Optimal Placement of Phasor Measurement Units in Power Grids Using Memetic Algorithms

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***Abstract*— Wide area monitoring, protection and control for power network systems are one of the fundamental components of the smart grid concept. Synchronized measurement technology such as the Phasor Measurement Units (PMUs) will play a major role in implementing these components and they have the potential to provide reliable and secure full system observability. The problem of Optimal Placement of PMUs (OPP) consists of locating a minimal set of power buses where the PMUs must be placed in order to provide full system observability. In this paper a novel solution to the OPP problem using a Memetic Algorithm (MA) is proposed. The implemented MA combines the global optimization power of genetic algorithms with local solution tuning using the hill-climbing method. The performance of the proposed approach was demonstrated on IEEE benchmark power networks as well as on a segment of the Idaho region power network. It was shown that the proposed solution using a MA features significantly faster convergence rate towards the optimum solution.**

Keywords—Memetic Algorithm, Optimal PMU Placement, Phasor Measurement Units, Power Grid, Situational Awareness

I. INTRODUCTION

Phasor Measurement Units (PMUs) have recently become the focus of work for many researchers primarily due to their potential on becoming one of the major enablers of the Wide Area Monitoring, Protection And Control (WAMPAC) for power network systems [1]. WAMPAC can be seen as one of the fundamental components of the envisioned smart grid concept. One of the major benefits of this technology is the improvement in stability, reliability and security of power production, transmission and distribution systems [1], [2], [3], [4].

PMUs are generally considered the most advanced synchronized measurement technology. When compared to previous solutions, PMUs offer the following major capabilities: 1) location independent measurement synchronization using Global Positioning System (GPS), 2) direct measurements of voltage and current phase angles and 3) increased accuracy, frequency, reliability and security of state measurements [5]. As such, the installation of PMUs can be seen as a major contribution to the overall resiliency of the critical infrastructure systems [4], [6], [7], [8].

Unlike standard voltage and current metering systems, PMUs are capable of observing the voltage and current phasors from all power network branches incident to a given power distribution center known as a power bus [9]. This observation of the voltage phasors on incident buses is enabled by combining the measurements of the outgoing current phasors with the knowledge of power line parameters, such as resistance. The major consequence of this measuring capability is that for a power system with n buses, a significantly smaller number of PMUs is required to be installed in order to ensure full observability of the entire power network [10]. For example, Brueni et al. presented mathematical proof that for power grids with at least 3 buses, no more than n/3 of the buses need to be equipped with PMUs to achieve full system observability [11].

The possibility of using a relatively small number of PMUs, combined with the high cost of both PMUs and their associated communication infrastructure, is the main driver behind the recent and significant research effort in designing methods for optimal PMU placement [12]. Various different solutions have been proposed in recent years [12]. One of the most widely used approaches is Integer Linear Programming framework where the topology of the network can be modeled and solved using linear constraints [13]-[15]. Integer Quadratic Programming approach was used in [16]. A probabilistic approach to the OPP was suggested in the work of Aminifar et al. [17]. Various nature inspired computational intelligence approaches such as Particle Swarm Optimization (PSO) [18], Binary PSO [19], Genetic Algorithms (GAs) [20], Nondominated Sorting GA [21], Immunity GA [22], Bacterial Foraging Algorithm [23], Adaptive Clonal Algorithm [24], Tabu Search [25] and Simulated Annealing (SA) [9] have also been presented. A distinctly different method of using an exhaustive binary search and sequential adding or removing of PMUs was proposed in [26], [27]. Prioritization of different PMU placement configurations based on multi-criteria decision making schemes such as analytic hierarchy processing or a simple weighted average was discussed in [28], [29]. Several authors also considered multi-staged PMU placement [13], [17], [29], [30], [31] placing PMUs with a limited number of measurements channels [32], or combining the PMU measurements with standard power flow measurements [33].

