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Flexible Genetic Algorithm Based Optimal Power Flow of Power Systems

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ABSTRACT

Nowadays, the power plant is changing the power industry from a centralized and vertically integrated form into regional, competitive and functionally separate units. This is done with the future aims of increasing efficiency by better management and better employment of existing equipment and lower price of electricity to all types of customers while retaining a reliable system. This research is aimed to solve the optimal power flow (OPF) problem. The OPF is used to minimize the total generations fuel cost function. Optimal power flow may be single objective or multi objective function. In this thesis, an attempt is made to minimize the objective function with keeping the voltages magnitudes of all load buses, real output power of each generator bus and reactive power of each generator bus within their limits. The proposed method in this thesis is the Flexible Continuous Genetic Algorithm or in other words the Flexible Real-Coded Genetic Algorithm (RCGA) using the efficient GA's operators such as Rank Assignment (Weighted) Roulette Wheel Selection, Blending Method Recombination operator and Mutation Operator as well as Multi-Objective Minimization technique (MOM). This method has been tested and checked on the IEEE 30 buses test system and implemented on the 35-bus Super Iraqi National Grid (SING) system (400 KV). The results of OPF problem using IEEE 30 buses typical system has been compared with other researches.

Key Words: Active power generator, Bus voltage magnitude, cost function, optimal power flow

الخوارزمية الجينية المرنة المستخدمة في سريان القدرة المثالي في انظمة القدرة

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الخلاصة

الهدف من دراسة سريان القدرة المثالي(OPF) هو للتقليل في دالة الهدف (كلفة الانتاج). سريان القدرة المثالي قد يكون احادي دالة الهدف او متعدد الدوال. في هذا الاطروحة تم تقليل كلفة الانتاج في توليد القدرة الحقيقية مع الحفاظ على قيم الجهد والقدرة الخارجة من كل محطة توليدية ضمن الحدود المسموح بها وابقاء النظام ضمن شروط الامان للنظام. هناك عدة طرق لحل مشاكل سريان

القدرة المثالي: التقليدية وطرق الذكاء الاصطناعي. الطرق التقليدية تعتمد على خواص المعادلات اما طرق الذكاء الاصطناعي فانها فقط تعتمد على دالة الهدف. الخوارزمية المقترحة لهذه الاطروحة هي الخوارزمية الجينية المرنة (الحقيقية) بعد فحصها وتطبيقها على نظام ال٣٠ عقدة ل IEEE تم تطبيقها على نظام ال ٣٥ عقدة للشبكة الوطنية العراقية ذات الجهد الفائق. تم مقارنة نتائج نظام ال٣٠ عقدة مع بحوث اخرى ذات نفس الصلة. في هذه الاطروحة المتغيرات المسيطرة هي القدرة الخارجة من كل عقدة توليدية ما عدا عقدة المرجع (slack bus) وهي محددات المساواة اما محددات اللامساواة فهي الحدود الدنيا والعليا للقدرة الفعالة والغير فعالة لكل عقدة توليدية والجهد لكل العقد في النظام. البيانات الحقيقة للشبكة العراقية قد تم الحصول عيها من وزارة الكهرباء.

الكلمات الرئيسية: فرق الجهد لكل عقدة, دراسة جريان الحمل المثالي, القدرة الحقيقة لكل محطة توليدية, دالة الكلفة.

