OPTIMAL REACTIVE POWER PLANNING USING GENETIC ALGORITHM

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Abstract:

This paper presents a new approach to solve the optimal reactive power planning (RPP) problem based on a genetic algorithm. The reactive power planning problem involves optimal placement and sizing of capacitors in a network such that the power loss cost and investment costs of new VAR sources are minimum. The genetic algorithm is a kind of search algorithm based on natural selection and genetics. This algorithm can search for global solution. The RPP problem is solved in two stages. The first stage determines the optimal placement of capacitors. The second stage determines the optimal sizing of such capacitors. The proposed approach incorporates detailed hourly loading conditions at each bus and achieves a fairly accurate estimate of the benefits from capacitor placement. The proposed method is applied to the IEEE 14-bus system and the IEEE 30-bus system and its results are compared with the results of a conventional method. Although this method is not as fast as sophisticated traditional methods, the applied concept is quite adequate for planning applications.

Keywords: Reactive power planning – Genetic algorithm – Optimal power flow

I- Introduction:

The optimal reactive power planning (RPP) problem refers to the decision for the locations, types and sizes of reactive power sources which guarantee a satisfactory system operation and particularly, adequate voltage levels throughout the system, at a minimum cost. The reduction of the transmission losses as well as the consideration of the system security and adequacy are aspects that may also be treated in the statement of the problem. In general, the mathematical formulation leads to a mixed nonlinear-integer problem of constrained optimization. The integer variables appear in the formulation with mathematical representation of:

i) the installation or fixed cost of new reactive power sources at the different locations, and

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i) the installation or fixed cost of new reactive power sources at the different locations, and

ii) the discrete availability of sizes or capacities of the reactive sources. [1]

During the past decade there has been a growing concern in power systems about reactive power operation and planning. Recent approaches to the RPP problem are becoming very sophisticated in minimizing installation cost and for the efficient use of VAR sources to improve system performance. Various mathematical optimization formulations and algorithms have been developed, which, in most cases, by using nonlinear [2], linear [3], or mixed integer programming [4], and decomposition method [5-9]. More recently, simulated annealing [10] and genetic algorithm [11,12] have also been used. With the help of powerful computers, it is now possible to do a large amount of computation in order to achieve a global optimal instead of local optimal solution.[13,14]

Genetic algorithm (GA) method is a powerful optimization technique analogous to the natural genetic process in biology. Theoretically, this technique converges to the global optimum solution with probability one, provided that certain conditions are satisfied. The GA method is known as a robust optimization method. It is useful especially when other optimization methods fail in finding the optimal solution.

In this paper the RPP problem is separated into two stages. At the first stage, the possible sites for installation of the new reactive power sources are determined. The problem in the second stage is solved using GA to decide the type, size and actual sites for installation of the reactive power sources instead of determining only the sites using GA as in [1].

II- Symbols:

N	Total number of buses
NG	Number of generating buses
NL	Number of load buses
NC	Number of buses with capacitors installed
i, j	Index for buses
P_{gi}	Real power generation at bus i (p.u.)
Q_{gi}	Reactive power generation at bus i (p.u.)
P_{di}	Real power demand at bus i (p.u.)
Q_{di}	Reactive power demand at bus i (p.u.)
Q_{ci}	Reactive power support from new capacitors at bus i (p.u.)
V_i	Voltage at bus i (p.u.)
Y_{ij}	Element of network admittance matrix (p.u.)
θ_{ij}	Phase angle of Y_{ij} (radian)
δ_i	Voltage angle at bus i (radian)

Q_{cmax}	Maximum reactive power support possible to add (p.u.)
Q_{gi}^{min}, Q_{gi}^{max}	Reactive power generation limits at bus i (p.u.)
V_{min}, V_{max}	Limits on bus voltage levels (p.u.)

III- Problem Formulation:

The reactive power planning problem has been stated to be an optimization problem, where the total cost of the installation of new reactive power sources and the cost of the active transmission power losses are minimized, subjected to constraints that define satisfactory operation. [1]

A modified optimal power flow (OPF) formulation is used for allocation and sizing of VAR sources on the load buses. These additional sources are required to provide the necessary reactive power support at load buses, more so, during the peak loads. OPF is computed for every hour of the load curve. The modified formulation of the OPF problem is described below[15]:

- *Objective function:*
  Total cost = Capacitor operating cost + Power losses cost.