As reviewed above both the global optimization techniques such as GA or PSO [18]-[20] and local search techniques such as SA and Tabu Search [9], [25] have been previously applied to the OPP problem [12]. However, experimental evidence suggests that global optimization techniques are sometimes unsuitable for fine-tuning of the result close to the optimal solution, and local search strategies are prone to convergence towards local minima. In order to alleviate these issues, this paper proposes to apply Memetic Algorithms (MAs) to the problem of OPP. MAs can be seen as a combination of global and local search strategies [34], [35]. The main principle behind MA is the combination of population-based meta-heuristic search such as GA with the added capability of individual learning [34].

The specific implementation of MA used for the research discussed in this paper combined a GA with the hill-climbing local learning strategy. The fitness of each solution is evaluated with respect to the requirement of full power grid observability and the desire to minimize the size of the set of required PMUs. To further prioritize between PMU placement with identical number of PMUs, the measurement redundancy index (see section IV) was used.

The implemented solution was applied to the IEEE 14-bus, 30-bus, 57-bus, and 118-bus test data sets and to a segment of the Idaho region power network. The experimental results compare the quality of the produced solution to the individual GA algorithm solution and to the hill-climbing local search solution. It is experimentally demonstrated that the MA solution provides fast and stable convergence towards optimal PMU placement configurations.

The rest of the paper is organized as follows. Section II reviews the optimal PMU placement problem. The concept of MA is outlined in Section III. Section IV presents the application of MA to the OPP problem. Finally, experimental results are demonstrated in Section V and the paper is concluded in Section VI. Appendix Section of this paper contains a description of the Idaho region power grid data set.

II. OPTIMAL PMU PLACEMENT PROBLEM

This Section provides an overview of the PMU placement problem.

A. Problem Definition

The power grid is composed of power buses, which are voltage step-up and step-down distribution centers and power lines which are connections between individual buses. An example of a power grid, the IEEE 14-bus test data set is depicted in Fig. 1. The topological representation of a grid can be encoded using a connectivity matrix A defined as:

$$\mathbf{A}(i,j)=\begin{cases}1 & \text{if } i=j\\ 1 & \text{if bus } i \text{ and } j \text{ are connected}\\ 0 & \text{otherwise}\end{cases} \quad (1)$$

PMU placement configuration in the power grid is determined by a vector x defined as:

$$x(i)=\begin{cases}1 & \text{if PMU is installed in bus } i\\ 0 & \text{otherwise}\end{cases} \quad (2)$$

Using the introduced notation the task of optimal PMU placement can be defined as:

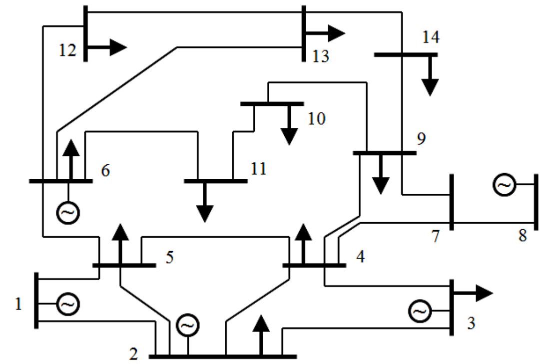


Fig. 1 IEEE 14-bus test data set (arrows and circles represent loads and generators, respectively).

$$\min\,(w^T x) \quad (3)$$

Subject to: $$\mathbf{A}x \geq b \quad (4)$$

Here, w is a vector, which expresses the relative cost of installing a PMU at particular bus and $b=[111\ldots11]^T$ is an observability constraint vector, which ensures that all buses are covered by PMU measurements. For simplicity sake the relative cost of all buses is considered equal, hence $w=[111\ldots11]^T$. It is important to note that variable weights of individual buses can also be accommodated by the proposed solution.