1. INTRODUCTION

The backbone of a power system is the load flow studies. They are the means by which the future operation of the system are known gaining of time. Digital computer have been used widely for power system analysis, and variables determinations under normal/contingent conditions, since their latest days and in particular for load flow studies. The problem of load flow study had been expressed in many altered methods and several different powerful result techniques have been established. The OPF has been taken years to improve effective algorithm for its solution because it is a very large. In general, the optimal load flow is a not convex, nonlinear, static optimization problem with both discrete and continuous control variables. OPF problem is non-convex because of the presence of the nonlinearity of the alternating current power flow equality limitations, Hari**, 2016**. Analysis of a simple power flow provides important and needed information but not an optimal. A simple economic load dispatch gives the optimal operating state of the power system such as real, reactive power balance which are not confirmed after the changes in generation pattern. The economic operation, the essential of reactive and real power balance are to limit physical and depended variables within boundaries, to develop an Optimal Power Flow (OPF), **Ravi** and **Christober, 2013**. From the observation point of OPF, the maintenance of system security need to care for every device in the power system within its normal operation. This will comprise maximum and minimum outputs for maximum MVA drifts of transformers and transmission lines, generators, in addition to maintaining the bus voltages of the system within their limitations. To perform this, the optimal load flow will implement all the normal control functions of the power plant. These functions may consist of the control of generator (excluding slack bus) and the control of transmission lines. Generators, the OPF will control generator MW outputs as well as generator voltage magnitude. For the transmission lines, the OPF may control the tap ratio of Under Load Tapping Transformer (ULTT) or Phase Shift Transformers (PST) and switched shunt control, **Wankhade** and **Vaidya, 2000**. Before two decades the Optimal Power Flow Problems are implemented by using numerical (conventional) methods like Gauss Seidal Method (G-S), Newton Raphson Method (N-R), Linear Programming Method, Lagrangian Multiplier Method, Quadratic Programming Method, Interior Point Method…. etc. The drawbacks of these methods are sometimes diverging; they depend upon the characteristics of the objective function for example, the 1st and 2nd derivatives of the mathematical model of the problem. Artificial Intelligence Methods (AI) remedy the drawbacks of these traditional approaches. The Artificial Intelligence Methods are Fuzzy Logic applications, Genetic Algorithm, Artificial Neural Networks and other intelligent systems.

2. OPTIMAL POWER FLOW

Carpentier and **Hari, 2016**, hade first introduced the optimal power flow (OPF). The purpose of OPF is to calculate the optimal settings of a given power system that optimize the system objective functions such as total generation (fuel) cost, network loss, the deviation of bus voltag, the generating units emission, number of control equipment's, and load shedding while satisfying its power flow problems, security system, and limits of operating equipment's. Many controlled variables, such as output active powere of generators and voltages, under load transformer tap settings, phase shift transformers, reactors and switched capacitors, are manipulated to perform an optimal system setting based on the problem formulation. There are various mathematical formulations for the optimal power flow problem according to different objective function, and constraints, they are classifid as follows, **Bhavani** and **Kumar, 2014**:

1. Linear mathematical making or problem which the constraints and objectives are linearly represented with continuous control variables.
2. The objectives or constraints as well as both combined are nonlinear problem with continuous control variables.
3. If control variables are discrete and continuous, unmix – integer linear problems are a must, **Ravi** and **Christober, 2013**.

The optimal power flow can be classified as Conventional and Intelligence approaches. The traditional approaches include the well-known approaches like Gradient method, Newton method, Quadratic Programming method, Linear Programming method, and Interior pointed method. Intelligent approaches include the recently developed and common methods such as Genetic Algorithm Solution approaches for optimal power flow problem, **Wankhade** and **Vaidya, 2014**. The main purpose of optimal power flow are to decrease the costs of generation (fuel cost) of a power system whereas maintaining the system security. From the topics of an optimal power flow, the system security needs maintaining any equipment in the power network within its required operation range at steady-state condition. The minimum and maximum outputs for generators must be inside theirs bounds. The maximum MVA flows on transmission lines and transformers, as well as keeping system voltages of bus writhin constrained limits, **Ravi, et al., 2014**. The calculation of system marginal cost data is the secondary purpose of an optimal power flow. This marginal cost data can support in then pricing of active power (MW) transaction as well as the voltage support through MVAr support is the pricing auxiliary services. The durability of optimal power flow for all of the controll function is essential for the power system. Whereas, the economic power dispatch of a power system must control generator MW output, the optimal power flow controls under load transformers tap ratios and phase shiftg angles as well. Monitoring system security issues like bus overload and high or low voltage problem must perform by optimal power flow. If any security problem occur, the optimal power flow will adjust its controls to repair them, i.e., remove a transmission line overload, **Bhavani** and **Kumar, 2014**.

2.1 Optimal Power Flow solution Methodology

The solution approaches can be classified into two methods which are:

1. Conventional (classical) approaches
2. Artificial Intelligence approaches.

The sub classification of each approach is given below **Fig. 1**, **Kumaraswamy** and **Ramesh, 2012**.

