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Effective Genetic Algorithms & Implementation on Economic Load Dispatch

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Abstract—This paper deals with some proposals to Conventional Genetic Algorithms to improve the performance (number of iterations needed to achieve convergence, time of execution). The advantages and disadvantages of each proposal have been noted. The disadvantage of a proposal is eliminated in the next proposal to the maximum extent. Thus, we finally landed up in a proposal with least time of execution and also less number of iterations for convergence. All the proposals made are tested by implementing on test function sine(x) and basic *hand calculations*. Later it has been implemented on Economic Load Dispatch with P_{min} and P_{max} constraints. The results of all the above have been highly satisfactory and a few are reported

Index Terms— Best Random GA with termination, Best Random without termination, Conventional GA, Economic Load Dispatch, Fixed Threshold, Genetic Algorithms(GA), Optional Crossover and Mutation.

1 Introduction

Concisely stated, a Genetic Algorithm (GA) is an evolutionary programming technique that mimics biological evolution as a problem-solving strategy. Given a specific optimization problem to solve, the input to the GA is a set of potential solutions to that problem, encoded in some fashion (mostly binary coded), and a metric called a *fitness function* that allows each candidate to be quantitatively evaluated based on its binary coded chromosome.

The variable x in f(x) is X_{actual}. The decoded X_{dec} is calculated value for each chromosome. X_{max} and X_{min} are the limits of the variable. In case of sine(x), the limits taken are [0 to 180]. The equation governing is equation 1.

These candidates are generated at random for the first iteration. For the later iterations, the *operators* such as elitism, cross-over and mutation come into picture. The size of population is taken as 40 and chromosomes are 8 bit binary coded. An elitism of 20% has been followed. Roulette wheel technique is considered for parent selection. Uniform cross-over is performed and probability of cross-over is taken as 0.7. The probability of mutation is considered as 0.005.

These operators modify the present generation and the chromosomes thus obtained are taken into next generation. This process is thus carried until a state of convergence is achieved. Convergence is the solution (for almost all problems pertaining to GA) where all the chromosomes will have their fitness function value as the maximum fit value of the function. Hence, the fitsum will be equal to sum of all fit values and that would be (maximum fit)*(population size).

However the following factors are found to affect the convergence and time of execution:

1) Dependence on the nature of randomly picked initial population,
2) The negative effects of the medieval operators such as cross-over and mutation.

These two fundamental issues enabled us to go for modified and highly effective proposals to Genetic Algorithms which emphasize more on these drawbacks of conventional GA.

2 Proposals to Genetic Algorithms

2.1 Conventional GA

In conventional GA approach, initial population (say 40 chromosomes) is generated randomly. If all the 40 chromosomes are having relatively good fit values, GA converges fast or else it takes more number of iterations. Hence, the quality of the initial population plays a very significant role. This motivated us for the following proposals.

2.2 Best Random without termination

Here, a random chromosome is generated and its fitness function value is calculated. The next chromosome is again picked up similarly from the search space and its fitness value is also calculated. However, this chromosome is considered only if its fitness value is greater than or equal to the fit value of the previous chromosome. Else it is discarded. The best fit value is updated. This process is carried till the required number of chromosomes (=40) had been generated.

In other words, the search space has been reduced drastically to *potential search space* by addition of a potential chromosome into the random generation. By this, the quality of the initial population is made better.

Advantages: The convergence was found to occur very soon compared to the conventional GA. For example, this technique when applied to sine(x) yielded convergence within 2 iterations while the conventional GA took about 25 iterations.

There was no need to use dynamic elitism to achieve convergence.

Disadvantages: The number of chromosomes discarded near to sag end of population size was relatively high and thus sizable time has been spent in generating a good initial population.

