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Economic Load Dispatch by Using Genetic Algorithm

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Abstract— In a practical power system, the power plants are not located at the same distance from the center of loads and their fuel costs are different. Also, under normal operating conditions, the generation capacity is more than the total load demand and losses. Thus, there are many options for scheduling generation. In an interconnected power system, the objective is to find the real and reactive power scheduling of each power plant in such a way as to minimize the operating cost. This means that the generator's real and reactive powers are allowed to vary within certain limits so as to meet a particular load demand with minimum fuel cost. This is called the optimal power flow problem. in this paper presented are the Overview of artificial intelligence-based algorithms, genetic algorithm, and its applications with the economic load dispatch.

Index Terms— GA, ELD, Neural Network, power system.

I. INTRODUCTION

One of the main problems in operational power systems is Economic Load Shipping (ELD). It is defined as a process in which the power of generators is distributed in such a way that the demand for electricity in an electricity grid is met in the most economical way, taking into account any constraints [1]. The complexity of the ELD problem depends on many factors, such as: B. the size of the system, the limits of the system and the properties of the generator. Various techniques have been introduced to solve ELD optimization, which can be divided into traditional and stochastic methods. Conventional methods use a deterministic approach such as the LaGrange multiplier, linear programming (LP) and dynamic programming (DP) [2]. These methods have limitations or disadvantages in addressing more complex problems. The LaGrange multiplier and LP cannot solve problems with non-linear and non-uniform properties. The DP method has a dimensionality problem as its memory requirements and execution time increase significantly as the number of generators increases and greater accuracy is required [3]. New techniques have been developed using stochastic approaches to solve optimization problems. Examples include an adaptive Hopfield neural network [4], the simulated annealing method [5] and genetic algorithms (GA).

The problem with ELD is to plan the output power for each dedicated production unit in such a way as to minimize operating costs with corresponding operating power limits, load requirements and meet various system constraints. The ELD problem is one of the main problems in the operation of a thermal/hydroelectric power plant. It is considered an optimization problem and is defined for minimized total production costs subject to various non-linear and linear constraints to meet electricity demand. The ELD problem is classified in two different ways, the convex ELD problem and the non-convex ELD problem. The convex ELD problem is modeled considering the objective function as a minimization of the cost functions of the generator taking into account the linear constraints. The non-convex ELD problem takes into account non-linear constraints / constraints along with linear constraints by reducing the cost function. Linear constraints, i.e. production capacity and power balance, drive the ELD problem as an approximate and simplified problem, and the characteristic curve is considered to be piecewise linear. A more precise and precise problem is modeled taking into account non-linear constraints such as prohibited operating zones, valve point effects, and ramp speed limits. The problem with ELD is typically multimodal, discontinuous and highly nonlinear. Although the cost curve for heat generating units is generally modeled as a smooth curve, the input/output characteristics are inherently non-linear due to the effects of valve point loading, no-zone zones (POZ), ramp rate limits, etc.

Large steam turbine generators usually have multiple valves in steam turbines. These valves are opened and closed to maintain effective power balance. However, this effect creates ripples in the cost function. This effect is known as the valve point loading effect. Ignoring the effects of the valve point results in inaccurate build shipment. Also, generator sets may have a certain area where operation is interrupted due to the physical limitations of the mechanical components.

The purpose of an economical shipment is to determine the optimum output power of the units involved in feeding the load. The sum of the total electricity production must correspond to the load required by the station. In a simplified case, transmission losses are neglected. This simplifies the task of the solution method. In practice, transmission losses must be taken into account. The inclusion of transmission losses makes the task of an economical shipment more difficult. Another solution method must be used to arrive at the solution.

II. INTRODUCTION OF INTELLIGENCE TECHNIQUES

The rapid growth in the size of the electricity grid and the demand for electricity, as well as the problem of reducing operating costs, have become more important, while the voltage and thermal safety limits of the branches of the transmission line are maintained. A large number of mathematical programs and artificial intelligence techniques have been applied to solve ELD (Economic Load Dispatch). In most general formulations, ELD is a large-scale non-linear, non-convex static optimization problem with continuous and discrete control variables. Mathematical programming approaches the more general formulation. ELD is a large-scale non-linear and non-convex static optimization problem with continuous and discrete control variables.