2.2 OPF Objective Function For Fuel Cost Minimization

The optimal power flow problem can be described as an optimization problem and is as follows: Total Generation cost function is expressed as, **Hari, 2016**:

$$F(P_{Gi}) = \sum_{i=1}^{N_G} \alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \tag{1}$$

Where: $\mathbf{F_i (P_{Gi})}$: cost function, $\boldsymbol{\alpha_i}$, $\boldsymbol{\beta_i}$, $\boldsymbol{\gamma_i}$: cost coefficients

The objective function is denoted as:

$$Min\ F(P_G) = f(x, u) \tag{2}$$

Subjected satisfaction of nonlinear equality constraint:

$$g(x, u) = 0 \tag{3}$$

and nonlinear inequality constraints are:

$$h(x, u) \le 0 \tag{4}$$
$$u^{min} \le u \le u^{max} \tag{5}$$
$$x^{min} \le x \le x^{max} \tag{6}$$

$F(P_G)$ is the total cost function for n of generators depend on the actual power of each generator and the cost coefficients for each generator too, which is obtained by experience or by calculation by least mean square, f (x, u) is the scalar objective, g (x, u) acts nonlinear equality constraints (equations of load flow), and h (x, u) is the nonlinear inequality constraints of vector arguments x, u, where x is the vector of dependent variables (the bus voltage and phase angles magnitudes), u is a vector of control variables (as active power generation and active power flow), **Selvakumar** and **Rajan, 2013**.

3. THE CONTINUOUS GENETIC ALGORITHM (REAL-CODED)

The binary genetic algorithm is imagined to solve many optimization problems that stump traditional methods. But, what if it will be tried to resolve a problem where the variables values are real and it needs to describe them to the full machine accuracy? In such a problem, individual variable needs several bits to represent it. The size of the chromosome is large, if the number of variables are large. Of course, zeros and ones are not the alone method to represent the variable. One could, in principle, use any illustration possible for encoding the variable. When the ariables are normally quantized, the binary genetic algorithm fit kindly. However, while if the variables are reals, it is further logical to represent them by floating-point numbers (real number). In addition, since the binary genetic algorithm has its accuracy limited by the binary representation of variables, using floating-point numbers in its place simply permits representation to the machine accuracy. This Real-Coded Genetic Algorithm also has the benefit of needful less storage than the binary genetic algorithm because a single floating-point number represents then variable other of

(**N_{bits}**) integers. The real-coded genetic algorithm (RCGA) is naturally quicker than the binary genetic algorithm, as the individuals do not have to be decoded prior to the evaluation of the objective function (cost function). Most of references name this kind of the genetic algorithm a real-coded genetic algorithm. But, the term continuous is used rather than real-coded genetic algorithm to avoid confusion between real and complex numbers.

3.1 Components of a Continuous Genetic Algorithm

The flow chart shown in the **Fig. 2** offers a "large picture" summary of a continuous genetic algorithm. Every block is illustrated in detail in the following sections. This continuous genetic algorithm is very like to the binary genetic algorithm, but the main difference is the fact that variables are shorter denoted bybits of ones and zeros, but in its place by floating-point numbers over whatsoever range is regard suitable. However, this simple fact adds some nuances to the implementation method that must be onsidered in carefulness way. In particular, show different crossover and mutation operators are shown, **Mitchell, 1999**.

3.1.1 The variables and Cost Function

A cost function generates and output from set of chromosomes (input variables). The cost function may be an experiment, a game, or a mathematical function. The aim is to adapt the output in some required style by discovering the suitable values for the input variables. The aim is to solve some optimization problem where minimum (optimum) solutions are searched for in regard to the variables of the problem. The term fitness is widely used to filter the output of the objective function in the genetic algorithm works. Fitness means a maximization problem. Although fitness has nearer association with biology than the term cost, we have assumed the term cost, later most of the optimization literature deals with minimization, hence cost. They are equivalent. If the individual has (**N_{var}**) variables (a N-dimensional optimization problem) given by (**$b_1, b_2, \ldots\ldots\ldots, b_{Nvar}$**), then the individual is written as a matrix with (**$1\times N_{var}$**) components so that, **Holland, 1975**:

$$chromosome = [b_1, b_2, b_3, \ldots\ldots\ldots, b_{Nvar}] \qquad (7)$$

In this case, the values of variable are denoted as real numbers. Every individual has cost value found by calculating the objective function (**f**) at the variables (**$b_1, b_2, \ldots\ldots\ldots, b_{Nvar}$**).

$$cost = f\,(chromosome) = f\,(b_1, b_2, \ldots\ldots\ldots, b_{Nvar}) \qquad (8)$$

Eqns. (7) and (8) along with appropriate limitations constitute the problem to be resolved.