- *The system operation constraints:*
  a) Load flow equations (equality constraints):
  $P_{gi} - P_{di} = \sum |V_i| |V_j| |Y_{ij}| \cos(\theta_{ij}+\delta_j-\delta_i)$ for i=1--N, excluding the slack bus
  $Q_{gi} - Q_{di} = -\sum |V_i| |V_j| |Y_{ij}| \sin(\theta_{ij}+\delta_j-\delta_i)$ for i=1--NG, excluding the slack bus
  $Q_{gi} - Q_{di} + Q_{ci} = -\sum |V_i| |V_j| |Y_{ij}| \sin(\theta_{ij}+\delta_j-\delta_i)$ for i=1--NL
  b) Inequality constraints:
  $Q_{gi\,min} \le Q_{gi} \le Q_{gi\,max}$ i=1--NG, excluding the slack bus
  $V_{min} \le V_i \le V_{max}$ i=1--NL
  $Q_{ci} \le Q_{cmax}$ i=1--NL

IV- Proposed Genetic Algorithms (PGA):

Genetic algorithms are inspired by the mechanism of natural selection, a biological process in which stronger individuals are likely be the winners in a competing environment. They presume that the potential solution of problem is an individual and can be represented by a set of parameters. These parameters are regarded as the genes of a chromosome and can be structured by a string of values in binary form. A positive value, generally known as fitness value, is used to reflect the degree of "goodness" of the chromosome for solving the problem.

The algorithm starts from an initial population generated randomly. A new generation is generated by using the genetic operations considering the fitness of a solution, which corresponds to the objective function for the problem. The fitnesses of solutions are improved through iterations of generations. When the algorithm converges, a group of solutions with better fitnesses is generated, and the optimal solution is obtained.[12]

A- String Representation: [13]

String representation is an important factor in solving the RPP problem using SGA. In order to accommodate different representations of object parameters.

B- Genetic Operations:

1) *Initial population generation*: Initial population of binary strings is created randomly. Each of the strings represents one feasible solution satisfying the problem constraints.
2) *Fitness evaluation*: The solution strings and each candidate solution is tested in its invironment. The fitness of each candidate solution is evaluated through some appropriate measure such as the inverse of the cost function. The algorithm is driven towards maximizing this fitness.[13]
3) *Selection:* Selection models nature's survival-of-the-fittest mechanism. In simple GA, a fitter string receives a higher number of offspring and thus has a higher chance of surviving in the subsequent generation. The simple GA uses the "roulette wheel" selection scheme to implement proportionate selection. Each slot on the wheel is paired with an individual in the population. The size of each slot is proportional to the corresponding individual fitness [12].

   A common way to implement roulette-wheel selection is to:

   1- sum up all the fitness values in the current population; call this value "sumfitness". It is the total area of the wheel.

   2- generate a random number between 0 and 1, called rand.

   3- multiply sumfitness by rand to get a number between 0 and sumfitness that we will call roulette value. Think of this value as the distance the imaginary roulette ball travel before falling into a slot.

   4- finally, we sum up the fitness values (slot sizes) of the individuals in the population until we reach an individual, which makes this partial sum greater or equal to roulette value. This will be the individual that is selected [12].
4) *Crossover:* Crossover is the process by which the bit-strings of two parent individuals combine to produce two child individuals. There are

many ways in which crossover can be implemented. The most primitive but highly efficient form of crossover is single-point crossover shown in figure (1). Crossover rate (p_c) controls the frequency with which crossover is applied [12], i.e. in each new population ($N*p_c$) structure undergo crossover, where N is the population size.

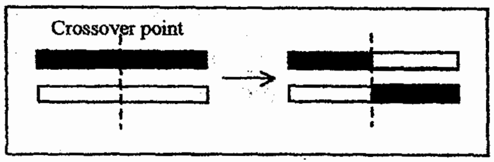

Figure (1): Crossover operation.

5) *Mutation:* Another important GA operator is mutation. It only acts on one individual at a time where a bit is inverted before copying from a parent to a child according to certain probability (rate) $\mathbf{p_m}$. An example of mutation process is shown in figure (2) [12]. The simple GA treats mutation only as a secondary operator with the rule of restoring lost genetic material. For example, suppose all the strings in a population have converged to a '0' at a given position and the optimal solution has a '1' at that position. The crossover cannot regenerate a 1 at that position, while a mutation could. Approximately ($N*L*p_m$) mutations occur per generation where L is the string length [16,17].

$$00\boxed{1}100110011 \longrightarrow 00\boxed{0}100110011$$

Figure (2): Mutation operation.

