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Reliably Optimal PMU Placement using Disparity Evolution-based Genetic Algorithm

Yoshiaki Matsukawa[1], Mohammad Lutfi Othman[2]*, Masayuki Watanabe[1] and Yasunori Mitani[1]

[1]*Department of Electrical & Electronic Engineering, Kyushu Institute of Technology, 1-1, Sensui-cho Tobata-ku Kitakyushu Fukuoka 804-8550, Japan*
[2]*Centre for Advanced Power and Energy Research (CAPER), Department of Electrical and Electronic Engineering, Faculty of Engineering, Universiti Putra Malaysia, 43400 UPM, Serdang, Selangor, Malaysia*

ABSTRACT

Phasor Measurement Units (PMUs) are an important component in Wide Area Protection (WAP)- based operations in power systems. It is needed that a certain placement scheme of PMUs is suggested if power system scale gets larger. The optimal placement of PMU in power systems has been considered and formulated in order to reduce the number of installed PMUs while accomplishing a desired level of reliability of observation. Optimal PMU Placement (OPP) problem as the combinatorial optimization problem has been formulated to determine the minimum PMU location in the power system. In this paper, Disparity Evolution-type Genetic Algorithm (DEGA) based on disparity theory of evolution is applied. Genetic Algorithm (GA) is employed for the purpose of comparison with DEGA. The optimization model is solved for IEEE 118 standard bus system. DEGA can find better placement suggestion compared with GA because of the nature of evolution that models the double spiral structure of DNA to hold the diversity of population.

Keywords: Observability, Phasor Measurements, Genetic Algorithm, optimization

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E-mail addresses:
p349532y@mail.kyutech.jp (Yoshiaki Matsukawa),
lutfi@upm.edu.com (Mohammad Lutfi Othman),
watanabe@ele.kyutech.ac.jp (Masayuki Watanabe),
mitani@ele.kyutech.ac.jp (Yasunori Mitani)
*Corresponding Author

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INTRODUCTION

Phasor Measurement Unit (PMU) plays a role in acquiring data to estimate the state of power system. This role is important in Wide Area Protection (WAP), where it provides reliable security prediction and optimized coordinated actions to mitigate or prevent large area disturbances. PMU can measure information of phase differences between different points synchronously because it uses GPS (Global Positioning System). The phase value synchronized by GPS can be calculated by PMU, and stored in the server over the internet. Using such data, it is analysable for oscillation features and power system characteristics. PMU data such as voltages and currents have been used for reliable distance protective relay operation (Othman et al., 2014) Synchro-phasor technology has grown from the PMU in the U.S. Pacific Northwest to a continental network of almost 2,000 PMUs in the past decade, which has helped to improve the reliability of the North American electric power grid since the late 1990s (Rurnett et al., 1994; Overholt et al., 2015).

However, if the scale of power system gets larger, it is needed that the optimal PMU placement scheme is chosen while considering reliability of observability which ensures whether the voltage phasor at that bus can be estimated or not in power system. In addition, the number of PMUs is needed to reduce in order to plan the placement schedule within limited cost. , Ghamsari-Yazdel and Enmaili (2015) reported that the price of a typical base PMU without measurement channels is around USD 20,000 and each measurement channel costs about USD 3,000. Thus, PMUs cannot be placed all buses because of limited budget. Therefore, Optimal PMU Placement (OPP) problem has been identified as a means to address the issue of budget constraint, where OPP works to reduce the number of PMUs placed in the power system while at the same time ensuring reliability of observability.

OPP problem has been proven to be completely NP (Non-deterministic Polynomial-time) by Brueni, Heath (2005) and can be defined as the binary combinatorial optimization problem. Hence, many heuristic algorithms and Integer Programming (IP) have been applied on OPP problem (Manousakis et al., 2012). Genetic Algorithm (GA) is one of the methods that has been proposed to solve combinatorial optimization problems. However, considering realistic system scale, e.g. above 100 bus system, normal GA approach might lapse into the evolution retardation due to missing the diversity of solution if the large number of evolutions is iterated to get better solution. i.e. similar individuals tend to be diffused into population by procedure of GA. This paper presents an application of Disparity Evolution-type Genetic Algorithm (DEGA) based on Disparity Theory of Evolution. GA is used for the purposes of comparing with DEGA. The optimization model is solved for IEEE 118 bus test system. Simulation shows DEGA approach performs better in robustness on 50 iterations. The proposed DEGA approach in this study serves as an important aspect of WAP scheme.