B. Radial Buses

Certain problem domain knowledge can be utilized to simplify the solution to the OPP problem. A radial bus is a power bus, which is connected to the rest of the grid via a single power line. An example of a radial bus is bus number 8 in Fig. 1. From the OPP point of view, the set of radial buses can be excluded from the set of candidate buses for PMU placement. It is trivial to show that placing a PMU at radial bus will always lead to requiring at least as many PMUs than when the PMU is placed on the single neighboring power bus of the radial bus. Hence, radial buses can be excluded from the set of candidate buses for PMU placement.

C. Zero Injection Buses

Some power buses are only used as transfer buses and do not contain any power injection (e.g. load or generator) into the grid. Such buses are called Zero-Injection (ZI) buses and they can be used to further reduce the minimal set of installed PMUs in order to ensure full system observability. This reduction can be accomplished by using Kirchhoff's Current Law (KCL) to indirectly infer the electrical measurements in specific configurations. Consider a zero-injection bus with n connected power lines. When current measurements are known on n-1 power lines, the current on the remaining power line can be computed.

For example, consider bus 7 in Fig. 1, which is a ZI bus. Placing a PMU on bus 9 will result in observing the voltage on buses 4, 7, 9, 10 and 14 as well as the current on the connecting power lines. Because the current is known on 2 out of 3 power line connections to bus 7, and bus 7 is a ZI bus, the KCL can

```
Genetic Algorithm
1:      Initialize the population with random solutions
2:      Evaluate population
3:      Repeat until population converged
  3.1: Select parents
  3.2: Recombine pairs of parents
  3.3: Mutate offspring
  3.4: Evaluate new population
  3.5: Select individuals for new population
```

Fig. 2 Pseudo-code of the Genetic Algorithm.

```
Hill Climbing Algorithm
1:      Randomly select an initial solution
2:      Repeat until termination condition
  2.1: Create new candidate solution
  2.2: If (fitness(new) > fitness(current)) Then
        current = new
```

Fig. 3 Pseudo-code of the Hill-Climbing algorithm.

be applied to compute the current in the line between buses 7 and 8 and to indirectly observe the voltage on bus 8.

III. MEMTIC ALGORITHMS

This Section first reviews the global optimization using Genetic Algorithms, and local optimization using the hill-climbing method. Next, the idea of Memetic Algorithms is discussed.

A. *Genetic Algorithms*

Genetic Algorithms (GA) are part of a broader field of evolutionary algorithms. The major unifier of evolutionary algorithms is the paradigm of simulated evolution. Simulated evolution is inspired by Darwin's theory of evolution that has been translated into an effective tool for global optimization [36]. The common underlying idea is that the algorithm maintains a set of individuals where each represents an encoded solution to the problem. The goodness of each individual can be evaluated based on an objective fitness function. Parents for the next generation are then selected using selection operators. New offspring are produced by recombination operators and randomly altered by mutation operators. The main cycle is repeated for a specified number of iterations or until another convergence criterion is met, such as the desired level of the best fitness value or the standard deviation of the fitness value within the population. The general pseudo-code of GA is summarized in Fig. 2.

B. *Local Search – Hill Climbing*

Unlike the population based genetic algorithm, the hill-climbing algorithm is a local search technique, which maintains a single solution. The main idea of this method is to repeatedly attempt to improve the quality or fitness of the candidate solution. The hill-climbing algorithm generates a new candidate solution from the current solution (e.g. using a random bit flip operation). If the fitness of the new solution is greater than the fitness of the current solution, the new solution is adopted as the current one. In the opposite case, the new solution is deleted and a new candidate solution is generated. Since the hill-climbing search can move only in the direction of increasing fitness value, it is prone to getting trapped in local minima. Pseudo code of the hill climbing algorithm is summarized in Fig. 3.

```
Memetic Algorithm
1: Initialize the population with random solutions
2: Optimize each solution using hill climbing
3: Evaluate population
4: Repeat until population converged
        4.1: Select parents
        4.2: Recombine pairs of parents
        4.3: Mutate offspring
        4.4: Optimize each solution using hill climbing
        4.5: Evaluate new population
   4.6: Select individuals for new population
```

Fig. 4 Pseudo-code of the Memetic Algorithm.