V- Implementation of GA to RPP Problem:

The systems tested and described are the IEEE 14-bus [18] and IEEE30-bus [19] networks. The following parameters are used for GA:

Population size: 30
Max. generation: 15
Crossover probability: 0.9
Mutation probability: 0.001

The number of parameters that consist the genetic chromosome is determined according to the number of load buses that need VAR source at a certain hour. The number of bits consisting the parameter length is determined according to the number of steps required to reach the maximum reactive power demand of the system at a certain hour transformed to binary form.

The results of GA are compared with the results which were obtained both by applying initial load flow calculations without any compensation and with the results obtained by applying a conventional method. In the conventional method, the weak load buses of the system are determined, then a reactive power equal to the reactive power of the load at each bus is injected. If the voltage of any of these buses exceeded the upper limit of the operating range, the injected VAR value is decreased gradually- starting from the bus with higher voltage- until all bus voltages are within the specified range.

A- The 14-bus system:

The initial load flow results show that, with no reactive power compensation, there are under-voltages at almost every load bus during the 24 hour. Thus the reactive power supply from generators is not adequate to maintain the required voltage profile.

After the reactive power planning is completed, the total reactive power compensation is summarized in table I. It is observed that the voltage profile is within the operating range of 0.95-1.05 p.u. Both voltage limits are satisfied. The VAR sources must satisfy the upper and lower limits of the required injected VAR at each load bus.

Table I: Results of 14-bus System

Variable	Initial load flow		GA		Conv. Method	
	Lower Limit	Upper Limit	Lower Limit	Upper Limit	Lower Limit	Upper Limit
V4 (pu)	0.946	1.012	0.95	1.012	0.95	1.048
V5	0.996	1.036	0.998	1.036	0.998	1.036
V7	0.972	1.023	0.98	1.023	0.981	1.031
V9	0.944	1.006	0.958	1.006	0.958	1.006
V10	0.946	1.003	0.958	1.003	0.958	1.007
V11	0.978	1.015	0.984	1.015	0.984	1.015
V12	0.992	1.015	0.996	1.015	0.996	1.015
V13	0.981	1.011	0.988	1.011	0.988	1.011
V14	0.923	0.987	0.951	0.987	0.951	1.032
Qc4(Mvar)	0.0	0.0	0.0	0.85	0.0	35.7
Qc5	0.0	0.0	0.0	0.0	0.0	0.0
Qc7	0.0	0.0	0.0	0.0	0.0	0.0
Qc9	0.0	0.0	0.0	7.45	0.0	1.2
Qc10	0.0	0.0	0.0	1.2	0.0	4.7
Qc11	0.0	0.0	0.0	0.0	0.0	0.0
Qc12	0.0	0.0	0.0	0.0	0.0	0.0
Qc13	0.0	0.0	0.0	0.0	0.0	0.0
Qc14	0.0	0.0	0.0	3.2	0.0	15.2
Total Cost in 24 hours (LE)			30283.02		85282.65	