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2.3 Best Random with termination

Best Random with termination: This is just a special case of the above proposal. This case arises when one of the chromosomes generated randomly in above manner has its fitness value as the "maximum fit value of the function". This is possible only if the maximum value of the fitness function is known in advance to the operator (say sine(x) =1=maximum fit value). The algorithm is terminated at this instant itself because "the maximum fitness value gives us the characteristics of that chromosome, and thus it is not necessary to go for further search." Hence this approach works very fast.
Results: Here is the implementation to test function f(x)=sine(x). Table-1 shows the random generation obtained. The so called convergence is achieved at 8th chromosome of the random generation itself. Hence the process is terminated at this point itself.
Advantages: The basic operators such as the static elitism, cross-over and mutation are found to have no impact on this solution and hence this approach converges very fast. The solution is obtained even before the random initial population is completely generated.
Disadvantages: The operator should know the maximum possible value of fitness function well in advance.

2.4 Fixed Threshold Approach

Fixed Threshold approach: The previous proposals were found to search the sample space a lot for the selection of a chromosome. Here, we assign a cutoff/threshold value (typically 20-50%) of maximum fitness value and all new chromosomes with fit value greater or equal to this are added to the next generation or else discarded. The operators like elitism, cross-over and mutation are then carried as usual. Usually, Roulette wheel technique is used for parent selection. But, we propose a new approach to pick up a parent with reasonably better fit as given by equation 2.
Advantages: The potential search space is separated from the general search space by assigning a threshold value.
Disadvantages: In spite of getting a good parent generation by the threshold setting, the number of iterations required has gone up to 6 to 10 iterations.
Inferences: As the iterations were carried, the fitsum was found to increase for a few iterations and decrease for some iterations, as per Fig-1. The reason for the decrease in fitsum was the production of low fitness function value chromosomes by relatively better parent chromosomes. This must be avoided to get convergence fast.

Table-2 gives comparison between the four techniques conventional GA, Best random with and without termination and Fixed threshold of 85% for f(x)=sine(x).

In case of conventional GA the convergence was found to occur at the 39th generation. This clearly shows us that, though better fitsum has been achieved in some generations, it could not be carried forward due to the misguiding operation of cross-over and mutation. Hence the following proposal has been made to improve the convergence property:

Optional Cross-Over & Mutation: This technique follows the principle of evolution strategy. The disadvantage of the above proposals is that even after obtaining a good parent generation the number of iterations required for convergence has been quite large. Also, if the graph between fitsum and iterations is plotted, it is found that the graph is not a set of straight lines with positive slopes, but rather it is a set of lines with some negative slopes too (can be observed from the fitsum values in the above table-2). This is because the operators like cross-over and mutation gave rise to low fit chromosomes in spite of good fit parent chromosomes. Hence, we have provided an option here, by which the better of the parent and child is taken into the next generation. This means the parent 1 and child 1 fit values are calculated and then compared and the best is sent to next generation. Similar is the case of parent 2 and child 2.

In conventional GA, fit values of child 1 and child 2 are not calculated before they are sent to next generation. Child 1 and child 2 are simply copied into next population. But, in the proposed approach, the fit values of child 1 and child 2 are calculated and compared with the fit values of respective parents. The parent or child with the best fit is copied onto next generation with appropriate fit value. Thus, it needs no extra computational burden as fit values of new chromosomes are already known.
Illustrative example:

In the Table-3, the cases where in the parent fit is better than the corresponding child are given (for a particular iteration). As mentioned earlier, the parent is taken into the next generation as the new child as per this proposed technique.
Advantages: The generation child(i+1) is always better than its generation by traditional approach. Hence, fast convergence is promised.

This approach would yield "fitsum vs iterations" graph with positive slopes, as shown in Fig-2.

The convergence condition can be thought of a horizontal straight line and the fitsum of each generation goes on increasing to reach this value, as shown in Fig-2.

Thus the convergence would occur at a very fast rate.
Disadvantages: This proposal has no disadvantages yet and can be employed in any problem be it maximization or minimization. This proposed approach can yield promised converged results without extra computational burden.
In the Table-4, a comparison between the Roulette Wheel technique and new parent selection approach is made. The function taken is f(x)=sine(x). The conventional GA is considered. Optional crossover and mutation is also applied to achieve convergence very fast.
Inferences: The number of iterations required has reduced drastically by optional cross-over and mutation approach.