PROBLEM FORMULATION

In this study, reliability based OPP problem is defined as a single objective optimization problem (Khiabani et al., 2014). This section provides the details about single objective PMU placement model.

Objective Function

In this study, the objective function includes minimization of the number of PMUs and maximization of reliability of observability. The mathematical objective function model is defined as follows:

$$z = \max\left\{ w_1\left(ROB - R_{\min}\right) + w_2\left(\sum_{i=1}^{n} x_i\right)^{-1} \right\} \tag{1}$$

where R_{min} is the desired minimum system wide reliability level, ROB is the overall system reliability of observability, $\sum_{i=1}^{n} x_i$ is the total number of buses to be placed in the system, n is the number of buses. w_1 and w_2 are weight coefficients associated with objective. Equation (1) will be modelled as a fitness function on GA and DEGA in later section.

The Range PMU Covers

The range of buses by which PMU covers is given. PMU which is placed at a bus measures the voltage phasor of that bus and the current phasors of adjacent lines. PMUs are not necessarily placed at all buses because the voltage phasors of adjacent buses can be obtained using Ohm's law. Thus, PMU placement at a given bus allows the measurement of voltage phasor at that bus directly, and voltage phasors at immediate neighbouring buses by calculation.

Figure 1 (a) shows the example the covering range of buses that one PMU covers. In Figure 1, a PMU which is allocated at bus 3 covers buses 1, 2, 3 and 4 since the PMU makes adjacent buses itself observable.

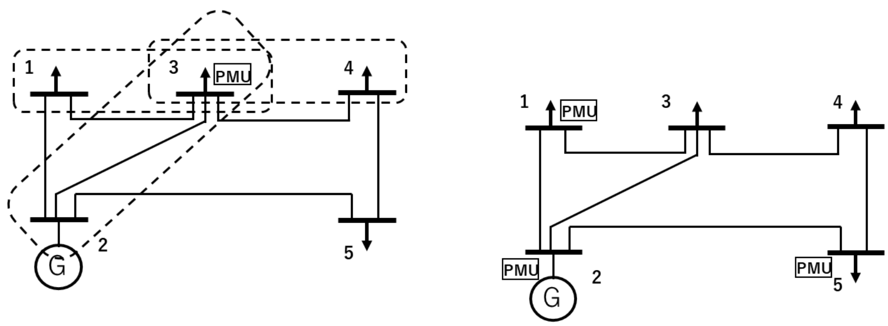
Reliability of observability

None of the PMUs are redundant, the failure of any PMU would result in system failure. Thus, it is necessary the reliability of observability is defined. The reliability of observability (Ghamsari-Yazdel and Enmaili, 2015) of the *i* th can be given as:

$$r_i = 1 - \prod_{j=1}^{f_i} q_j \tag{2}$$

where r_i represents the reliability of the *i* th bus, q_j is the probability of failure of the PMU, f_i denotes the total number of PMUs covering the i th bus. Also, (2) can be described as:

$$r_i = 1 - \prod_{j=1}^{f_i} (1 - R_{PMU}) \tag{3}$$



(a) (b)

Figure 1. Covering range of the PMU; (b) Reliability example in case of IEEE 5 bus system

where, R_{PMU} is a value of reliability that one PMU has. For example, consider the IEEE 5 bus system in Figure 1 (b) with PMUs placed at buses 1, 2, and 5. Then it is assumed that one PMU has a reliability of $R_{PMU} = 0.90$. At this time, the reliability of observability of bus 4 will be 0.90 because it is observed by one PMU which is placed at bus 5 only. However, bus 1 is covered by two PMUs which are placed at bus 2 and bus 1 itself. Therefore, the reliability of observability of bus 1 is given as $r_1 = 1 - \{(1 - 0.90) * (1 - 0.90)\} = 0.99$.

Especially, this study is interested in the maximization of overall system reliability. Then, it is defined by taking direct product of reliability of observability of all buses as follows:

$$ROB = \prod_{i=1}^{n} r_i \tag{4}$$

where n is the number of the buses in the power system.