C. *Memetic Algorithms*

Memetic Algorithms (MA) can be seen as a combination of global and local search strategies. Population based GA are not well suited for fine-tuning of a solution, when in the close neighborhood of the optimal solution. In contrast, single solution based local search is prone to getting trapped in local minima when searching far from the global optimum. MA combines the advantages of both strategies into a robust optimization algorithm with fast convergence.

The main principle of MA is the combination of population-based meta-heuristic search such as GA inspired by Darwinian principles of natural evolution and the Dawkins principle of memes taken as elementary units of cultural evolution capable of individual learning [32]. In one of its simplest forms MA combines the population based GA used to maintain the population of solutions and to reproduce a new generation of individual solutions, with the hill-climbing local optimization strategy applied each generation to every individual in that generation. Pseudo-code of the MA is summarized in Fig. 4. More complex forms of MA use more advanced search techniques than simple hill-climbing for local search.

IV. MEMETIC ALGORITHMS FOR OPP

An MA of the form presented in the previous section was applied to the problem of optimal placement of PMUs in the power grid. The implemented MA uses a GA to maintain a population of PMU placement configurations and to reproduce the new generation. For each generation, hill-climbing method is used for local learning and fine tuning of each individual solution.

A gene of the GA individual is represented as a binary vector similar to the vector x described in (2). A value of 1 means that a PMU is placed at the particular power bus and a value of 0 represents a power bus without an installed PMU. As addressed earlier in Section II, knowledge of radial buses is used to reduce the dimensionality of the search space. Here, radial buses are excluded from the gene of the GA. The GA uses tournament offspring selection, two-point cross-over operation, and random bit flip mutation.

After recombination and mutation of the GA population, the hill-climbing algorithm is applied to each solution for a specified number of iterations. In each iteration, random bit flip operation is used to generate a new PMU placement configuration, resulting in either adding a new PMU into the grid or removing a PMU from the grid. The new solution replaces the original solution if the new fitness of the PMU placement configuration is better than the original fitness.

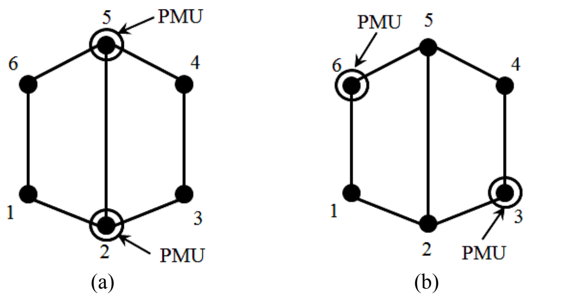


Fig. 5 Demonstration of measurements redundancy index.

The fitness of each candidate solution, which is to be minimized, is evaluated with respect to ensuring the desired full observability of the power grid and with respect to minimizing number of PMUs needed. The fitness value *F(x)* of particular solution x can be calculated as follows:

$$F(x) = \begin{cases} N_{PMU} + N_{Bus} + (N_{Bus} - N_{Observ}) & \text{if unobservable} \\ N_{PMU} + (1 - RI) & \text{if observable} \end{cases} \quad (5)$$

Here, N_{PMU} stands for the number of installed PMUs, NBUS is the number of power buses in the grid, N_{Observ} expresses the number of power buses that are currently observed, and *RI* is the measurement redundancy index of the current PMU placement configuration. *RI* value can be computed as follows:

$$RI = \frac{(\mathbf{A}x)^T(\mathbf{A}x)}{N_{Bus}} \quad (6)$$

Redundancy index expresses the average number of PMU measurements per bus. As an example consider a simple power grid depicted in Fig. 5 with two PMU placement configurations depicted in Fig. 5(a) and Fig. 5(b). The *RI* for these two configurations is 1.33 and 1.00, respectively. Hence, despite using 2 PMUs and providing full-network observability in both cases, the configuration in Fig. 5(a) also offers increased measurement redundancy and should be preferred during the design process. It is important to note that the value of *RI* will always be greater than 0 and, for all tested power grid data sets, it was also found to be less than 1. This is primarily due to the fact that only coverage of directly incident PMU is considered in (6), while further indirect measurements (e.g. the zero-injection buses) are considered in assessing the full system observability.

