Optimal Placement of Phasor Measurement Units Using Immunity Genetic Algorithm

Farrokh Aminifar, *Student Member, IEEE,* Caro Lucas, *Senior Member, IEEE*, Amin Khodaei, and Mahmud Fotuhi-Firuzabad, *Senior Member, IEEE*

***Abstract*—This paper investigates the application of immunity genetic algorithm (IGA) for the problem of optimal placement of phasor measurement units (PMUs) in an electric power network. The problem is to determine the placement sites of the minimal set of PMUs which makes the system observable. Incorporating immune operator in the canonical genetic algorithm (GA), on the condition of preserving GA's advantages, utilizes some characteristics and knowledge of the problems for restraining the degenerative phenomena during evolution, so as to improve the algorithm efficiency. This type of prior knowledge about some parts of optimal solution exists in the PMU placement problem. So, the IGA is adopted in this paper to solve the problem. Also, a new effect which is preventing from familial reproduction is studied which shows an increase in converging speed. The effectiveness of the proposed method is verified via IEEE standard systems and a realistic large-scale power system.**

***Index Terms*—Genetic algorithm (GA), immunity genetic algorithm (IGA), observability analysis, optimal placement of PMUs (OPP), phasor measurement unit (PMU).**

I. Introduction

PMUs have evolved into a practical tool for measurement of positive sequence associated with power system voltage and current phasors. These devices are synchronized via signals from global positioning system (GPS) satellite transmission [1]. They can enhance many present applications such as state estimation and bad data detection [2], stability control [3], remedial action schemes [4], and disturbance monitoring [5]. As the voltage and current phasors are measured, the equations of state estimation problem become linear and the solution can be obtained straightforwardly [6].

It is neither economical nor necessary to install a PMU at each bus of a wide-area power network. As a result, the problem of OPP concerns with where and how many PMUs should be implemented to a power system to achieve full observability at minimum number of PMUs. The theory of network observability can be divided into two groups of techniques: numerical and topological [7]. The former is based on whether the measurement gain or Jacobian matrix is of full rank or not. This technique suffers from huge matrix manipulation which means being computationally expensive. The latter, as the commonly used technique, is however based on whether the spanning tree of full rank can be constructed or not.

Strategies for the OPP problem have been concentrated as a research interest. In this area, considerable interesting works have been reported and each of them has its own pros and cons. In [8], the problem was solved using dual search algorithm along with simulated annealing (SA) method, which is apt to be suffered from excessive calculation burden if applied to a large power system. SA is a powerful stochastic optimization technique that can, theoretically, converge asymptotically to a global optimum solution. However, it is very time consuming to reach a near-global minimum.

Reference [9] proposed three approaches aiming at reducing computational burden of the OPP problem. First, SA method was modified in setting the initial temperature and cooling procedure. Second, direct combination (DC) method was suggested using a heuristic rule to select the most effective sets in the observability sense. Last, Tabu search (TS) method was employed to reduce the searching space effectively. The literatures appeared after this paper revealed that its results were not the optimal values even in small studied cases.

In [10], the OPP problem was dealt with non-dominated sorting genetic algorithm (NSGA). The proposed method estimates each optimal solution of objective functions by the graph theory and simple GA. The best tradeoff between competing objectives is then searched by using NSGA. As the proposed method requires more complex computations, it is restricted by the size of problem.

A GA-based procedure for solving the OPP problem was presented in [11]. There is no implication on the aspects of converging speed and execution time. Also, the examined test systems are relatively small comparing to those needed in practice.

An integer programming based approach for the optimization of PMUs' installation costs has been applied in [12]. In this paper, it has been implicated that some terms should be neglected to make the model tractable. Although the authors have mentioned that this approximation has no effect on the optimization of simulated cases, but it results in lack of generality for the proposed model.

F. Aminifar, A. Khodaei, and M. Fotuhi-Firuzabad are with Electrical Engineering Department, Sharif University of Technology, Tehran, Iran (e-mail: frkh_aminifar@ee.sharif.edu, a.khodaei@ee.sharif.edu, fotuhi@sharif.edu).

