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Placement of Phasor Measurement Units in Power Grids Using Memetic Algorithms

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Abstract: Power grid systems uses wide area monitoring, protection and control for greater stability and minimizing faults. Phasor Measurement Units (PMUs) which is a type of Synchronized measurement technologyis an important part of this system and greatly improves reliability and secure full system observability. Placement of PMUs (OPP) is a matter of identifying a minimal no. of power buses where the PMUs must be installedso that the whole system is observable. This paper presents a optimal placement algorithm of phasor measurement units (PMU) by using memetic algorithm. By implementing MA, we are combining the global optimization power of genetic algorithms with local solution tuning using the hill-climbing method. The algorithm is simulated on IEEE benchmark power networksThe placement problems under those cases are formulated and memetic algorithm saves the CPU computation time greatly. The proposed solution has faster convergence rate and simulation results show that the proposed algorithm can be used in practice.

Key words: Optimal PMU Placement · Phasor Measurement Units · Memetic Algorithm · Power Grid · Situational Awareness

INTRODUCTION

The increased utilization of electric power systems is ofmajor concern to most utilities and power grids. Advanced control and supervision systems allow the power system to operate closer to its limits by increasing power flow without hampering reliability constraints.The introduction of phasor measuring units is a major step towards an efficient and reliable network operation. PMUs rely on a GPS time signal for accurate time-stamping of the system information. A GPS satellitereceiver provides a precise timing pulse,which is combined with sampled voltage and current inputs typically the three phase voltages of a substation and the currents in transmission lines, transformers and loads ending at the substation.

As compared to basic metering systems, PMUs has the capacity of observing the voltage and current phasors from all power network branches incident to a given power distribution center known as a power bus. Measurement of the voltage phasors on incident buses is done by combining the outgoing current phasors with the information of power line parameters, such as resistance. The importance of this measuring capability is used for a ‘n’ bus power system, a small number of PMUs is required to be installed for full observability of the entire power network. For example, Brueni et al. presented mathematical proof that for grids with at 3 buses, not more than n/3 of the buses need to be equipped with PMUs to achieve full system observability. We can use a relatively small number of PMUs, in addition to their high cost of both PMUs and their GRSinfrastructure, is the main motivation behind the research effort in designing methods for optimal PMU placement [1]. Many types of solutions for this problem have been proposed in recent years. One of the most widely used approaches is Linear Programming where the topology of the network can be modeled and solved using linear constraints [2]-[4]. Integer Quadratic Programming approach was also used [5]. Some of the various computational intelligence approaches such as Particle Swarm Optimization, Binary PSO, Genetic Algorithms (GAs), Bacterial Foraging Algorithm, Immunity GA,Adaptive Clonal Algorithm, Tabu Search and Simulated Annealing (SA) [6] have also been used to solve this problem.

However, upon experimenting it suggests that global optimization techniques do not fine-tune the result close to the optimalsolution and local search methods are easilyconverging towards local minima. So to fix all this issues, thispaper suggeststo use Memetic Algorithms (MAs) to this problem. MAs is basically a combination of

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globaland local search methods. The main objective behind MA is the combination of population-based search such as GA with the added capability ofindividual learning.

In this paper we implementMA which combines a GA with the hill- climbinglocal learning strategy. The fitness of each solution is calculatedw.r.t the need of power grid observabilityand to minimize the no. of required PMUs.Also the measurement redundancy indexwas used to distinguish between PMU placement with identical number of PMUs.The implemented solution was applied to the IEEE 14-bus, 57-bus and 118-bus test data sets. These resultscompare the quality of the produced solution to the individualGA solution and to the hill-climbing local searchsolution. It is later shown that by using MAsolution provides quick and stable convergence.

Optimal PMU Placement Problem: This Section gives an overview of the PMU placementproblem.

Problem Definition: The power grid comprises of power buses, which consists of voltage step-up and step-down distribution and power lines which are connections between individual buses. Anexample aIEEE 14-bus test data set isshown in Fig. 1. The topological representation of a grid canbe encoded using a connectivity matrix A defined as:PMU placement configuration in the power grid is determined by a vector *x* defined as:

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

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

Using the notation, the problem of optimal PMUplacement can be defined as:

$$min(w \quad (3)$$

$$\text{Subject to: } f(x) \geq 1 \quad (4)$$

Where, *w* represents a vector defining the cost ofinstalling a PMU at particular bus and f(*x*) makes sure that all buses are covered by PMU measurements. To simplify the problem,the relative cost of all buses is considered equal, which makes *w* = [1111....1.