Calculation of the fitness function can be explained as follows. When a solution provides full network observability the fitness value is primarily controlled by the number of PMUs installed. Hence, a solution with smaller number of PMUs will be preferred. In most power grid configurations it is possible to obtain several different configurations with the minimal number of PMUs. In such cases, the solution, which provides the maximum degree of measurement redundancy is preferred according to the *RI* value. Again, note here that *RI* is typically between 0 and 1. The higher the *RI* value the more information about the state of the power grid can be retained should a PMU malfunction.

TABLE I

DATA SET DESCRIPTION FOR IEEE TEST CASES

Test Case	Number of Lines	Number of ZI buses	Location of ZI buses
14-bus	20	1	7
30-bus	41	5	6, 9, 25, 27, 28
57-bus	78	15	4, 7, 11, 21, 22, 24, 26, 34, 36, 37, 39, 40, 45, 46, 48
118-bus	179	10	5, 9, 30, 37, 38, 63, 64, 68, 71, 81

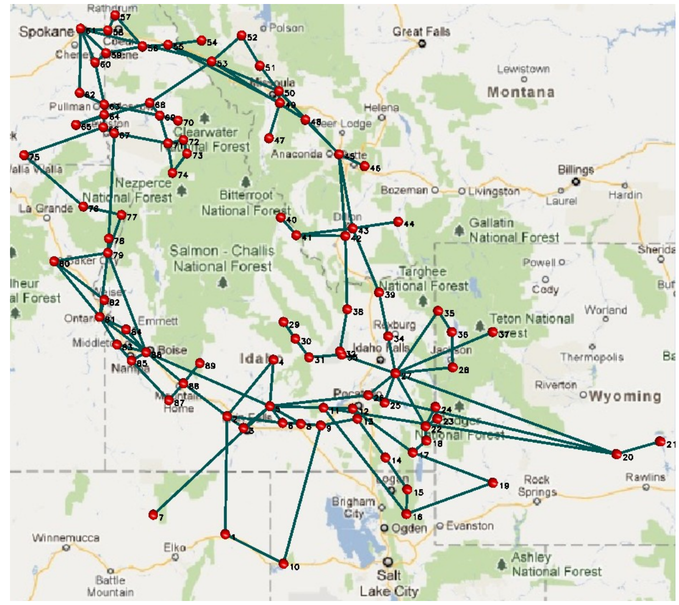


Fig. 6 The Idaho region power grid data set.

In cases when the candidate solution does not provide full grid observability, the fitness value is penalized by adding the number of power buses. Hence, any solution which does not guarantee full grid observability will be worse than any solution that does provide full observability of the network. However, to further guide the search algorithm towards the desired solution, the PMU placements that do not provide full observability but cover larger portions of the power grid are preferred.

V. EXPERIMENTAL RESULTS

This Section describes experimental test cases, followed by the experimental results.

A. Test Cases

The implemented MA was applied to the standard set of IEEE bus test systems. Namely, the IEEE 14-bus, 30-bus, 57-bus and 118-bus system were used. For these systems the knowledge of Zero-Injection (ZI) buses was used to derive indirect measurements in the power grid. Locations of ZI were adapted from [37] and for clarity they are summarized in Table I.