The abovementioned reliability index is included into PMU placement constraints as follows:

$$x_i = \begin{cases} 1 & \text{if the PMU is present at bus } i \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

$$A_{ij} = \begin{cases} 1 & \text{if either } i = j \text{ or } i \text{ is adjacent to } j \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where x_i is defined as a binary decision variable vector which represents whether the PMU is placed at i th bus or not, and A_{ij} is called connection matrix which represents the connection condition of each bus in the power system. Then, the number of PMUs covering the i th bus can be introduced as follows:

$$f_i = \sum_{j=1}^{n} A_{ij} x_j \tag{7}$$

Thus, it can be known how many buses that cover the i th bus from f_i.

DESCRIPTION OF ALGORITHMS

Disparity Evolution-type Genetic Algorithm

GA is a method to solve the optimization problem by modeling the evolutional theory. DEGA which was first developed by Maeda (2001) is an improved GA modelled on the disparity theory of evolution (Furusawa and Doi 1998). DEGA exploits the concept of gene reproduction and different mutation rates by faithfully modelling the double spiral structure of DNA. In the disparity theory of evolution, when double DNAs duplicate, they are divided into two kinds of chains that is called leading strand with low mutation rate and lagging strand with high mutation rate. Different mutation rates make DEGA's evolution speed improve by maintaining diversity of solutions, whereas it is difficult to increase diversity in GA's procedure. The procedure of DEGA for OPP problem is described in Figure 2. In this solution approach for OPP problem, a binary encoding is implemented where the string of chromosome means the total number of buses in the system. For representative value in the chromosome, if the PMU is placed on that particular bus, then the representative at that particular bus takes 1, and it takes 0 if otherwise.

```
Algorithm: DEGA (evol, n, pc, pmle, pmla)
//Initialize of 0th generation
k ← 0;
Le_k ← a population of n/2 randomly-generated chromosomes (leading strand);
La_k ← bit reversed individuals of Le_k (lagging strand);
P_k ← Le_k + La_k;
//Evaluate Le_k
Compute fitness (i) for each i ∈ Le_k;
While (k < evol)
{       //Create generation k + 1;
        //Crossover (two-point crossover)
        cp1, cp2 ← Generate two random numbers for each Le_k and La_k
        Crossover between cp1 and cp2; Select pc*n members of Le_k and La_k in P_k; pair them up; produce
        offspring Le_k', La_k';
        O_k ← Le_k' + La_k';
        //Mutate
        pm ← Generate random numbers for each gene;
        Mutate for Le_k' in O_k; If pm < pmle, then invert the bit; occur at low mutation rate;
        Mutate for La_k' in O_k; If pm < pmla, then invert the bit; occur at high mutation rate;
        //Duplicate
        La_k" ← create new lagging strand by bit inversion of Le_k';
        Le_k" ← create new leading strand by bit inversion of La_k';
        O_k ← Le_k' + La_k' + Le_k" + La_k";
        //Evaluate Le_k', Le_k" and select the individuals which survive into next generation by roulette
        selection and elitism
        Compute fitness
        Preserve limited number of elites in P_k, O_k;
        Evaluate each leading strand in the individual; Select the individuals P_k+1 within n by roulette
        selection;
        //Increment
        k ← k + 1;
}
Return the best solution in population;
```

Figure 2. Pseudo-code of the DEGA model

Fitness Function

The fitness function is defined in order to decide the relative merits of the solution. It is calculated as:

$$fitness = \sum_{j=1}^{4} \omega_i \theta_i \tag{8}$$

where, each term θ_i is defined as:

$$\theta_1 = \frac{Number\ of\ buses\ covered\ by\ PMUs}{Total\ number\ of\ buses} \tag{9}$$

$$\theta_2 = \frac{Number\ of\ buses\ that\ no\ PMU\ is\ placed}{Total\ number\ of\ buses} \tag{10}$$

$$\theta_3 = \begin{cases} 1\ ROB \geq R_{min} \\ 0\ ROB < R_{min} \end{cases} \tag{11}$$

$$\theta_4 = ROB \tag{12}$$

ω_1 denotes corresponding weights coefficients with the criteria that are listed above. Equation (8) is customizable by changing each ω_1 the summation of all ω_1 should be 1. In this study, solutions which have high fitness value have a higher chance to be chosen into next generation because the roulette selection is used as the selection method. θ_i means the fraction of buses covered by PMUs. θ_2 is associated with minimizing the number of placed PMUs. θ_3 denotes the required overall reliability of observability in the system, if the solution cannot satisfy desired reliability, 0 will be given as penalty in this term. θ_4 directly has the value of reliability of observability. The weight coefficients ω_1 are configured as shown in Table 1, whereby ω_1 is set as the highest value to have consideration for the complete observability, and is the second highest value to satisfy the required reliability of observability. ω_4 is lowest because if solution satisfies the minimum reliability of observability, it is not needed that reliability of observability is improved keenly. After satisfying the reliability, the number of PMUs are reduced.