3.1.2 Initial Population

The genetic algorithm begins with a set of individuals known as the population. It has been defined initial population of (**N_{ind}**) individuals. An array acts the population with every row in the matrix being a (**$1\times N_{var}$**) arrays (individual) of continuous values. Assume an initial population of (**N_{ind}**) individuals, the full array of (**$N_{ind}\times N_{var}$**) arbitrary values is created. All variables are regulated to have values between (**1**) and (**0**), the range of an identical casual number generator. The variable values "un-normalized" in the cost function, **Holland, 1975.**

3.1.3 Selection

In this operator, two individuals are chosen from the breeding pool of (**N_{keep}**) individuals to generate two new children (offspring). Combination take place in the breeding population tilled (**$N_{ind} - N_{keep}$**) offspring are born to change the rejected individuals. Combining individuals in a genetic algorithm can be as different and interesting as coupling in and animal species. Tere are many selection approaches, like Roulette-Wheel, Rank-Weighted Roulette-Wheel, and Tournament Selection.

3.1.4 Crossover

As for the binary algorithm, two parents are selected, and then children are some mixture off these parents. Several altered methods haven been tried for crossing over in continuous genetic algorithm. The easiest approaches select one point or more in the individual to mark as the crossover points. Then the variable among these repoints care only changed between then dad and mam. The blending method is used with RCGA, **Holland, 1975**.

3.1.5 Mutation

Random mutations changes a certain percentage of the genes in the list of individuals. Sometimes it can be found way working so well. If care is not taken, the genetic algorithm can converge too fast into one area of the cost surface. If this region is in the area of the global minima, that is well. Though, some functions, for instance the one showing, have several local minima. If nothings is done to resolve this propensity to converge fast, it might end up in a local minima instead of a global minima. To prevent this problem of very quick convergence (premature convergence), the routine is forced to discover other regions of the cost surfaceby arbitrarily presenting alterations, or mutation, in some of the parameters. Points of mutation are arbitrarily chosen from the (**$N_{var} \times N_{ind}$**), over-all number of genes in the matrix of population. Increasing the number of mutations means increasing of the freedom of algorithm to search out of bounds the current area of parameter space. For the binary genetic algorithm, this amounted to only altering a bit from a (**1**) to a (**0**), and vice versa. The mutation basic way is not much more complex for the continuous genetic algorithm The best mutation rate is between 5% to 20% range, **Holland, 1975**.

4. IMPLEMENTATION AND RESULTS

4.1 '30 Bus-Bars' Typical Test System Results

The IEEE 30-bus standard system contains (30) bus bar, (6) generator buses including the slack bus and (26) load buses, and (41) transmission lines. This system will be used first to test the continuous genetic algorithm method to solving OPF problem. If the test is successful, this method will be applied on Super Iraqi National Grid (400 KV). **Fig. 3** shows fitness value which is inversely proportional to the total generation cost for "30 bus-bars" typical test system to minimize the total cost of generation and regulate the real and reactive power of generator and the voltage magnitude at each bus bar. Control variables are generator real power (excluding slack bus), reactive power of each generator buses, and voltage magnitudes of load buses. **Table 1** shows the output of real power generation, reactive power generation, total production cost, transmission losses and active power, reactive power for all generators. The executed results are more suitable and best compare with other papers. **Fig. 4** shows the output real power of generators in MW and the minimum and the maximum of one. The red column is maximum active power, the blue column is the minimum active power and the green column is the actual active power.