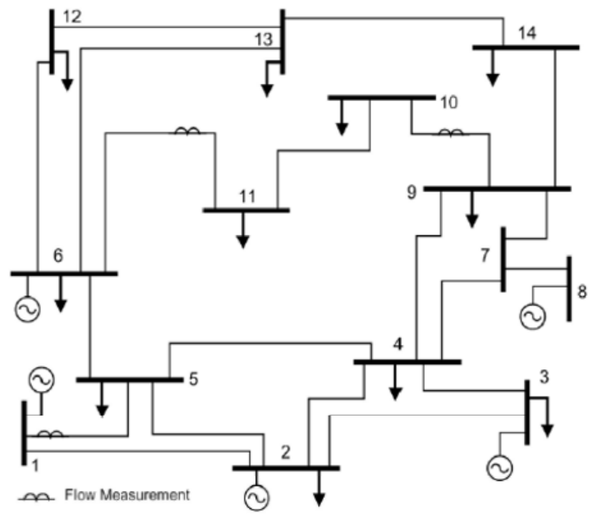

Fig. 1: IEEE 14-bus system (arrows and circles represent loads and generators).

Radial Busses: If wewant to further simplify the solution to the OPP problem, we can consider Radial busses too. A radial bus is connected to the rest of the grid via a single line. An example of a radial bus is bus no. 8 in Fig. 1. These radial buses can be excluded from the set of candidate buses for PMU placement. It is not important to show that placing a PMU at radial bus will be same as placing PMU on the single neighboring power bus of the radial bus. So radial buses can be excluded from the set of candidate buses for PMU placement.

Zero Injection Busses: Zero-Injection (ZI) buses are power buses that do not contain any power injection (e.g. load or generator) into the grid. Such buses are called and they can be used to further decrease the minimal no. of installed PMUs in order to ensure full system observability. This can be accomplished by using Kirchhoff's Current Law (KCL) to calculate the electrical measurements in certain busses. Let us consider a zero injection bus with n connected power lines. When we know the current measurements for n-1 power lines, the current on the remaining power line canbe calculated. Let us consider bus 7 in Fig. 1, which is a ZI bus. If we place a PMU on bus 9 this will result in observing the voltages on buses 4, 7, 9, 10 and 14.As we know the current in 2 out of 3 power line connections to bus 7 and since bus 7 is a ZI bus, we can apply KCL to calculate the current in the line between buses 7 and 8.

Memetic Algorithm: Memetic Algorithms (MA) is basically a combination of global and local search strategies. Population based GA is not suitable forfineuning of a solution, if the solution is in close neighborhood of the optimalsolution. Now a single solution based local search is also likely to get trapped in local minima when searching very far off from the global optimum. MA basically combines the positives of both algorithms into a better optimization algorithm with faster convergence. The main objective of MA is combiningpopulation-based random search such as GA and individual learning. It uses the GA used to maintain the population of solutions and to reproduce generations of individual solutions and with the hill-climbing local optimization strategy is applied to each generation and to every individual in that generation. An algorithm with pseudo-code of the MA is given in Fig. 2.

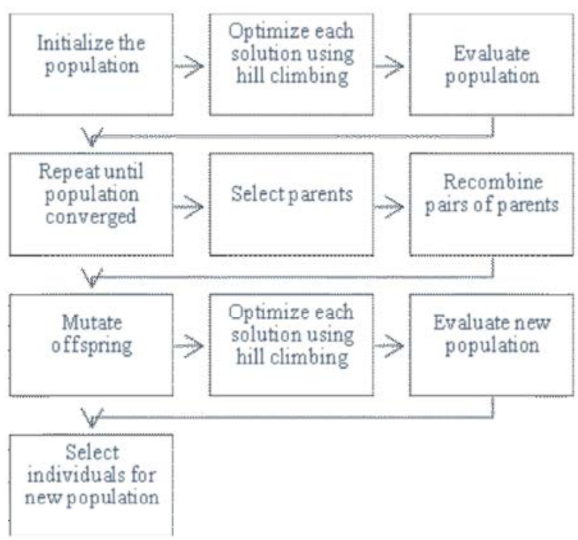

Fig. 2: Pseudo code of the memetic algorithm.