The new parent selection scheme is much better than the Roulette wheel technique.

2.5 Implementation on Economic Load Dispatch

The Economic Load Dispatch (ELD) problems are one of the major areas of applications of Genetic Algorithms. The ELD problem is about minimizing the fuel cost of generating units for a specific period of operation so as to accomplish optimal generation dispatch among operating units and in return satisfying the system load demand, generator operation constraints like P_{min} and P_{max}.

Thus, the objective is to minimize the nonlinear function which is the total fuel cost of thermal generating units. The objective function for the entire power system can be written as the sum of the quadratic cost model for each generator as per the equation 4.

The economic load dispatch problem is made simpler by neglecting the transmission losses and the constraints on bus voltages. The only constraints are on the real power outputs of the generation units. The difference between the demand on load side and total power generation, Pg (=sum of all real power outputs) is called the error function, er[i]. The fitness function is taken as equation 5.

Typical values of k in the above formula are 1, 2, 5 and 10. Thus, the load dispatch problem has turned into maximization problem of f(i).

Illustrative example:
A ten unit system is considered & is solved using the above proposed methods. At convergence, the incremental fuel cost, λ=1207.92 Rs/Mwhr. Real Power Demand is 2608 MW.

The economic load dispatch problem is solved by the above proposed methods and with conventional GA. A comparison between these has been made in the following Table-6.

The value of k is taken as 1. The probability of cross-over is taken as 0.7. The probability of mutation is taken as 0.005.

Inferences: The conventional GA has taken more number of iterations and needs more time of execution compared to the proposed methods.

The method "Best random with termination" is found to give the best results of all.The fixed threshold approach along with the "best random without termination" method, has been proved to be much better than the conventional GA.

In the Table-7, a comparison between the Roulette Wheel technique and new parent selection approach is made. The conventional GA & proposed methods are implemented on Economic Load Dispatch.

Inferences: The above table clearly shows that the fixed threshold approach for parent selection is much better than the Roulette Wheel technique.

3 Figures

Fig-2: Without proposed Optional Cross-Over and Mutation

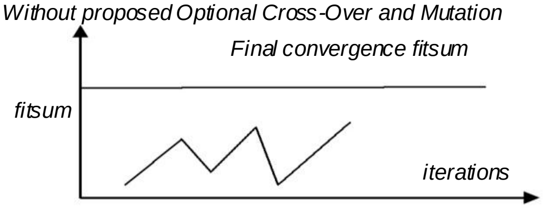
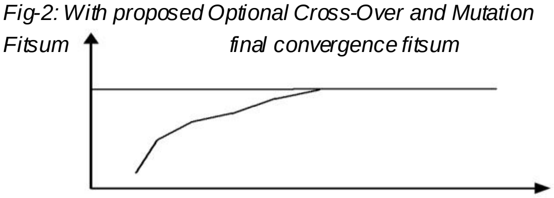


Fig-2: With proposed Optional Cross-Over and Mutation



4 Equations

$$X_{actual}=X_{min}+X_{dec}(X_{max}-X_{min}). \quad \text{Eq. (1)}$$

The decoded X_{dec} is calculated value for each chromosome. X_{max} and X_{min} are the limits of the variable. In case of sine(x), the limits taken are [0 to 180].

$$j=0.5*f(i)*i*(N/fitsum) \quad \text{Eq. (2)}$$

where f(i) is the fitvalue of the i^{th} chromosome and N its population size, fitsum is the sum of the fitvalues of their chromosomes arranged in descending order of their fit and j is the chromosome to be taken as parent.

$$F_t=\sum_{i=1}^{ng} f[p(i)] \quad \text{Eq.(3)}$$

Where $f(P_i)=a_iP_i^2+b_iP_i+C_i$, $i=1, 2, 3, ..., n_g..., n$.

$$f[i]=(1/1+(k^*|er[i]|)) \quad \text{Eq.(4)}$$

5 Tables

Chromosome	Fitness	Number of chromosomes discarded
00000000	0	0
10010000	0.980741	0
01111010	0.997305	3
10000011	0.999315	7
01111101	0.999330	82
10000001	0.999922	2
10000001	0.999922	19
10000000	1	34
Search process completed in 0.050s		

Table-1:"Best Random with termination" implemented on sine(x).