SIMULATION STUDY

DEGA and GA are tested on a standard IEEE 118 bus system using MATLAB 2013a. Table 1 shows the parameters of DEGA and GA in this simulation. GA as the standard approach for global optimization is chosen for the purposes of comparison with DEGA. The PMU placements are proposed with desired reliability R_{min} = 0.90, PMU inherent reliability R_{PMU} = 0.99 for each method. In order to verify robustness of proposed method, the simulations have been tried by 50 iterations using different random numbers. Moreover, this simulation considers the concept of zero injection bus. The results proposed by DEGA and GA are shown in Figure 3 and Tables 2 and 3. The graph in Figure 3; (a) shows the generation characteristics for fitness value in the iterations which get best fitness value in each method, also (b) shows the most inferior fitness case. The graphs show the best and average fitness value in the population

Table 1
DEGA and GA parameters

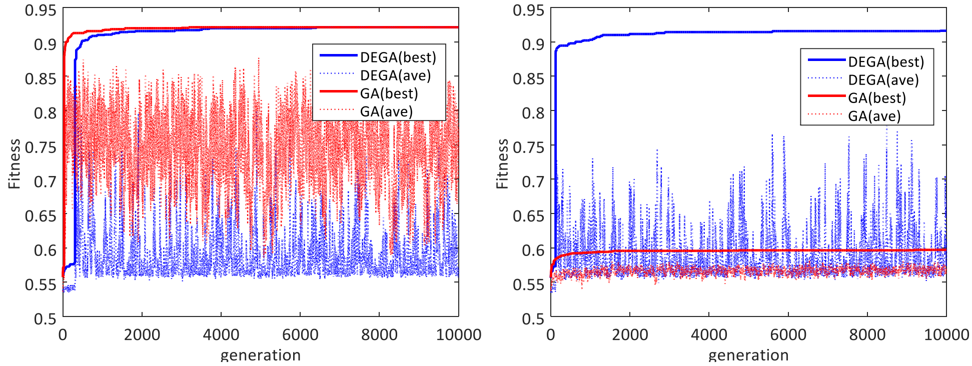
Parameter	DEGA	GA
Population size	50	50
Generation limit	10000	10000
Crossover probability	0.4	0.8
Mutation probability	-	0.01
Mutation probability on leading strand	0.01	-
Mutation probability on lagging strand	0.5	-
Number of preserved elites	3	3
ω_1	4/9	4/9
ω_2	1/6	1/6
ω^3	1/3	1/3
ω_4	1/18	1/18

Table 2
The practical best and most inferior solutions in each method

	The best solution		The most inferior solution	
	DEGA	GA	DEGA	GA
Fitness	0.9214	0.9214	0.9163	0.5970
The number of PMUs	52	52	56	33
ROB	0.9071	0.9075	0.9164	0.5843

Table 3
The fitness average in 50 iterations

	DEGA	GA
The fitness average	0.9190	0.7659



(a) (b)

Figure 3. (a) Generation-Fitness characteristics in the best iterations; (b) Generation-Fitness characteristics in the most inferior iterations

of each generation. DEGA seems to have slower convergence rate and lower average fitness value in generations, but finally DEGA got approximately same fitness with GA. However, DEGA can also get sufficient fitness even though GA's evolution stops in the case of Figure 3(b). GA obviously could not satisfy the minimum desired ROB as shown in Table 2. DEGA has better average fitness value in 50 iterations than GA. It can be considered that DEGA can maintain diversity of solution in the progress of evolution because of the procedure. That is why DEGA has lower average fitness value in each generation due to diversity of individuals. Results prove that in OPP problem, DEGA has good capacity to solve the problem in several cases. In some cases of larger system scale, DEGA is expected to be able to find better PMU placement.

CONCLUSION

This paper proposed the novel GA-based algorithm called DEGA to deal with the issue of OPP problem. Simulations were done in DEGA and GA for IEEE 118 bus system. Results indicate that DEGA could be potentially useful in solving the OPP problem.

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