III. LITERATURE REVIEW

Zhi-xinZheng et al. [6] in this study, a hybrid invasive weed optimization algorithm (HIWO) was proposed, which hybridizes the invasive weed optimization algorithm (IWO) and the genetic algorithm (GA) to solve economic shipping (ED) problems in electrical systems. In the proposed algorithm, the IWO algorithm is used as the main optimizer to examine the solution space, while the crossover and AG mutation operations are developed to greatly improve the IWO optimization capability. Furthermore, an effective repair method is built into the proposed algorithm to correct impractical solutions by addressing various practical limitations of erectile dysfunction problems.
Y. Di et al. [7], the restriction is managed by the marginal exploration operator. This method provides an optimal solution for emissions and fuel costs such as BBO and NSGA-II. It has a better overall search ability.

K. Bhattacharjee et al. [8] used the backtracking search algorithm (BSA) and a different strategy for the mutation, using the target individual and the variable in and for a new type of crossbreeding strategy to create new test subjects in each generation for better research overall. Compared to the other method, BSA offers an optimal solution for different generator sets.
A.Y. Abdelaziz et al. [9] had a new algorithm elaborated as the Flower Pollination Algorithm (FPA) through the process of reproducing the flowers from the pollination process. It has better performance for CEED and ELD problems with a much faster convergence rate.

R M. K. Bavisetti et al. [10] This paper presents an evolutionary computational method (EC) called Genetic Algorithm (GA) and a metaheuristic algorithm called Ant Colony Search Algorithm (ACSA) to solve the combined Economic and Emission Dispatch (EED) problem with transmission losses. Economic Load Distribution (ELD) and Economic Emission Distribution (EED) were used to achieve optimal fuel costs and optimal emissions from production units. The combined transport of economic emissions problem is solved with both economic and emissions targets in mind. A true coded GA has been implemented to minimize both shipping costs and emissions while respecting all equality and inequality constraints.

P.K. Singhal et al. [11] In this document, an ELI (Enhanced Lambda Iteration) algorithm is developed to solve the problem of the economic shipment (ED) of thermal units taking into account the constraints of the generator for a lossless system. With the classic lambda iteration technique, an incorrect selection of the initial lambda value (incremental costs) can lead to slow convergence and thus divergence. The presented algorithm is able to manage the problem taking into account the concept of equal incremental cost criterion to decide the value of the initial lambda and also to easily manage the equality and inequality constraints. The algorithm is tested on small and large heat production units, which shows the feasibility of the algorithm.

IV. OVER VIEW GENETIC ALGORITHM

GA starts with a random generation of the initial population, then "selection", "cross" and "mutation" are added until the maximum generation is reached. The important steps of the AG are described below.

A. Selection

The choice of parents for future generations plays an important role in GA. The lens allows you to select the strongest most often to breed. A group of selection methods is available in the literature [12]: "universal stochastic sampling", "uniform", "ranking" and "tournament" etc. The "universal stochastic sampling" selection is used in this book by "Genetic Algorithm and Direct" uses Search Toolbox "in MATLAB. In this selection, parents are created using" roulette "and" unified sample "based on expectations and to the number of parents.

B. Crossover

Crossover is a major GA operator. It is responsible for structural recombination (exchange of information between mating chromosomes) and the rate of GA convergence and is normally used with high probability (0.6-0.9). After the selection process, the simple crossing will continue. The main purpose of the crossover is to rearrange the information of two different people and create a new one. The "Crossover Scattered" function is used in this chapter of "Genetic Algorithm and Direct Search Toolbox" in MATLAB. This is a location-independent crossover function that creates cross-children of the respective population.

C. Mutation

Mutation is an underlying operator that causes spontaneous changes in different chromosomes. In artificial genetic systems, the mutation operator protects against irreversible loss. This is an occasional random change of the value in the string position. The mutation is necessary because, although reproduction and crossing are efficient in finding range terms and recombining them, they can occasionally lose potentially useful genetic material. This book uses the "Uniform Mutation" multipoint mutation feature in the MATLAB toolkit. The mutated genes are evenly distributed over the area of the gene.