4.2 Practical System (Super Iraqi National Grid, 400 KV)

Finally, the genetic algorithm has been applied to the optimal power flow problem for Super Iraqi National Grid 400 KV. The Super Iraqi National Grid contains (35) buses consisting of (18) buses generating plant excluding the **slack bus** and (16) load buses and (52) transmission lines. The real data of Iraqi network has been taken from Iraq operation and control center. In practical system the generation power stations used four types of fuels, Crude oil, Natural gas, Heavy oil and Gas oil. So the cost coefficients will be different according to the type of fuel that used to each generator. **Table 2** shows the output of real power generations, total power losses, total output power generation for each generator and the total production cost. **Fig. 5** shows the output real power at each generator in Super Iraqi National Grid, also the maximum and minimum of each generator. The red column is maximum active power, the blue column is the minimum active power and the green column is the actual active power.

5. CONCLUSIONS

In this paper a Real-coded Genetic Algorithm (RCGA) based approach to solve the optimal power flow (OPF) problem. This method has been successfully implemented on the typical 30-bus IEEE test system and on the practical system (Super Iraqi National Grid) system (400 KV). Genetic algorithm has been modeled to be flexible to any practical power system with giving any input bus data, transmission lines data and the cost coefficients of the generators of the power plants. Genetic algorithm has been chosen because it showed the best results (minimum cost) compared with other methods. The executed results are superior in comparison with IEEE data sheet of 30-bus IEEE test system and the recent existing papers and literatures to solve OPF problem, also on the practical system Super Iraqi National Grid (400 KV). Genetic Algorithm determined the best optimal configuration of control variables (all real power of generators buses excluding slack bus and reactive power of generators) to achieve minimum objective function, which is the production cost (total generations fuel cost) and minimize the transmission losses. Voltages magnitudes of all load buses are enhanced within allowed limitation and maintaining system security. In this thesis the cost coefficients of Iraqi National Power stations have been calculated according to Least Square Method. Cost coefficients obtained to four types of fuels which used in the generation power stations, cheapest fuels (Crude oil), cheap fuels (Natural gas), expensive fuels (Heavy oil) and the most expensive fuels (Gas oil). In construction each power station can operate on all types of fuels due to the flexibility of genetic algorithm to in force extent range of constrained and ability optimize cost curve.

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7. LIST OF SYMBOLS

$F(P_{Gi})$: total generation cost.
P_{Gi}: Active power of generator.
α_i , β_i , γ_i : cost coefficients.
f (x, u): the scalar objective.
g (x, u): nonlinear equality constraints (equations of load flow).
h (x, u): nonlinear inequality constraints of vector arguments x, u.
x: the vector of dependent variables.
N_{var}: number of variables.
b1, b2,…, b_{inv}: chromosomes.