C. Lucas is with CIPCE, Department of Electrical and Computer Engineering, University of Tehran, Tehran, Iran (e-mail: lucas@ut.ac.ir).

In [13], the search tree and SA techniques were used for the OPP problem. Novel concepts of incomplete observability and depth of unobservablity were introduced in this literature and different types of the problem were worked out.

Reference [7] introduced a novel topological method based on the augment incidence matrix and TS. Although, TS has been described as a global optimization algorithm, but comparing its results with those of previous papers does not justify the claimed statement.

Referring to the above mentioned features associated with different techniques, it is evident that most of the introduced methods suffer from a very time consuming process to reach a near-global optimum. In [14], IGA was developed and its effectiveness was verified on the traveling salesman problem (TSP) as a benchmark. It was revealed that IGA is not only feasible but also effective and is conducive to alleviate the degeneration phenomenon in the original GA, thus greatly increases the converging speed. The main idea behind IGA is employing the prior knowledge of problem in the search process. This notion is applicable in the OPP problem since some buses which are/are not required having PMU can be determined initially.

Based on the above consideration, this paper attacks the OPP problem by means of IGA. Three effective vaccines are abstracted using the rules associated with topological observability analysis. This paper also studies the effect of preventing from familial reproduction, which was inspired from nature, on the considered problem. Furthermore, a novel rule in the observability assessment of electric network is employed. By considering this rule, the minimum number of required PMUs is decreased in some cases. The proposed model is justified using the IEEE standard test systems also a realistic large power system.

This paper is organized as follows. Section II discusses the optimization issues associated with IGA. In Section III, the OPP problem is described and novel statements of observability rules are presented. Section IV shows the implementation of IGA on the OPP problem and discusses the simulation results. Finally, conclusions attained by this paper are summarized in Section V.

II. Optimization Algorithm

Some outstanding algorithms have surfaced in recent decades. Some of these methods include the GA (Holland, 1975), SA (Kirkpatrick et al., 1983), particle swarm optimization (Parsopoulos and Vrahatis, 2002), ant colony optimization (Dorigo and Maria, 1997), and evolutionary algorithms (Schwefel, 1995) [15]. They represent processes in nature that are remarkably successful at optimizing natural phenomena. They rely on an intelligent search of a large but finite solution space using statistical methods. The algorithms do not require taking cost function derivatives and can thus deal with discrete variables and non-continuous cost functions. This feature is the most important one associated with employing these algorithms in optimal placement problems such as OPP problem.

As mentioned earlier, the IGA is adopted as the optimization tool to deal with the OPP problem. So in this section, two models, i.e. GA and immune algorithm (IA), are initially introduced and then IGA is briefly presented.

A. Genetic Algorithm (GA)

GA was inspired by the natural evolution of species. In natural evolution, each species searches for beneficial adaptations in an ever-changing environment. As species evolve, new genetic information is encoded in the chromosomes. This information changes by the exchange of chromosomal material during breeding (crossover) and also mutation [16]. From the engineering standpoint, if we have two solutions with good approximation for a given problem, their combination might lead to a better solution. So, GA pertains to the search algorithms with an iteration of generation-and-test [14]. With the characteristics of easier application, greater robustness, and better parallel processing than most classical methods of optimization, GA has been widely used for combinatorial optimization [17], structural designing [18], machine learning rule-based classifier systems [19], and etc. The disadvantages associated with GA will be expressed in Subsection C of this section.

B. Immune Algorithm (AI)

IA mimics a basic immune system defending against bacteria, viruses and other disease-related organisms. It is equipped with dramatic and complex mechanisms that recombine genes to defeat invading antigens by reducing the number of antibodies and keeping out the antigens [20]. Using this mechanism, the IA provides a good performance as an optimization algorithm. The idea of immunity is mainly realized through two steps based on reasonably selecting vaccines, i.e. a vaccination and an immune selection [14]. These are used in IGA to enhance the performance of canonical GA.