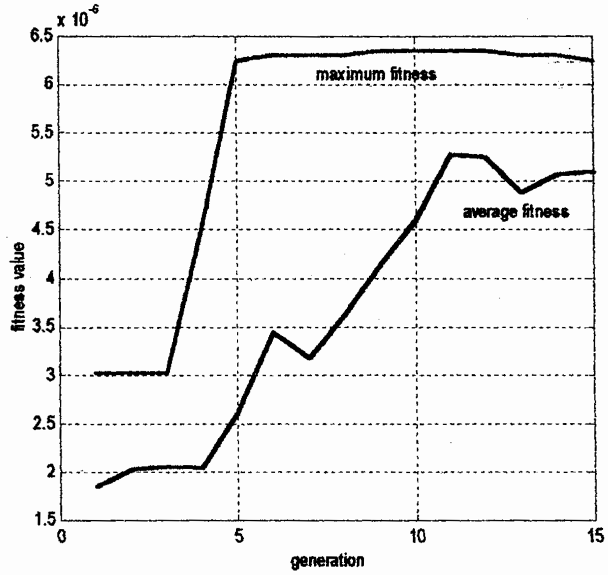

Figure (3): GA Iteration Results at The 20th Hour

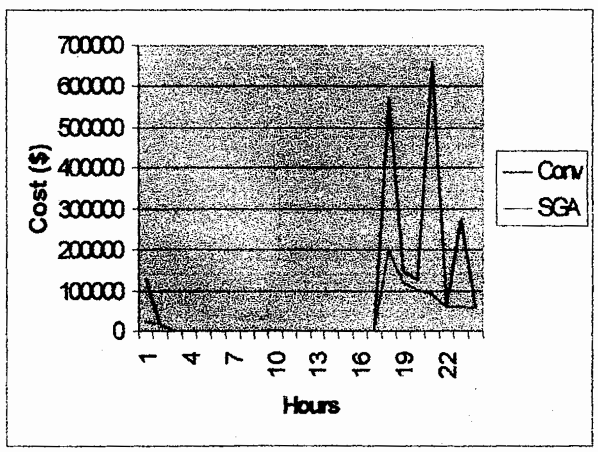

Figure (4): The total cost through 24 hours.

B- The 30-bus system:

The results before and after reactive power compensation are shown in table II.

Table II: Results of 30-bus System

Variable	Initial load flow		GA		Conv. Method	
	Lower Limit	Upper Limit	Lower Limit	Upper Limit	Lower Limit	Upper Limit
V3 (p.u.)	0.967	1.024	1.002	1.024	0.992	1.024
V4	0.948	1.016	0.989	1.016	0.978	1.016
V6	0.941	1.013	0.984	1.013	0.975	1.016
V7	0.913	1.003	0.964	1.006	0.955	1.032
V9	0.95	1.039	1.019	1.045	0.997	1.045
V10	0.913	1.025	0.997	1.044	0.97	1.042
V12	0.95	1.046	1.026	1.048	0.994	1.048
V14	0.914	1.032	1.001	1.035	0.966	1.035
V15	0.908	1.028	0.999	1.036	0.965	1.038
V16	0.922	1.031	1.005	1.038	0.972	1.037
V17	0.908	1.021	0.992	1.039	0.963	1.035
V18	0.888	1.016	0.981	1.032	0.953	1.044
V19	0.882	1.012	0.973	1.033	0.951	1.046
V20	0.888	1.015	0.978	1.034	0.954	1.045
V21	0.894	1.018	0.985	1.036	0.955	1.041
V22	0.894	1.018	0.985	1.036	0.957	1.041
V23	0.888	1.017	0.987	1.033	0.954	1.041
V24	0.874	1.011	0.979	1.033	0.952	1.039
V25	0.871	1.007	0.98	1.026	0.966	1.042
V26	0.844	0.99	0.958	1.009	0.955	1.033
V27	0.882	1.012	0.991	1.032	0.98	1.048
V28	0.932	1.011	0.984	1.011	0.974	1.013
V29	0.833	0.933	0.966	1.025	0.96	1.041
V30	0.799	0.979	0.951	1.021	0.951	1.043
Qc3 (Mvar)	0	0	0	0	0	0
Qc4	0	0	0	0	0	0
Qc6	0	0	0	0	0	0
Qc7	0	0	0	6.65	0	23.26
Qc9	0	0	0	0	0	0
Qc10	0	0	0	3.75	0	0
Qc12	0	0	0	0	0	0
Qc14	0	0	0	2.35	0	2.05
Qc15	0	0	0	2.2	0	1.15
Qc16	0	0	0	1.35	0	0
Qc17	0	0	0	2.75	0	2.1
Qc18	0	0	0	1.25	0	2.4
Qc19	0	0	0	4.95	0	7.37
Qc20	0	0	0	1.1	0	1.45

Qc21	0	0	0	3.45	0	8.4
Qc22	0	0	0	0	0	0
Qc23	0	0	0	1.95	0	2.74
Qc24	0	0	0	3.55	0	2
Qc25	0	0	0	0	0	0
Qc26	0	0	0	2	0	3.57
Qc27	0	0	0	0	0	0
Qc28	0	0	0	0	0	0
Qc29	0	0	0	2.2	0	2.38
Qc30	0	0	0	4.65	0	5.55
Total Cost in 24 hours (LE)			114871.1		116895.1	