V. GENETIC ALGORITHM

GA is a global stochastic research method that mimics the metaphor of natural biological evolution such as selection, crossing and mutation [13-14]. GA works on string structures, where the string is made up of binary digits that represent an encoding of the control parameters for a specific problem. All the parameters of the given problem are encoded with bit sequences. The single bit is called a "gene" and the content of each gene is called an "allele". Generally, genetic algorithms have three stages: initialization, evaluation, and genetic functioning. The fitness function for the maximization problem is,

$$f(x) = F(x)$$

and for the minimization problem is

$$f(x) = \frac{1}{1+F(x)}$$

Where f(x) is fitness function and F(x) is objective function.

In the genetic operation stage, we use genetic operators to generate a new population from the previous population. They are reproduction, crossing and mutation. Reproduction is the operator by which the old chromosome is copied to the carpet pool at its best value. The higher the suitability of the chromosome, the higher the copy number in the next generation chromosome. The different chromosome selection methods for parents to cross are roulette wheel selection, Boltzmann selection, tournament selection, grade selection, steady state selection, etc. the pairing pool has a probability proportional to the physical form [15].

The roulette-wheel mechanism is expected to make fi/fit_{avg} copies of i_{th} string of the mating pool. The average fitness is

$$fit_{avg} = \sum_{j=1}^{n} \frac{fj}{n}$$

The basic operator for creating a new chromosome is the crossover network. In this operator, information is exchanged between strings in the matting pool to create new strings. The last genetic operator in the algorithm is the mutation. In general evolution, mutation is a random process in which one allele of one gene is replaced with another to create a new genetic structure. Mutation is an important operation because newly created individuals have no new information about heredity and the number of alleles is constantly decreasing.

VI. Economic Load Dispatch

A. Economic load dispatch

Economic shipping can be defined as the process of assigning generation levels to generation units so that the system load is delivered in full and in the most economical way. For a network system it is necessary to minimize costs. Economic cargo shipping is used to define the production level of each asset so that the total cost of generation and transmission is minimal for a prescribed load plan. The goal of economical cargo shipment is to minimize total generation costs.

B. Generator Operating Cost

Total cost of ownership includes fuel costs, labor costs, supplies and maintenance. Typically, labor, delivery, and maintenance costs are fixed percentages of incoming fuel costs. The performance of fossil fuel power plants is subsequently increased by opening a series of valves to its steam turbine at the entrance. Throttling losses are large when a valve is open and small when fully open.

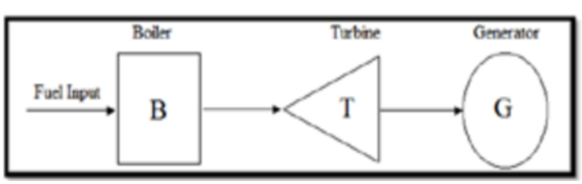


Fig. 1 Simple model of a fossil plant

Figure 1 shows the simple fossil plant expedition model. Cost is usually estimated from one or more square segments. The operating costs of the plant have the form shown in figure 2.

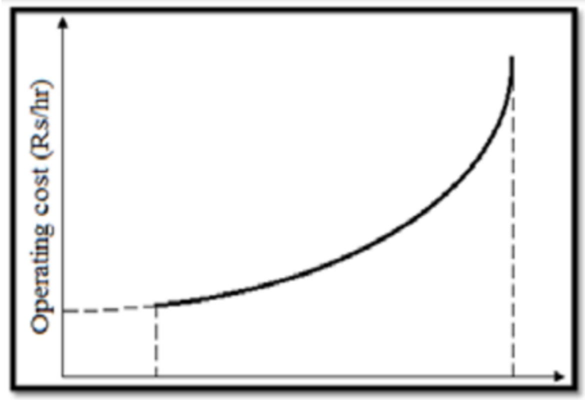


Fig. 2 Operating costs of a fossil fired generator

The fuel cost curve can have a series of discontinuities. Discontinuities occur when the power output is increased through the use of additional boilers, steam condensers, or other equipment. They can also arise when the cost represents the operation of an entire plant and the cost of connecting the generators in parallel therefore presents discontinuities. In the area of continuity, the additional cost of fuel can be expressed as a number of short line segments or piecewise linearization. The min Pgi is the minimum load limit below which device operation is uneconomical (or technically impossible), and the max Pgi is the maximum output limit [16].