In addition, a power network data set extracted from a segment of the Idaho region power network was used. This Idaho region data set is composed of 89 buses and 124 power lines. For this data set, the knowledge of ZI buses was not available and thus the propagation of indirect measurements due to ZI buses was not used. Hence, all power buses are considered to have either a generator or a load. A view of the Idaho region power network is depicted in Fig. 6. Connections of the Idaho region data set are provided in Appendix A.

TABLE II
BEST OPP SOLUTION USING MA

Test Case	Number of PMUs	RI	Location of PMUs
14-bus	3	0.300	2, 6, 9
30-bus	7	0.354	2, 4, 10, 12, 15, 20, 27
57-bus	12	0.256	1, 4, 9, 15, 20, 25, 29, 32, 47, 51, 54, 56
118-bus	29	0.360	3, 8, 11, 12, 17, 21, 27, 31, 32, 34, 37, 42, 45, 49, 53, 56, 59, 66, 72, 75, 77, 80, 85, 86, 90, 94, 101, 105, 110
Idaho State	27	0.419	2, 5, 9, 15, 17, 20, 22, 27, 30, 32, 36, 41, 43, 45, 49, 52, 55, 56, 61, 64, 67, 69, 73, 76, 81, 86, 88

TABLE III
STATISTICAL COMPARISON OF THE OPP ALGORITHMS

Test Case	Memetic Algorithm	Genetic Algorithm	Hill-Climbing
14-bus	3.00 ± 0.00	3.10 ± 0.30	3.48 ± 0.50
30-bus	7.00 ± 0.00	7.10 ± 0.30	7.40 ± 0.60
57-bus	12.36 ± 0.48	14.42 ± 0.94	15.08 ± 1.11
118-bus	30.52 ± 0.85	33.28 ± 1.41	36.16 ± 2.03
Idaho State	27.52 ± 0.61	29.08 ± 1.15	31.44 ± 2.04

B. *Experimental Testing*

As mentioned in Section IV, the implemented MA combines the GA with the hill-climbing local learning strategy. Performance of the proposed MA solution was experimentally compared to solutions using only GA and using only hill-climbing.

Implementation details of the GA are as follows. The population consisted of 100 individuals and the optimization was terminated after 100 iterations. Two-point cross-over and a random bit-flip mutation operators were used with a mutation rate set at 0.2. Tournament selection was used for parent selection with tournament size of 4.

Finally, the hill-climbing only algorithm used a random bit-flip mutation operator to generate new solutions and it was allowed 10000 iterations to converge. The above mentioned algorithm parameters were empirically selected based on extensive experimental testing. Initial solutions for all methods were randomly initialized in the solution space.