C. Immunity Genetic Algorithm (IGA)

Crossover and mutation as two operators of GA award each individual the chance of optimization and ensure the evolutionary tendency with the selection mechanism of survival of the fitness. Since the two genetic operators make individuals change randomly and indirectly during the whole process, they can cause certain degeneracy. In some cases, these degenerative phenomena are very obvious which restrict the application of GA. On the other hand, there are many basic and obvious characteristics or knowledge in the problems that the GA operators can not employ them in a fashion of appearance of some torpidity when solving the problems. Some tricks of IA can be combined with GA, resulting IGA, to enhance the optimization performance.

IGA utilizes the local information to intervene in the globally parallel process and restrain or avoid repetitive and useless work during the course, so as to overcome the blindness in action of the crossover and mutation. During the actual operation, IGA refrains the degenerative phenomena arising from the evolutionary process, thus making the fitness of population increase steadily. Fig. 1 depicts the flowchart of IGA [14]. The dashed rectangle represents the new immune operator which is added to the GA. As noted earlier, vaccination and immune selection are performed as the immunity operator in IGA. Generally speaking, the vaccination is used for raising fitness, and the immune selection is for preventing the deterioration. They are explained in the following of this subsection.

It has to be noted that as IGA is a novel-introduced algorithm with low previous applications, a brief explanation on its notions is presented to make the readers familiar with it. Detailed explanations and proofs are available in [14].

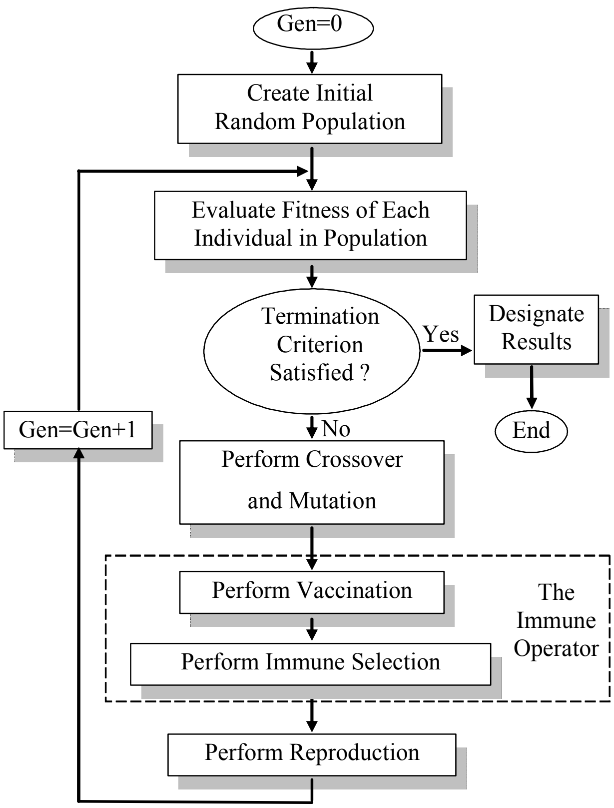

Fig. 1. IGA flowchart.

1) Vaccination: It means modifying some genes of some individuals to gain higher fitness or greater probability. A vaccine is abstracted from prior knowledge or local information of the problem. In the problem considered by this paper, relatively significant information can be deduced by detailed analysis of the problem. As expected, the vaccine's information amount and validity play an important role in the performance of the algorithm. The amount of injection associated with each vaccine, i.e. the number of individuals being vaccinated in each population, can be selected randomly based on the immune probability or by a fixed value based on the previous experiences. It has to be noted that in a certain problem such the one considered here, there may not be only one vaccine. In such a case, the injection can be carried out by either selecting any vaccine randomly or getting them together.

Appropriate using of vaccination can improve the efficiency of the algorithm greatly. In contrast, if the prior estimations of the problem are wrong, the vaccination will hold back the searching actions. Hence, the abstraction of vaccines and their injections are so crucial operation in the IGA technique.

Self-adapting selecting vaccines is a superior feature of IGA that should be implied here. In some of the optimization problems, it is difficult or even impossible to abstract prior information about these problems. On the other hand, in possible cases, it may greatly increase the workload of the method and decrease its efficiency. So, in such cases, the information needed for vaccines can be abstracted from genes of the present optimal individual during the evolutionary process. Reference [14] has provided detailed explanations about this subject.