VII. Proposed Methodologies

A. Evolutionary Programming (EP), Simulated Annealing (SA), Tabu Search (TS)

Although heuristic methods do not always guarantee the discovery of optimal solutions globally in a finite time, they often provide a quick and sensible solution. EP can be a rather powerful evolutionary approach; however, for some problems it is rather slow to approach optimal values. SA and TS can be very useful for solving complex reliability optimization problems. However, SA is time-consuming and cannot simply be used to set the preheat program control parameters. TS is difficult to define efficient storage facilities and problem-dependent strategies.

B. Dynamic Programming (DP)

If the cost functions are not convex, the same incremental cost method cannot be used. In such circumstances, there is a way to find an optimal shipment that uses a dynamic planning method. Dynamic programming is an optimization technique that converts a maximization (or minimization) problem with n decision variables into n problems with only one decision variable at a time. This is done by defining a sequence of functions with value V1, V2… ..Vn, where an argument y represents the state of the system. The definition of Vi (y) is the maximum that can be reached when decisions 1, 2 ... I are available and the system state is y. The V1 function is easy to find. For I = 2, new system state when this decision is made. Since Vi -1 has already been calculated for the requested states, the above operation returns Vi for all the requested states. Finally, in the initial state of the system, Vn is the value of the optimal solution. Optimal values of decision variables can be restored individually by plotting the calculations already performed.

C. Hopfield Neural Network (HNN)

Hopfield was introduced in 1982 [17] and 1984 [18]. Hopfield neural networks have been used in many different applications. The important property of the Hopfield neural network is the decrease in energy by a finite quantity as the inputs vary. Hopfield's neural network can then be used for optimization. Tank and Hopfield [19] described how several optimization problems can be quickly solved by tightly interconnected networks of a single analog processor, which is an implementation of the Hopfield neural network. Park et al [20] presented the economic shipment of cargo for piecewise square cost functions using the Hopfield neural network. The results of this method were compared very well with those of the numerical method in a hierarchical approach. King et al [21] used the Hopfield neural network in the economic and ecological transport of electrical systems. However, these applications involved a large number of iterations and often showed oscillations during transients. This suggests that convergence should be improved by an adaptive approach, for example by the adaptive learning speed method developed by Ku and Lee [22] for a diagonally repeating neural network.

D. Genetic Algorithm (GA), Differential Evolution (DE)

GA ensures that the colony evolves and that solutions are constantly changing. However, sometimes it does not have a strong ability to produce better offspring and causes slow convergence near the global optimum, sometimes it can get trapped in the local optimum. Due to the premature convergence of GA, performance decreases and search capacity decreases. Price and Storn [23] invented differential evolution (DE). It involves three fundamental operations, such as: B. Mutation, crossing and selection to obtain an optimal solution. It was found that DE, using its different traversal strategies, provides a better and faster solution and satisfies all the constraints of unimodal and multimodal systems. However, as the complexity and size of the system increases, the DE method cannot better summarize all the unknown variables. In DE, all variables are edited together during the crossover operation. The individual variable is not voted on separately. So in the startup phase the solutions move very quickly to the optimal point, but in a later phase, when some fine tuning is needed, DE doesn't work any better.

E. Particle Swarm Optimization (PSO)

In the mid-1990s, Kennedy and Eberhart invented the PSO [24]. Only a few parameters need to be adjusted in PSO, which makes PSO more attractive. Simple concept, easy implementation, robustness and calculation efficiency are the main advantages of the PSO algorithm. A closer look at how the algorithm works reveals that once the algorithm is in the optimal range, it advances slowly because it cannot adjust the speed step size to continue the finer-grained search. For the multimodal function, particles sometimes do not reach the overall optimal point. Compared to other methods, PSO is cost-effective in terms of memory and speed. The most interesting functions of PSO can be summarized as follows: simple concept, simple implementation, fast calculation and robust search function. Artificial Immune System (AIS) The Artificial Immune System (AIS) [25] is another population-based or network-based soft computer optimization technique that has been successfully implemented in various human health problems: power supply system.

F. Bacterial Foraging Algorithm (BFA)

Inspired by the survival mechanism of bacteria eg. B. E. coli, an optimization algorithm called Bacterial Foraging Algorithm (BFA) has been developed [26]. Chemo taxis, reproduction and dispersion are the three processes by which the overall research capacity of this algorithm was achieved. These properties have helped BFA to be successfully applied to various types of power system optimization problems. However, meeting the limitations poses few problems with BFA.