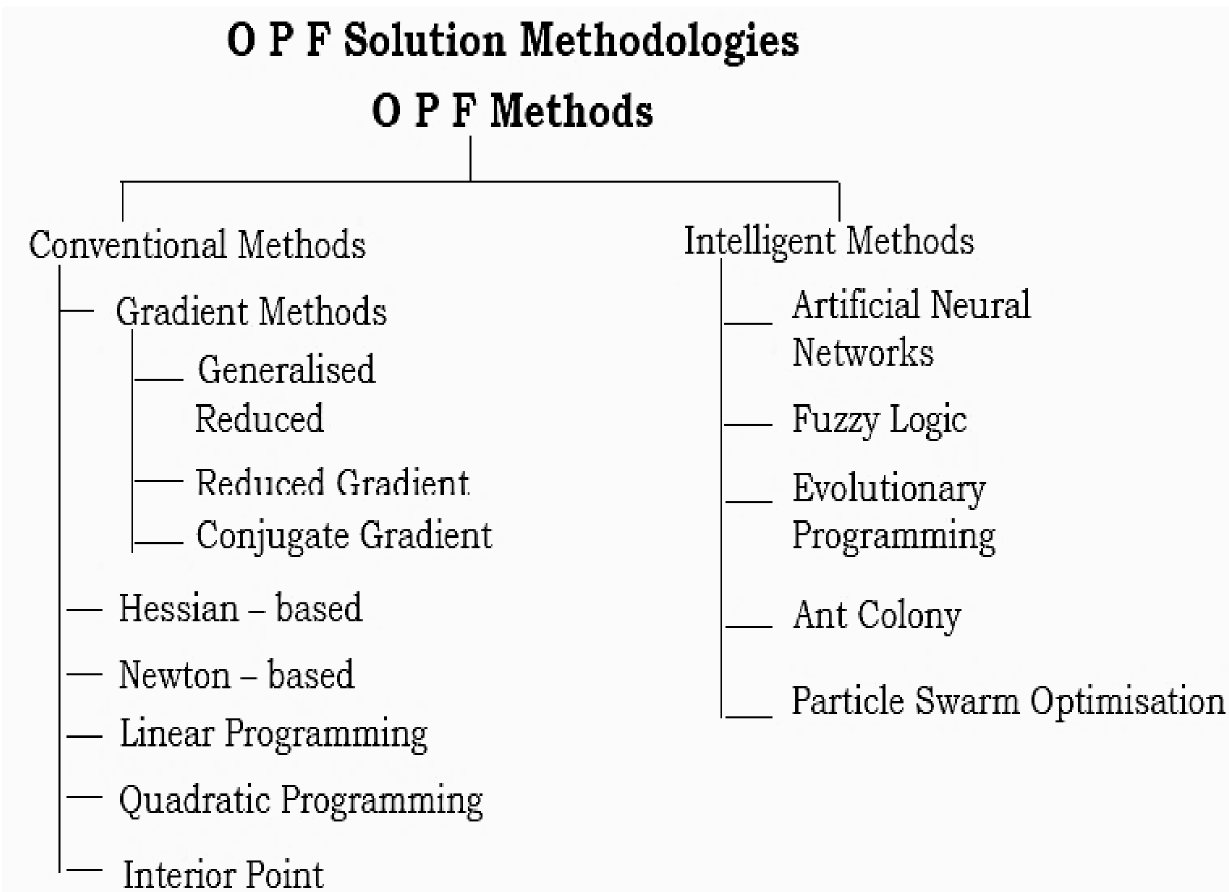

Figure 1. Tree Diagram Indicating OPF Methodologies.

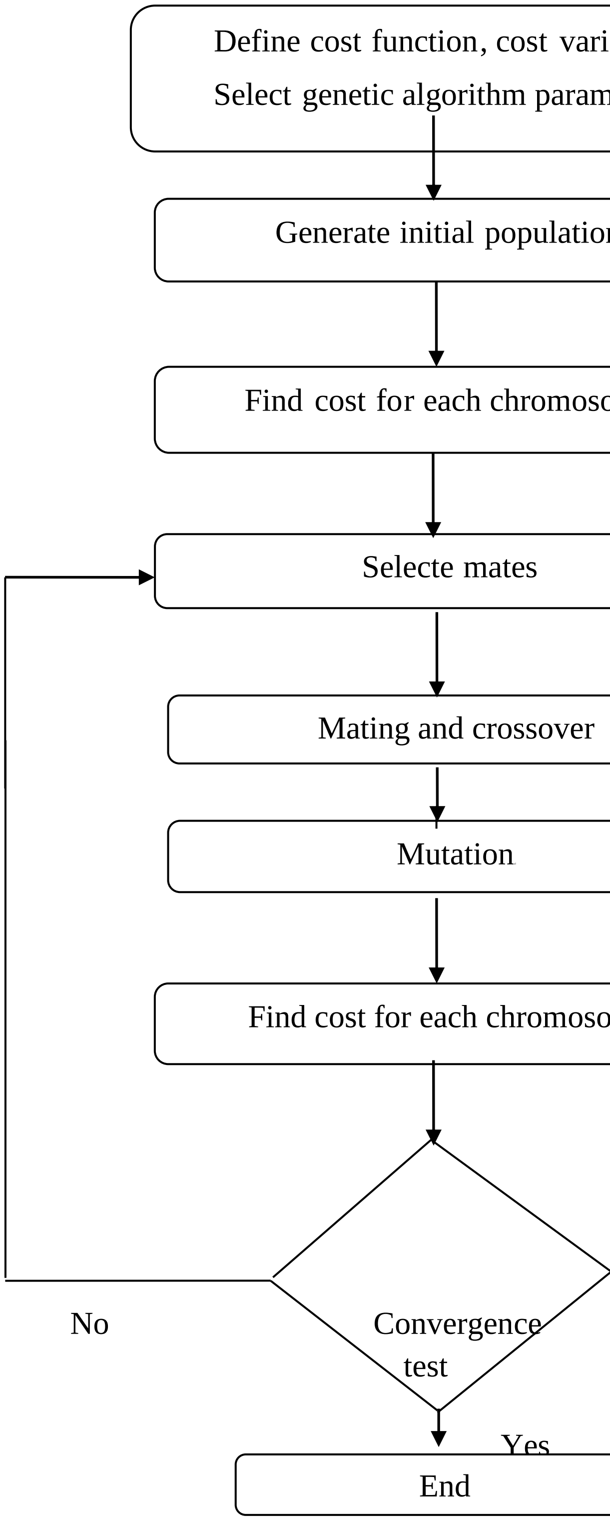

Figure 2. Flow chart of a Continuous Genetic Algorithm.