2) Immune Selection: It is the next process after the vaccination. This operation consists of two stages. Immune test is the first one to be continued to test the individual vaccinated. If the fitness rises, then go to the next stage; or else make the parents take part in the competition of selection instead of the offspring. The second stage is the probabilistic selection. Selection is based on the annealing process which means that the probability of joining individual x_i to the new parents is as below:

$$P(x_i) = \frac{e^{f(x_i)/T_k}}{\sum_{j=1}^{n_o} e^{f(x_j)/T_k}} \tag{1}$$

where n_0 is the number of present offspring, $f(x_i)$ is the fitness of the individual i, and T_K is the annealing temperature approaching zero with the progress of generations. The annealing temperature is calculated by

$$T_k = ln(\frac{T_0}{k} + 1), \quad T_0 = 100 \tag{2}$$

where k is the generation number.

D. Familial Reproduction Effect

The genetic investigations have proven that in the human species, the familial reproduction results in some disorders and diseases in the offspring [21]. Considering that in most human societies, the marriage between two parents' offspring, i.e. a son and a daughter from identical parents, is illegal and against the religious principles, this observation has been inferred from higher level familial marriages, e.g. between cousins. However, it is expected that the degenerative effect of familial recombination between offspring generated from identical parents appears similar to the other familial marriages. We called this phenomenon as *familial reproduction effect* and try to investigate it on and by means of the considered problem. Fig. 2 illustrates this phenomenon in a simple pictorial manner.

The left hand side of Fig. 2 shows the recombination of two parents while generating two offspring. Since the parents are likely with good fitness that they are selected to mating, both offspring have chances to be better than parents based on the *building block schemata*. Assuming that these offspring are adopted to mate in the next generation(s), it is probable to generate their parents as depicted clearly by the right hand side of Fig. 2. However in a generic view, even if the crossover point of offspring in generation of Gen+1 is different from that of their parents, the resultant offspring have very similarities to their grand parents or maybe their aunts or uncles. Occurrence of this phenomenon makes repetitive and useless work during the solution search course and reduces the converging speed.

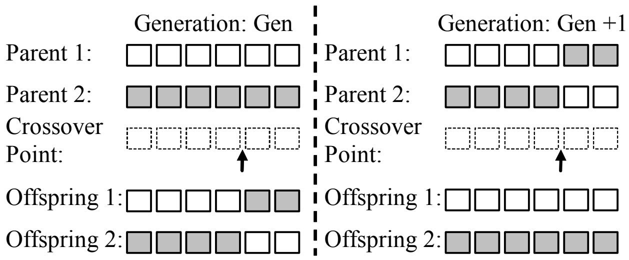

Fig. 2. Familial crossover effect.

Based on the above consideration, it is expected that avoiding from familial mating up to a given level can enhance the converging process of algorithm and its efficiency. However, similar to the other ideas in the field of heuristic algorithms, this can not be a general observation and should be examined in the specific cases. Simulation results on the OPP problem verify the expected results associated with this phenomenon particularly when the number of individuals in each population is few.

III. Description of OPP Problem

The description of OPP problem is briefly presented here. Detailed explanations can be found in [7, 8, 12]. The OPP problem concerns with where and how many PMUs should be implemented in a power system to achieve full observability at minimum number of PMUs. So, minimizing the number of PMUs is the objective function of this optimization problem and the constraint of the problem is being full observable of the electric network. According to a commonly used method, the problem constraints can be added to the objective function weighted by appropriate multipliers. So, the objective function of the problem is calculated according to

$$C(x_i) = w_1 N_{PMU} + w_2 N_{UO} \tag{3}$$

where w_1 and w_2 are constant weights which are respectively selected equal to 1 and 3 in the OPP problem. These values are selected based on the experiences of different case studies. However, they can be tuned for any specific case to improve the efficiency of the method. In (3), N_{PMU} is the number of PMUs and N_{UO} is the number of unobservable buses associated with chromosome *i*. Knowing that (3) should be minimized, the fitness of individual *i*, i.e. $f(x_i)$ in (1), can be assumed as the inverse of $C(x_i)$.