Memetic Algorithms for Opp: The Memetic Algorithm introduced in the previous section is used for the optimal placement of PMUs in the power grid. Here we implement using a GA to generate and observe a population for various PMU placement possibilities and to reproduce a new generation. We use hill-climbing method on each new generation for local search and improving each individualsolution.A binaryvector such as vector x is taken as a gene of the GA. If x=1, itmeans that a PMU is installed on the power bus and if the value is 0 it means there are no PMU in the power bus.If we know the position of radial buses,we canreduce the search space. Radial buses are taken out from the gene of the GA. Hereweuse two-point cross-overoperation and random bit flip mutation. Hillclimbing algorithm is applied to each solution for aspecified number of iterations. Random bit flipoperation is applied to generate new PMU placementconfiguration, resulting in either addition of a new PMU into thegrid or removal of a PMU. The old solution isreplaced by the new solution after comparing the fitness of the PMUplacement configuration.

The fitness value *F(x)* of can be calculated as follows:

$$F(x) = \begin{cases} N_{PMU} + N_{Bus} + (N_{Bus} - N_{observable}) \\ N_{PMU} + (1 - RI) \end{cases}$$

Where N_i is the number of installed PMUs, N represents the power buses in the grid, $N_{observable}$ is the number of power buses that areobserved and *RI* is the measurement redundancy index of the configuration. *RI* value can be computed as follows:

$$RI = \frac{[Ax] * [Ax]'}{length(Ybus)}$$

Redundancy index is basically denotingthe average number of PMU measurements per bus. Let us take an example where a simple power grid as shown in Fig. 3 with two PMU placement is given in Fig. 3(a) and Fig. 3(b). The *RI* for these bus arrangementis 1.33 and 1.00, respectively. So in spite of using 2 PMUs and having full-network observability in eachcases, Fig. 3(a) has increased measurement redundancy and is a better alternative of the two. The value of *RI* will be greater than 0 and less than 1. This is because of directly incident PMU is considered.

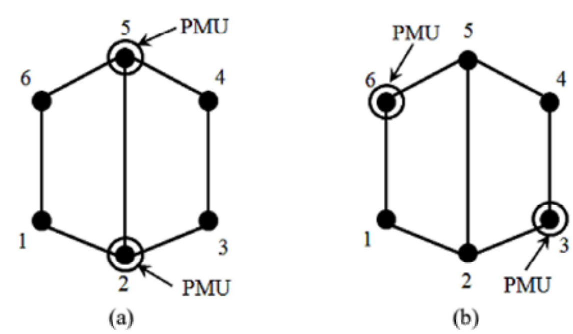

Fig. 3: Example of Measurement redundancy index

Fitness function is calculated in the following way. When we get a solution which provides full network observability, the fitness value is obtained by the number of PMUs installed. So a solution with smallernumber of PMUs is preferred. In all the different power grid configurations, there is a possibility that we can get several different configurations with the least amount of PMUs. Then in this case, we take the solution which provides the maximum degree of measurement redundancy according to the *RI* value. We know that *RI* is typically between 0 and 1. The higher the *RI* value the more information about the state of the grid can be kept should a PMU does not work.

Ifsome solution does not provide full grid observability, then the fitness value is increased by adding the number of power buses. So this solution is even worse than solution that provides full observability. However, to further guide the search algorithm towards the desired solution, the PMU placements which does not provide full observability but cover larger portions of the power grid are preferred.

Experimental Results: This Section gives experimental test cases, which is followed by the experimental results

Test Cases: The implemented MA was applied to the set of IEEE bus test systems. Namely, the IEEE 14-bus, 57-bus and 118-bus system were used. We had information about Zero-Injection (ZI) buses So we can get the measurement indirectly. Locations of ZI were usedas shown in Table I.

Table 1: Data Set Description for Ieee Test Cases

Test Case	Number of lines	Number of ZI busses	Location of ZI busses
14 bus	20	1	7
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

Experimental Testing: As we have already discussed in Section IV, the MA which we used combines the GA with the hill-climbing local learning strategy. We compared MA solution to using only GA. The details of the GA are as follows. Thepopulation consisted of 100 individuals and the optimizationwas stopped after 100 iterations. Two-point cross-over and arandom bit-flip mutation operators were used with a mutationrate set at 0.2. Now we used the hill-climbing algorithm which used a random bitflipmutation operator to generate new solutions and it was allowed 1000 iterations to converge. Thealgorithm parameters were selected based on experimental testing. Initial solutions for these methods were randomly initialized in the solution space.