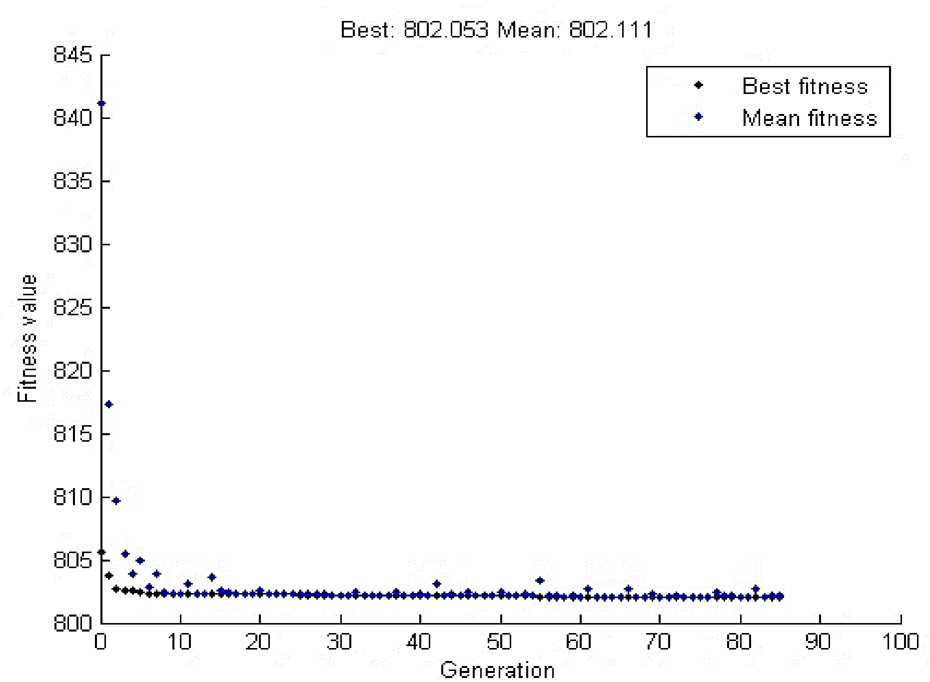

Figure 3. Fitness value inversely proportional with total generations.