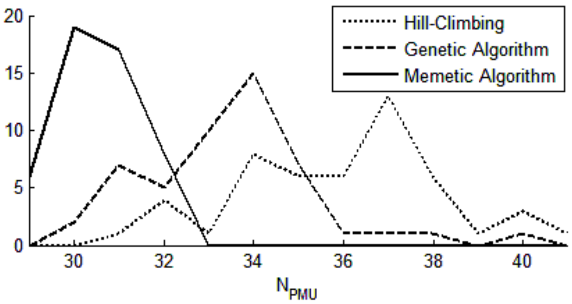
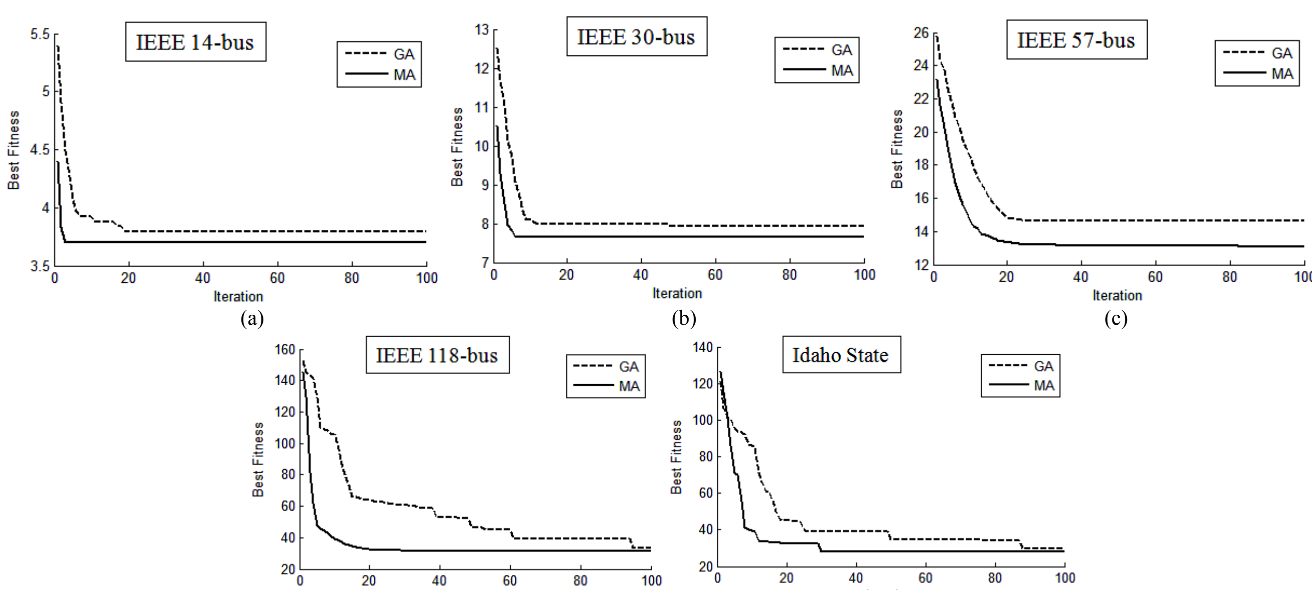


Fig. 7 Distribution of the number required PMUs for IEEE-118bus problem for 50 runs of the algorithms

First, the MA was used to search for the solution to the OPP problem, which yields the minimum number of required PMUs and a maximum measurement redundancy index. Table II summarizes the number of required PMUs, the measurement redundancy index and the list of PMU locations for the test cases used. By comparing the results achieved on the IEEE test sets in terms of the number of required PMUs to the available literature it can be concluded that the proposed solution is capable of locating the optimal solution [37].

Next the performance of MA was statistically compared to GA and hill-climbing. The statistical comparison of the performance of individual algorithms is necessary due to the stochastic nature of the algorithms. Each algorithm was applied to all test data sets 50 times, then the average and the standard deviation of the number of required PMUs was computed. Running each algorithm 50 times was considered as a reasonable compromise between the required computational time and the statistical significance of the result (Table III).

It can be observed that the MA solution provides the best results with the smallest standard deviation, followed by the population based GA and the hill-climbing local search technique (see Table III). To further illustrate these results Fig. 7 depicts the distribution of the number of PMUs N_{PMU} for the performed 50 runs of the MA, GA and hill-climbing algorithms applied to the IEEE 118-bus data set. These results confirm that the MA based solutions are more stable compared to GA based solutions and hill-climbing based solutions.



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

Fig. 8 Comparison of the convergence of the MA and GA for IEEE 14-bus (a), 30-bus (b), 57-bus (c), 118-bus (d) and Idaho State (e) data sets.

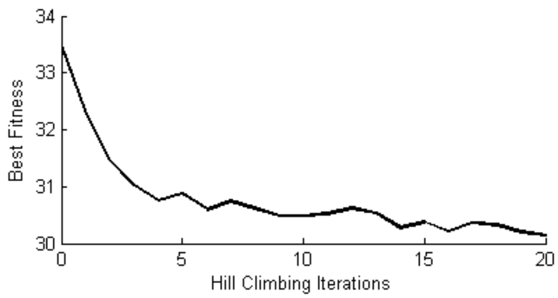


Fig. 9 Average best fitness of the MA as a function of the number of local learning iterations.