Determination of N_{UO} should be done using observability analysis. Similar to the most literatures [7, 8, 11, 12], topological analysis is used by this paper for the observability assessment. It is defined as the existence of one spanning measurement tree of full rank in the network [8]. The observability implies that each bus of the network must have one phasor voltage measurement or a phasor voltage pseudo-measurement. Obviously, having the voltage phasor of all buses, any other parameter of the network such as branch currents or load currents can be obtained. Determination of the voltage phasor measurement, direct or pseudo, needs to use some rules. In this paper, we use only the voltage phasors to observability analysis unlike other literatures which use both voltage and current phasors. It should be noted that this simplifies only the statement of the rules; however, they exactly express the same thing with the rules of other literatures. The rules used by this paper are expressed as follows.

Rule 1: Installation of a PMU in a given bus makes itself and other buses incident to that bus observable. This implies that the voltage phasors of these buses are known.

Rule 2: If only one bus is unobservable among a zero-injection bus and its entire incident buses, it can be observable using the Kirchhoff's current law (KCL) at the zero-injection bus.

These two rules include all four conditions mentioned by [7]. Rule 2 should be applied recursively until no new observable bus is identified.

Rule 3: If the entire incident buses to *n* connected unobservable zero-injection buses are observable, the zero-injection buses can be observable applying KCL at them [22].

A. Abstraction of Vaccines

As it was mentioned earlier, vaccines are abstracted from prior knowledge or local information of the problem. Fortunately in the OPP problem, some types of prior knowledge can be extracted as discussed in the following. The single line diagram of a 9-bus system is shown in Fig. 3 and it is used to simplify the explanation of vaccines' abstraction. Buses 7 and 8 in Fig. 3 are zero-injection buses.

Vaccine 1: The buses with only one incident line should have no PMU, e.g. bus 1 in Fig. 3. The reason for this is that installation of PMU in bus 1 only makes itself and bus 4 observable. However, this PMU can be installed in bus 4 to make other buses, i.e. buses 5 and 9, observable in addition to buses 1 and 4. It is important to point out that as the abstraction knowledge of vaccine 1 is always true, this vaccine should be injected in the entire individuals with probability one.

Vaccine 2: If the other side bus of the line connected to a bus with only one incident line is not a zero-injection bus, it should be assigned as a PMU place, e.g. bus 4 in Fig. 3. Similar to vaccine 1, as the knowledge behind vaccine 2 is always true, this vaccine should be injected in the entire individuals with probability one. The benefit expected with the injection of vaccines 1 and 2 is due to this point that eliminating even one PMU candidate results in reduction of search space by a half.

Vaccine 3: Zero-injection buses may not need to have PMU. It is evident that the benefits raised by rules 2 and 3 to reduce the number of PMUs are achievable only when the zero-injection buses are not be equipped with PMU. The reason for this is that installation of a PMU in a zero-injection bus measures all its current phasors; consequently, there will be no unknown current phasor to be determined by KCL at that bus. In contrast with vaccines 1 and 2, the idea behind vaccine 3 is not true all the time and for all cases. For instance, for the system shown in Fig. 3, although the minimum required PMUs are 2 at buses 4 and 7, but injection of vaccine 3 increases the number of PMUs to 3 at buses 4, 6, and 9. According to the illustrated reason and to have opportunity of finding the global optimum, vaccine 3 should not be injected into the entire individuals. Assume that N_p is the number of individuals in the population, $N_{v3}=\alpha\times N_p$ will be the number of individuals randomly selected to be injected by vaccine 3. We called α as the *vaccination rate* and it is assumed to be 0.5 in the simulated cases.

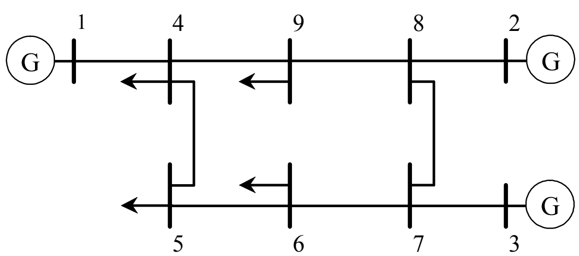

Fig. 3. 9-bus system used for explanation of vaccines.