First, we used MA to search for the solution to theOPP problem, which gives us the minimum number of required PMUs and a maximum measurement redundancy index. TableII shows the number of required PMUs, the measurementredundancy index and the list of PMU locations. By comparing the results achieved on the IEEE test bus system in terms of the number of required PMUs to the previousliterature it can be concluded that the proposed solution iscapable of locating the optimal solution.

Nowwe compared the performance of MA toGA and hill-climbing. The statistical comparison of eachalgorithms is necessary due to the probabilistic nature of the algorithms. It was observed that the MA solution provides the absolute bestresults with the smallest deviation, followed by thepopulation based GA and the hill-climbing local searchtechnique. These results shows that the MA based solutions are more stable as compared to GAbased solutions and hill-climbing based solutions.

Table 2: Best Opp Solution Using MA

Test Case	Number of PMUs	RI	Location of PMUs
14 bus	5	0.3	1,2,3,6,8
57 bus	16	0.256	1,6,9,15,19,22,25,28,32, 36,38,41,47,51,53,57
118 bus	38	0.360	4,6,8,10,12,15,18,19,24,25, 31,34,36,40,42,46,59,60,61, 69,70,72,73,80,85,87,89,95, 97,100,103,104,105,107,110, 111,113,115

As we see the advantages of MAs whencompared to other techniques is their high convergence speed. To see if the convergence improves, the MA and the Gahave been both applied to the IEEE test data sets 20 times andthe fitness of the solution at each generation was computed. Fig. 4 shows the results, which demonstrate the increased convergence rate of the MA. It is seen that theamount of local solution search during each generation helpsin improvingefficiency and convergencespeed of the MA. To study this behavior, MA was used on the IEEE 118-bus test data with random number of hill climbingiterations. Thehill-climbing iterations was varied from 0 to 20,where 0 is equal to using a GA without any hill-climbing. The results are described in Fig. 4.

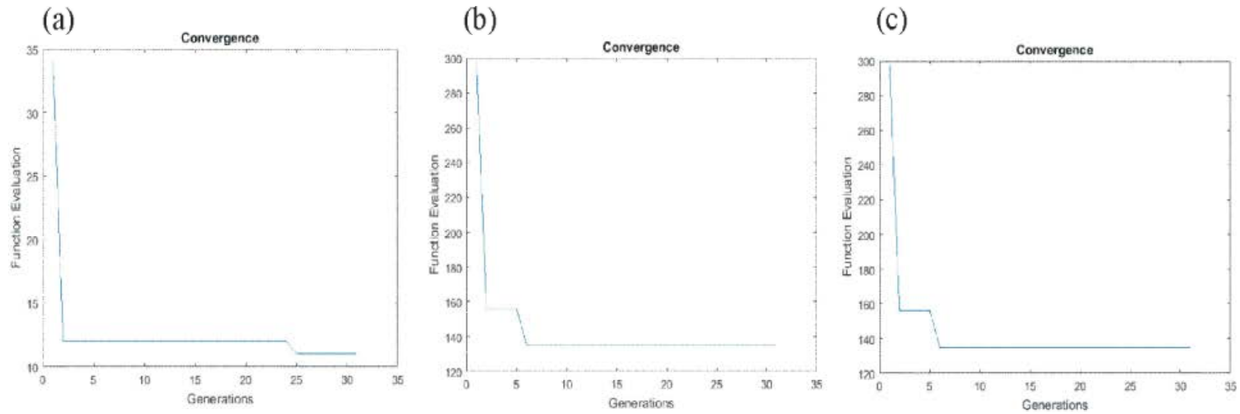

Fig. 4: Convergence of the MA for IEEE 14-bus (a), 57-bus (b),118-bus (c)

CONCLUSIONS

This paper tackles the problem of Optimal Placement of PMUs (OPP),which is locating a minimal no. of power buses where PMUs must be placed so as to provide full system observability. A proposed solution to the OPP problem via Memetic Algorithms (MA) was formulated. The MA used here combines the global optimizationpower of GAs with local solution using the hill-climbing method. The performanceof the proposed MA based approach wasdemonstrated on IEEE benchmark power networks. It was experimentally shown that the MA provides faster and more stable convergence towards the optimal solution. Further work can be done on studying advantages anddisadvantages of using 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. We can also improve fitness function to express more detailedrequirements.

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