One of the most recognized advantages of MAs when compared to other techniques is their high convergence speed. To verify the convergence improvements, the MA and the GA have been both applied to the IEEE test data sets 20 times and the average fitness of the best solution at each generation was computed. Fig. 8 shows the obtained results, which clearly demonstrate the increased convergence rate of the MA.

Finally, it is interesting to investigate how much does the amount of local solution learning during each generation of MA contribute to the improved performance and convergence speed of the MA. To investigate this behavior, MA was applied to the IEEE 118-bus test data set with varying number of hill-climbing iterations per each individual in each generation. The number of hill-climbing iterations was varied from 0 to 20, where 0 is equal to using a GA without any hill-climbing. For each value of the number of hill-climbing iterations the number of PMUs in the produced OPP solution was averaged over 50 runs of the algorithm. The results are depicted in Fig. 9. It can be seen that the first 10 hill-climbing iterations provided significant improvement in the average best fitness value, while additional local learning iterations provided only minor improvements.

VI. Conclusions

This paper addressed the problem of Optimal Placement of PMUs (OPP), which consists of locating a minimal set of power buses where PMUs must be placed in order to provide full system observability. A novel solution to the OPP problem via Memetic Algorithms (MA) was proposed. The implemented MA combines the global optimization power of GAs with local solution tuning using the hill-climbing method.

The performance of the proposed MA based approach was demonstrated on IEEE benchmark power networks and on a segment of the Idaho region power network. It was experimentally shown that the MA provides faster and more stable convergence towards the optimal solution.

Future work entails further exploration of advantages and disadvantages of utilizing MA for OPP and applying the proposed solution to larger real-world power grids. The proposed MA will be further advanced by utilizing more complex local search techniques. Finally, the utilized fitness function can be improved to express more detailed requirements.

Appendix A – Idaho Region Power Grid Dataset

This appendix contains a description of the created Idaho region power grid data set. This data set is composed of 89 power buses and 124 power lines. Table IV contains the list of connections of all power buses.

TABLE IV
Bus Connections for the Idaho Region Power Grid

Bus No.	Connected Buses		Bus No.	Connected Buses		Bus No.	Connected Buses
1	2,10		31	30,33		61	53,58,59,60,62
2	1,3,4,6,88		32	33,32		62	61,63
3	2,5		33	27,31,32		63	60,62,64,69
4	2,5		34	27,39		64	63,65,66
5	3,4,6,7,8,11,26,86		35	27,36		65	64,68
6	2,5,8		36	28,35		66	64,67,75
7	5		37	27		67	66,71,78
8	5,6,9		38	32,42		68	53,65,69
9	8,10,13		39	34,43		69	63,68,70,71
10	1,9		40	41		70	69
11	5,12,16,20		41	40,42,43		71	67,69,72,74
12	11,13,17		42	38,41,45		72	71,73
13	9,12,14		43	39,41,44,45		73	72,74
14	13,15		44	43		74	71,73
15	14,16		45	42,43,46,48,50		75	66,76
16	11,15,19		46	45		76	75,77
17	12,18,19		47	49		77	76,79
18	17,22		48	45,50,53		78	67,79
19	16,17		49	47,50,55		79	77,78,80,81,86
20	11,21,26,27		50	45,48,49,51,55		80	7,81,82
21	20		51	50,52		81	79,80,82,83,84
22	18,23,24,27		52	51,53		82	80,81
23	22,24		53	48,52,61,68		83	81,85,86
24	22,23		54	55		84	81,86
25	26,27		55	49,50,54,56		85	83,86,87
26	5,20,25,27		56	55,57,59		86	5,79,81,83,84,85,88
27	20,22,25,26,28,33,34,35,37		57	56,58		87	85,88
28	27,36		58	57,61		88	2,86,87,89
29	30		59	56,60,61		89	88
30	29,31		60	60,61,63			

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