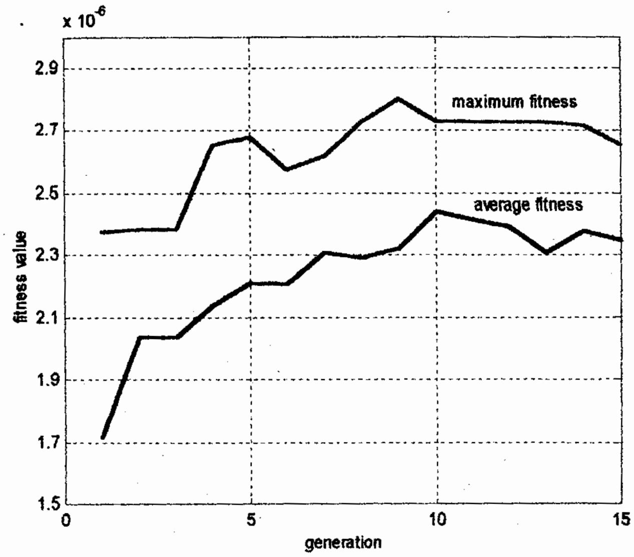

Figure (5): GA Iteration Results at The 22nd Hour

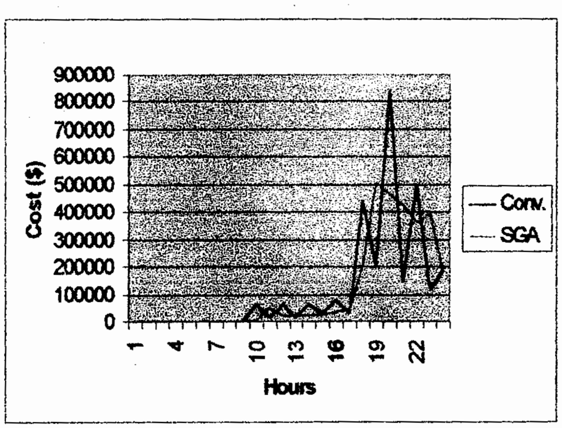

Figure (6): The total cost through 24 hours.

VI- Conclusion:

In this paper, the optimal RPP problem was solved by minimizing the total cost which includes the operation costs of new VAR sources and the cost of transmission power loss. The IEEE 14-bus and IEEE 30-bus systems were tested. The genetic algorithm (GA) was used to solve such a problem. The voltage profile throughout the planning period was improved from the under-voltage seen in the initial load flow to the required operation range. It was also found that new VAR sources are installed at or near load buses that exhibit under-voltage violation. Also it was noticed that the total cost achieved by the conventional method was greater than that achieved by using the GA method. The GA is characterised by the lack of assumptions for linearity or convexity. The resulting analysis accuracy can not be surpassed by any other AI technique. The results show the effectiveness of the proposed technique in the area of power system planning.

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التخطيط الأمثل للقدرة الغير فعالة باستخدام خوارزم جينى

أ٠د٠جمال الدين على
كلية الهندسة- جامعة طنطا
طنطا - جمهورية مصر العربية

أ٠د٠حسين الدسوقى   م٠أمانى الزنقلى
الأكاديمية العربية للعلوم و التكنولوجيا
الإسكندرية - جمهورية مصر العربية

ملخص:

يقدم هذا البحث طريقة جديدة لحل مشكلة التخطيط الأمثل للقدرة الغير فعالة و ذلك عن طريق استخدام خوارزم جينى أما التخطيط الأمثل للقدرة الغير فعالة فيتضمن تحديد القيم و الأماكن المثلى للمكثفات في الشبكة بحيث يتم تحقيق أقل فقد في القدرة الفعالة وأقل تكلفة لشراء مصادر جديدة للقدرة الغير فعالة ٠

والخوارزم الجينى هو طريقة بحث تعتمد على طرق الاختيار التي تطبقها الطبيعية في الجينات الوراثية ، هذا الخوارزم يستطيع البحث والوصول إلى الحل الأمثل النهائي للمشكلة ، ويتم حل مشكلة التخطيط الأمثل للقدرة الغير فعالة على مرحلتين ، في المرحلة الأولى يتم تحديد الأماكن المثلى لوضع المكثفات ، أما المرحلة الثانية فيتم فيها تحديد القيم المثلى لهذه المكثفات ٠ طريقة الحل المقترحة اعتمادا على حالة التحميل كل ساعة عند كل موزع تحقق إلى حد ما توقع دقيق للعائد من إدخال المكثفات في الشبكة ٠ الطريقة المقترحة تم تطبيقها على كل من نظامي IEEE 14 –bus و IEEE 30 – bus والنتائج تم مقارنتها مع تلك النتائج التي تم الحصول عليها باستخدام إحدى الطرق التقليدية في الحل ٠

على الرغم من أن هذه الطريقة ليست سريعة كالطرق التقليدية إلا أنها تعبر عن تصور مناسب لتطبيقات التخطيط ٠