IV. Simulation Results and Discussion

Simulations are carried out on several systems including IEEE 14-, 30-, 57-, and 118-bus test systems [23] as well as a large-scale real power system with 2746 buses. The network's data of the large system were taken from [24]. The technical specifications of the computer used for simulations are Centrino 1.6 GHz CPU with 512 MB of RAM.

The characteristics of the IGA are as follows: Single point crossover, mutation rate of 0.5 %, 100 chromosomes for each population, and Roulette wheel fitness based selection. The best result found in all generations is considered as the solution of the problem. The stopping criterion of the program is adopted as reaching the iteration number to 1000.

Here, different features associated with the proposed method are investigated and presented in separate subsections.

A. *Results of the IEEE Test Systems Excluding Rule 3*

As previously noted, almost all literatures have only used rules 1 and 2 for their observability analysis. To compare IGA method with the others, the problems should be solved in an equal condition or in other words with an identical fitness function. So in this subsection, rule 3 is excluded from the observability analysis. As the results of different methods on four commonly used IEEE test systems have been reported, these systems are adopted to investigate the efficiency of the IGA technique.

The results obtained by IGA and other methods are shown in Table I. As it can be seen from this table, the IGA method can find the best result for all cases. It is interesting that in the IEEE 57-bus test system, which is a relatively small system, the minimal solution, i.e. 11 PMUs, has not been found by the other techniques except by [13]. Table II gives the PMU locations for different cases. In this case, the execution times associated with the 14-, 30-, 57-, and 118-bus test systems are respectively 2, 4, 11, and 72 seconds. Note that, these values are obtained by changing the stopping criterion from a fixed generation number to the criterion that predefined optimal results must be reached.

B. *Results of the IEEE Test Systems Including Rule 3*

Rule 3 can be beneficial and reduces the required number of PMUs while maintaining the network completely observable. Here, rule 3 is included in the observability analysis and the optimal locations of PMUs are shown in Table III for the test systems.

TABLE I
Results of Different Techniques and IGA Excluding Rule 3

	Test Systems			
	14-bus	30-bus	57-bus	118-bus
IGA	3	7	11	29
Dual Search and SA [8]	3	--	--	29
SA and DC and TS [9]	3	7	13	--
NSGA [10]	--	--	--	29
GA [11]	3	7	12	29
Integer programming [12]	3	--	12	29
Search tree and SA [13]	3	7	11	--
TS [7]	3	--	13	--

TABLE II
Optimal PMU Locations Obtained by IGA Excluding Rule 3

Test System	PMU Location (Bus #)
14-bus	2 6 9
30-bus	1 5 10 12 18 24 30
57-bus	1 6 13 19 25 29 32 38 51 54 56
118-bus	3 8 11 12 17 21 25 28 34 35 40 45 49 53 56 62 63 72 75 77 80 85 86 90 94 102 105 110 114

TABLE III
Optimal PMU Locations Obtained by IGA Including Rule 3

Test System	PMU Location (Bus #)
14-bus	2 6 9
30-bus	1 5 10 12 18 24 30
57-bus	1 6 13 19 25 29 32 38 51 54 56
118-bus	3 8 11 12 17 21 25 28 34 35 40 45 49 53 56 62 72 75 77 80 85 86 90 94 102 105 110 114

The required number of PMUs for the IEEE 14-, 30-, 57-, and 118-bus test systems are respectively 3, 7, 11 and 28. By comparing these results with those of condition excluding rule 3, it is revealed that the required number of PMUs is decreased by one for the 118-bus test system. However, rule 3 has no impact on the observability assessment of other cases. It is evident that this impact strictly depends on the configuration of the network, number of zero-injection buses and their connections. For 118-bus test system, comparing the PMU locations in Table II with those of Table III indicates that the PMU of bus 63 is omitted by including rule 3. This result is theoretically justified since buses 63 and 64 are two zero-injection buses connected each other and it is evident that rule 3 can be beneficial.