Iterati--on Count	*Conventional GA: "fitsum" with new approach for parent selection (from 3rd iteration)*	*Best random without termination: "fitsum"*	*Best random with termination: "fitsum"*	*Fixed threshold approach: "fitsum"*
0	25.8154	38.9765	8th chromo-some got fit=1. Problem converged very fast	38.1903
1	32.265	37.3887		36.7376
2	33.5592	39		37.1688
3	33.7404	40		34.3614
4	39.8742	--------------		37.2437
5	39.9111	--------------		38.2021
6	39.2672	--------------		39.9978
7	38.2269	--------------		39.9988
8	39.9312	--------------		40
39	40	--------------		------------

Table-2: *Comparison between proposed methods implemented on sine(x); population size=40*

Child-fit	Parent-fit	Child(i)	Parent(i)	Child(i+1)
0.90923	0.998105	01011101	10000101	10000101
0.914105	0.997305	10100010	01111010	01111010
0.313334	0.995164	11100110	10001000	10001000
0.302044	0.993928	00011001	01110111	01110111
0.963712	0.992503	10010110	01110110	01110110
0.963821	0.992453	01101010	10001010	10001010
0.975651	0.980741	10010010	10010000	10010000

Table-3: *Cases where parent fit is better than the child fit.*

Method	*Number of iterations required for convergence*	*Time of execution, in seconds*
Roulette Wheel parent selection for GA	42	2.617
Roulette Wheel selection & Optional cross-over and mutation	13	1.532
New parent selection approach & Optional cross-over and mutation	6	1.116

Table-4: *Comparison between Roulette wheel technique and new parent selection approach.*

unit	*a[i]*	*b[i]*	*c[i]*	P_{min} *[i]*	P_{max} *[i]*	*Power output, P[i]*
1	0.3133	796.9	64782	220	550	550
2	0.3127	795.5	64670	200	500	500
3	0.7075	915.7	172832	114	500	413
4	0.4211	1250.1	91340	110	500	110
5	2.5881	238.1	190928	65	315	315
6	0.4921	696.1	39197	120	272	272
7	0.3572	803.2	28770	110	260	260
8	9.693	655.9	13518	20	38	38
9	23.915	1633.9	83224	25	60	25
10	1.1421	805.4	22233	60	125	125

Table-5: *Power Outputs of various units for ELD*

Proposal	*Iterations required for convergence*	*Time of execution(secs)*
Conventional GA	4	1.582
Best Random without termination	1	0.899
Best Random with termination	0(convergence at 7th chromosome of first generation)	0.057
Fixed threshold(with threshold of 0.20)	2	1.000

Table-6: *Comparison between the proposed methods, for ELD*

Method	*No of iterations required for convergence*	*Execution time, in secs*
Roulette wheel parent selection	4	1.582
Roulette wheel selection & Optional cross-over & mutation	3	1.129
Fixed Threshold approach for parent selection & Optional cross-over & mutation	2	1.107

Table-7: *Comparison between Roulette wheel technique and Optional Cross-Over & Mutation, Fixed threshold approach.*

6 Conclusion

Initially, the conventional GA has been studied in detail. The various factors affecting the nature of convergence of conventional GA have been explored. Taking these factors as motivation, a few effective methods such as "Best Random with Termination", Best Random without termination", "Fixed Threshold approach along with new parent selection approach" & "Optional cross-over and mutation" have been proposed. The proposed methods have been tested on the test function sine(x) and later implemented on Economic Load Dispatch. It has been observed that the proposed methods would offer convergence very fast as compared to the conventional GA. Especially, the "Best Random with termination" was observed to be giving the best results. These proposed algorithms can be treated as a basic contribution in the area of Genetic Algorithms.

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