30-bus system with considering the ZIB

No	Year	Method	Number of PMUs	Redundancy
1	2016	MICA [16]	7	29
2	2018	MOBPSO [17]	7	28
3	2020	FPA [18]	7	29
4	2021	DFS [5]	7	29
5	2022	CSA [6]	7	31
6	2023	PFA [7]	7	31
7	2024	ILP [8]	7	30
8	-	Proposed BHHO	7	31
9	-	Proposed MOBHHO/R	7	32

In Table 9, for a 30-bus system, with considering the ZIB, the redundancy index of 31 and 32 has been reached in two algorithms, BHHO and MOBHHO/R, respectively, which is a competitive performance compared to other algorithms.

In Table 6 to Table 9, the results of the proposed method are compared with other algorithms proposed in other papers. The results indicate the superiority of the proposed algorithm in the convergence of the solution as the system and system information become larger due to the use of the repository or archive property to maintain the system with each simulation run.

4. Conclusion and Suggestion

The results demonstrate the success of the proposed algorithm in both minimizing the number of PMUs and maximizing the measurement redundancy index. The success of the proposed algorithm was due to the use of the property of the repository or archive to store the non-dominated answers in each step of the simulation. On the other hand, the success of the proposed algorithm is quite evident compared to the latest articles in the field of optimal placement of phasor measurement units (OPP). Convergence of optimal solutions and increasing efficiency by increasing the number of power grid buses are among the unique features of the proposed algorithm.

Topics like:

• The development of state estimation utilizing the archival property in the proposed algorithm.

• The employment of alternative objective functions such as reliability, voltage stability, along with observability.

• The employment of artificial intelligence in the development of the power grid in order to maximize observability.

can be considered as suggestions for future studies.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Masoud Hashemi: Writing Original draft, Simulation, Research & Investigation, Revise & editing **Mohsen Kalantar:** Conceptualization, Project administration, Supervision.

Funding

No funding was received for this work.

References

[1] T. johnson and T. Moger, " A critical review of methods for optimal placement of phasor measurement units," *International Transactions on Electrical Energy Systems*, Vol. 31, No. 3, November 2021.

[2] M. P. Vigliassi, J. A. Massignan, A. C. B. Delbem, and J. B. A. London, " Multi-objective evolutionary algorithm in tables for placement of SCADA and PMU considering the concept of Pareto Frontier," *International Journal of Electrical Power & Energy Systems*, vol. 106, No. 4, pp. 373–382, March 2019.

[3] R. Babu, S. Raj, B. Dey and B. Bhattacharyya, " Modified branch-and-bound algorithm for unravelling optimal PMU placement problem for power grid observability: a comparative analysis," *CAAI transactions on intelligence technology*, Vol 6, No 4, pp. 450–470, March 2021.

[4] V. Yuvaraju and S. Thangavel, " Optimal phasor measurement unit placement for power system observability using teaching–learning based optimization," *International Journal of Electrical Power & Energy Systems*, Vol 137, No 1, May 2022.

[5] E. O. Okendo, C. W. Wekesa and M. J. Saulo, " Optimal placement of Phasor Measurement Unit considering System Observability Redundancy Index: case study of the Kenya power transmission network," *Heliyon*, Vol. 7, No. 7, July 2021.

[6] T. Johnson and T. Moger, " Security-constrained optimal placement of PMUs using Crow Search Algorithm," *Applied Soft Computing*, Vol. 128, No. 3, October 2022.

[7] O. Tshenyego, R. Samikannu, B. Mtengi, M.

Mosalaosi and T. Sigwele, " A Graph-Theoretic Approach for Optimal Phasor Measurement Units Placement Using Binary Firefly Algorithm," *Energies*, Vol. 16, No. 5, September 2023.
[8] M. M. Ahmed, M. Amjad, M. A. Qureshi, M. O. Khan and Z. M. Haider ," Optimal PMU Placement to Enhance Observability in Transmission Networks Using ILP and Degree of Centrality," *Energies*, Vol. 17, No. 2, April 2024.
[9] A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja and H. Chen, " Harris hawks optimization: Algorithm and applications," *Future generation computer systems*, Vol 97, No 2, pp. 849-872, August 2019.
[10] Y. Meraihi, A. R. Cherif, M. Mahseur and D. Achelia," A chaotic binary salp swarm algorithm for solving the graph coloring problem," In *Modelling and Implementation of Complex Systems: Proceedings of the 5th International Symposium, MISC 2018, December 16-18, 2018, Laghouat, Algeria 5*, pp. 106-118, Springer International Publishing, 2019.
[11] D. W. Corne, J. D. Knowles and M. J. Oates, " The Pareto envelope-based selection algorithm for multiobjective optimization," In *10th International conference on parallel problem solving from nature*, pp. 839-848. Berlin Heidelberg, Springer, 2000.
[12] C. A. C. Coello, G. B. Lamont and D. A. V. Veldhuizen , " *Evolutionary algorithms for solving multi-objective problems*," Illinois, IL, USA, Second Edition, Springer, 2007.
[13] M. Nazari and B. Mohammadi, " Application of heuristic algorithms to optimal PMU placement in electric power systems: An updated review," *Renewable and Sustainable Energy Reviews*, vol. 50, No. 4, pp. 214–228, May 2015.
[14] V. Becejac and P. Stefanov, " Groebner bases algorithm for optimal PMU placement ," *International Journal of Electrical Power & Energy Systems,* Vol. 115, No. 3, February 2020.
[15] A. Mahari and H. Seyedi, " Optimal PMU placement for power system observability using BICA considering measurement redundancy," *Electric Power Systems Research*, Vol. 103, No. 2, pp. 78–85, June 2013.
[16] S. A. Taher and H. Mahmoodi and H. Aghaamouei, " Optimal PMU location in power systems using MICA," *Alexandria Engineering Journal*, Vol. 55, No. 1, pp. 399–406, December 2016.
[17] L. A. Azzeddine, M. R. Djamel, K. Abdellah and R. M. Mounir, " Optimal PMU placement in power system based on multi-objective particle swarm optimization," In *15th International Multi-Conference on Systems, Signals & Devices (SSD)*, pp. 941-946, Yasmine Hammamet, Tunisia, March 2018.
[18] A. A. Abdelsalam , K. M. Hassanin , A. Y. Abdelaziz and H. H. Alhelou, " Optimal PMUs placement considering ZIBs and single line and PMUs outages," *AIMS Energy,* Vol. 8, No. 1, pp. 122-141, March 2020.

Masoud Hashemi was born in Ahvaz, on 1997. He received the M.Sc. degree in electrical engineering from Iran University of Science and Technology in 2022. He is currently working as an electrical and instrument supervisor engineer in a petrochemical company. His research interests are power systems, FACTS, and Wind and Solar Power Generation.

Mohsen Kalantar, He received his Ph.D. from Indian Institute of Technology, New Delhi, India in 1991. Dr. Kalantar is currently a Professor in the Department of Electrical Engineering at Iran University of Science and Technology in Tehran. He is also member of Center of Excellence for Power System Automation and Operation. His field of interest includes Wind and Solar Power Generation, Power System Dynamics and Control, System Stability and Optimization, Power System Deregulation, and FACTS Devices.