C. Impact of Immune Operator

For illustrating the impact of immune operator on the canonical GA, the OPP problem on the IEEE 57-bus test system is solved twice with GA and IGA. As deduced in the previous subsections, employing rule 3 has no reducing effect in this test system so it is excluded in these simulations. All specifications of GA are the same with those in IGA. The prevention from familial reproduction is included in both algorithms. Since the best result of this problem is known, the stopping criterion used in this case is reaching to the number of 11 PMUs without unobservable buses, i.e. $C_i(x)$ of 11 or $f_i(x)$ of 0.0909.

Fig. 4 depicts the variation of fitness with respect to the generations for both canonical GA and IGA. It can be seen that both methods find the best solution. However, the IGA finds it after 31generation while GA finds it after 68 generations which shows an increase of more than 50% in the algorithm convergence. The other impact of immune operator that can be seen in Fig. 4 is initializing the method with higher fitness. Note that due to stochastic nature of the heuristic optimization techniques, the final result of different executions can be varied. So, the curves of Fig. 4 are the best results after 30 executions.

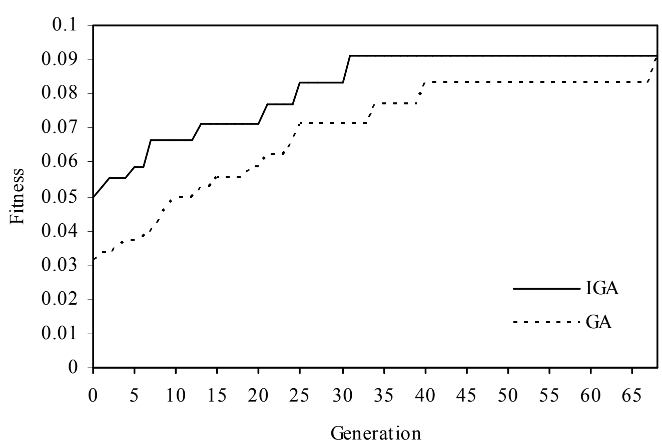

Fig. 4. Comparison between GA and IGA.

It is essential to point out that the immune operator (consisting vaccination and immune selection) has some overhead computation in each generation, so the execution time of a generation in IGA is a little longer than that in GA. However, as the required generations to achieve an acceptable solution are decreased, the efficiency of IGA is still superior to that of GA.

D. Impact of Prevention from Familial Reproduction

As mentioned earlier, it is expected that preventing from familial recombination may enhance the converging process of GA or IGA. Here, the performance of IGA with and without this effect is investigated using the OPP problem on the IEEE 57-bus test system. The simulation results reveal no improvement in the algorithm convergence since the number of individuals is relatively large, i.e. 100, and the probability of familial recombination is very small. However, after reducing the number of individuals from 100 to 12, the expected effect is appeared. In this case, the obtained results are shown in Fig. 5. It can be seen form this figure that preventing from familial reproduction decreases the required number of generations from 64 to 57, which shows a growth of nearly 10 %. Thus, it can be concluded that the prevention from familial reproduction can be useful when the number of individuals is few. For individual numbers ranging from 8 to 30, the convergence growth decreases from 37% to 6%. It should also be noted that in this paper this prohibition is only imposed on the first degree of offspring. It is expected that generalization of this prohibition up to the higher degrees enhances the algorithm's efficiency more.

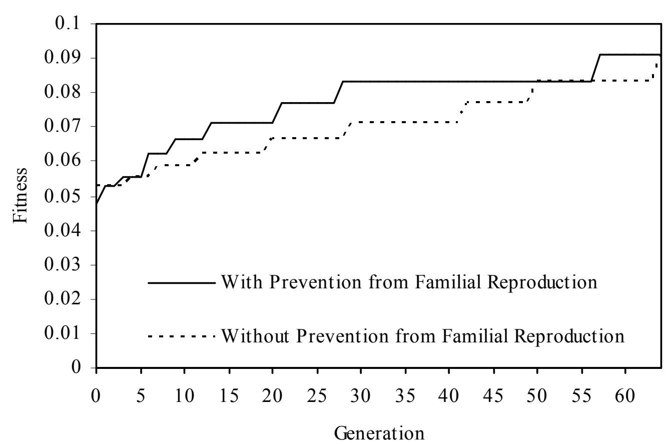

Fig. 5. Impact of prevention from familial reproduction.