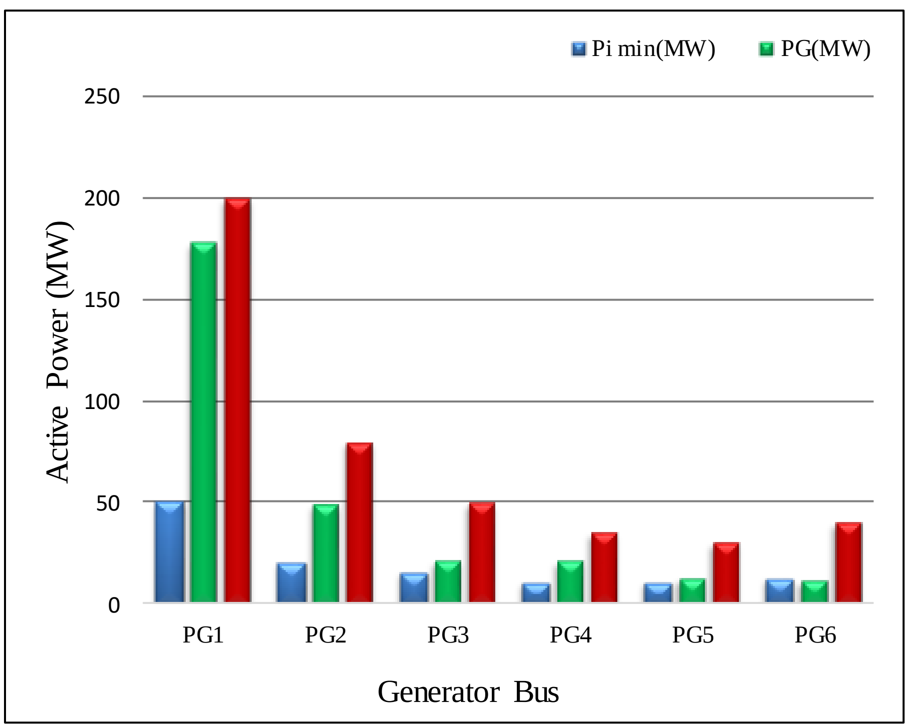

Figure 4. Active Power Generation of 30-Bus IEEE Test System.

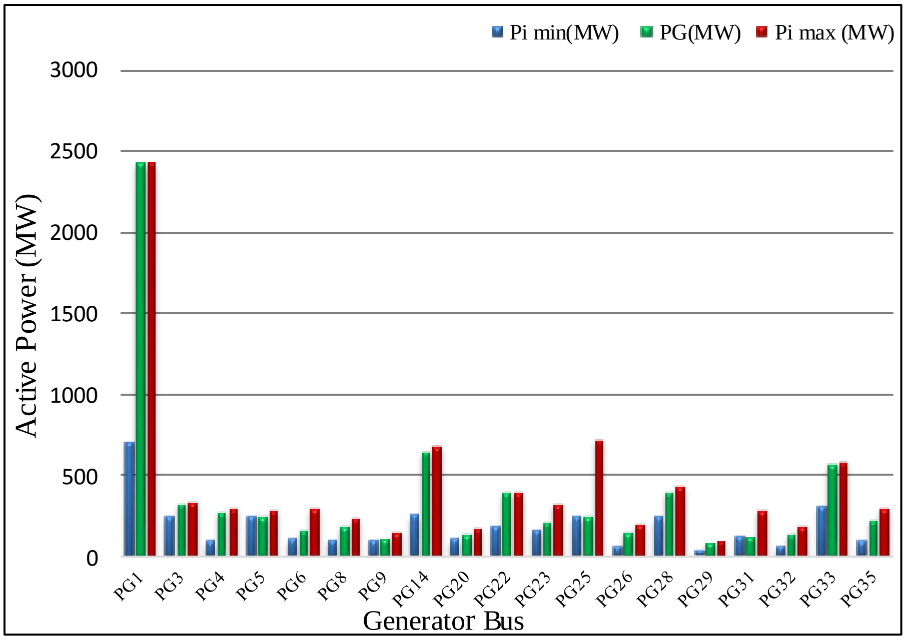

Figure 5. Active power generation of 35-bus SING Practical System.

Table 1. Active Power Generation, Active Power Losses and e Production Cost of 30-Bus IEE.

Gen. No.	P_G (MW)	Q_G (MVar)
1	177.8193	-2.4729
2	49.1225	29.4046
5	20.9021	26.1004
8	20.9723	16.5207
11	12.6509	15.1844
13	11.4115	8.4165
Total active power (MW)	**292.8786**	
Active power losses (MW)	**9.4786**	
Production cost ($/h)	**801.8674**	

Table 2. Active Power Generations, Active Power Losses and the Production Cost of 35-Bus SING Practical System (400 KV).

Gen. Name	Gen. No.	P_G (MW)	Q_G (MVar)
KUPT	1	2440	-221.80
HMMD	3	320.5	-433
GNENW	4	267.8	54.9
SBJ	5	245.9	-84.27
GBG	6	158.8	-65.21
TAZG	8	189.8	78.1
GKR	9	112.4	-11.362
GQD	14	640.1	107.61
HHD	20	137.8	62.74
MUSP	22	399.4	-47.18
MUSG	23	216.1	-87
GKHER	25	246	-23
DWANG	26	154.2	10.82
SNS	28	393.3	52
AMRG	29	85.2	-15
HRTH	31	126.4	-20
GKA	32	135.3	9
RMUL	33	567.2	105.6
SHBR	35	220.6	-103.8
Total active power (MW)		7056.8	
Active power losses(MW)		64.003	
Production cost ($/h)		213086.538	