E. Simulation of Large–Scale Real Power System

A very large-scale power system is examined to study the performance of the proposed technique. This system has 2746 buses including 3514 lines and 705 zero-injection buses. According to the large dimension of the problem, it is expected that an acceptable near optimal solution may be found after a large number of generations. The stopping criterion of the algorithm is adopted as the number of generations equal to 5,000. The average time for the execution of each generation is about 30 seconds. So, the total computation time of this case is about 44 hours. After ten executions, the best obtained result is 609 PMUs. It is worth noting that although it seems that the long computation time is a very important restriction of the heuristic optimization methods, but better parallel processing than most classical methods improves applicability of these techniques. Also, the computation time burden can be alleviated by careful portioning a large-scale problem into a set of medium-scale problems. This idea is called *decomposition technique* and has a practical background since in practice, the large power system is split into small sub-networks and each sub-network is managed by its local control center [25].

V. CONCLUSION

In this paper, the application of the IGA method to the OPP problem was presented. Utilization of the local and prior knowledge associated with the considered problem is the main idea behind IGA. The prior knowledge of the OPP problem was inferred based on the topological observability analysis and it was abstracted as some vaccines. The injection of these vaccines into the individuals of generations revealed a remarkable increase in the convergence process. The vaccine's information amount and validity play an important role in the performance of the algorithm. Also, the prevention from familial reproduction was modeled in the technique. This effect was revealed some enhancement in the converging speed of the algorithm particularly when the number of individuals in each population is few. The comparison of the obtained results on IEEE standard cases with those of other methods exhibited that the proposed method can successfully compete with the others.

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BIOGRAPHIES

Farrokh Aminifar (S'07) received the B.S. (Hon.) degree in electrical engineering from Iran University of Science and Technology, Tehran, Iran, in 2005 and M. S. (Hon.) degree in electrical engineering from Sharif University of Technology, Tehran, Iran, in 2007 where he is currently working toward the Ph.D. degree.

His research interests include power system reliability, optimization, operation, and economics.

Caro Lucas (SM'87) received the M.S. degree in Electrical Engineering from the University of Tehran, Iran, in 1973, and the Ph.D. degree from the University of California, Berkeley, in 1976. He is a Professor at Center of Excellence for Control and Intelligent Processing, in the Department of Electrical and Computer Engineering, University of Tehran, Iran, as well as a Researcher at the Intelligent Systems Research Faculty (ISRF), Institute for Studies in Theoretical Physics and Mathematics (IPM), Tehran, Iran. His research interests include biological computing, computational intelligence, uncertain systems, intelligent control, neural networks, multi-agent systems, data mining, business intelligence, financial modeling, and knowledge management.

Amin Khodaei obtained the B.S. degree in electrical engineering from University of Tehran, Tehran, Iran, in 2005 and M.S. degree in electrical engineering from Sharif University of Technology, Tehran, Iran, in 2007. He is currently a Ph.D. student in the Electrical and Computer Engineering Department at the Illinois Institute of Technology (IIT), Chicago.

His research interests include operation and economics of power systems.

Mahmud Fotuhi-Firuzabad (SM'99) was born in Iran. Obtained B.S. and M.S. Degrees in Electrical Engineering from Sharif University of Technology and Tehran University in 1986 and 1989 respectively and M.S. and Ph.D. Degrees in Electrical Engineering from the University of Saskatchewan in 1993 and 1997 respectively.

Dr. Fotuhi-Firuzabad worked as a postdoctoral fellow in the Department of Electrical Engineering, University of Saskatchewan from Jan. 1998 to Sep. 2000 and from Sep. 2001 to Sep. 2002 where he conducted research in the area of power system reliability. He worked as an assistant professor in the same department from Sep. 2000 to Sep. 2001. He joined the Department of Electrical Engineering at Sharif University of Technology in Sep. 2002. Presently he is head of the Department of Electrical Engineering, Sharif University of Technology. He is a member of Center of Excellence in Power System Management and Control in Sharif University of Technology, Tehran, Iran.