G. Quantum-inspired Evolutionary Algorithm (QEAs)

The quantum-inspired evolutionary algorithms (QEA) [27] then proposed are based on the concepts and principles of the quantum computer, with which it is easier to find the right balance between exploration and exploitation than conventional EAs. Meanwhile, QEAs can explore the research space with fewer people and use holistic solutions in a short period of time. In QEA and PSO research, optimization of quantum-inspired particle showers (QPSOs) is proposed. Two main definitions used in QEAs are introduced: quantum bits and quantum rotation gates. The quantum bit is used as a probabilistic representation of particles, which are defined as the smallest unit of information. A quantum bit sequence consists of a single quantum bit. Quantum Rotation Gate is also defined as an implementation to bring individuals to better solutions and ultimately to find a global optimum.

H. Snake Algorithm

The snake algorithm has been shown to overcome the drawbacks of traditional snake / contour algorithms to follow the most effective and efficient contour of multiple objects. The experimental results of the tests carried out have shown that the proposed method is robust, efficient and precise for finding solutions to the limits of multiple objects.

VIII. CONSTRAINED ECONOMIC DISPATCH FORMULATION

To solve the standard economic dispatch problem, consider the operation of a power system with N units, each loaded to P_i, to satisfy a total load demand P_D including total transmission losses P_L. Let the fuel input-power output cost function of each unit be represented by a function F_i. The units are to be loaded so that the total fuel cost, F_T for the N number of generating units is minimized subject to the power balance and unit upper and lower operating limits:

$$\min \sum_{i=1}^{N} F_i\left(P_i\right) \quad (1)$$

subject to:

$$\sum_{i=1}^{N} P_i - \left(P_D + P_L\right) = 0$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,2,\ldots,N \quad (2)$$

For units with prohibited operating zones, there are additional constraints on the unit operating range:

$$P_i^{\min} \le P_i \le P_{i,1}^{L} \text{ or}$$

$$P_{i,k}^{U} \le P_i \le P_{i,k}^{L} \;\; k = 2,\ldots,n_i, \text{ or}$$

$$P_{i,n_i}^{U} \le P_i \le P_i^{\max} \quad (3)$$

where:

i = unit index

$P_i^{\min}$ = unit minimum generation limit

$P_i^{\max}$ = unit maximum generation limit

n_i = number of prohibited zones for unit i

k = index of prohibited zones of a unit

$P_{i,k}{}^{L,U}$ = lower/upper bounds of the k th prohibited zones of unit i.

IX. GENETIC ALGORITHM SOLUTION

A genetic algorithm [28] represents a class of evolutionary computation techniques based on natural selection and biological evolution. These methods have proved useful in search spaces that are not well understood, or which are too large to be effectively searched by standard methods. The GA paradigm works on population of solutions in contrast to conventional search techniques which operate on a single solution. The most powerful feature of GA is that although they do not need any prior information or space limitations, like smoothness or convexity of the function to be optimized, their performance is very good on a majority of problems.

A. Real Coded GA

In this GA, the output of each generating unit is represented by a floating-point number, instead of binary coding, resulting in absolute precision, hence dependence of accuracy on string length (number of bits) is eliminated. The outputs of all generators are consolidated to form a solution string called *chromosome*. A population of chromosomes is initially generated randomly. The *population size* is an important parameter of GA and its selection needs to be done carefully for each problem. Each chromosome in the population represents a possible solution to the problem. A *fitness value*, derived from the problem's objective function is then evaluated for each solution string in the population. Strings that have better solutions are awarded higher fitness values, ensuring their survival in the coming generations.

B. Parameters of GA

The GA searches for better solutions by letting the fitter individuals take over the population through a combined stochastic process of selection and recombination. The main three operators that influence the GA performance are *selection*, *crossover* and *mutation*. Their interaction is highly complex and slight variations in their implementations results in a variety of models. The different models depend on many factors like selection method and mechanism, parent replacement method, crossover and mutation method, serial or parallel implementation, and the type of problem to be solved. The GA model to be used is chosen after a careful analysis of the problem to be solved.

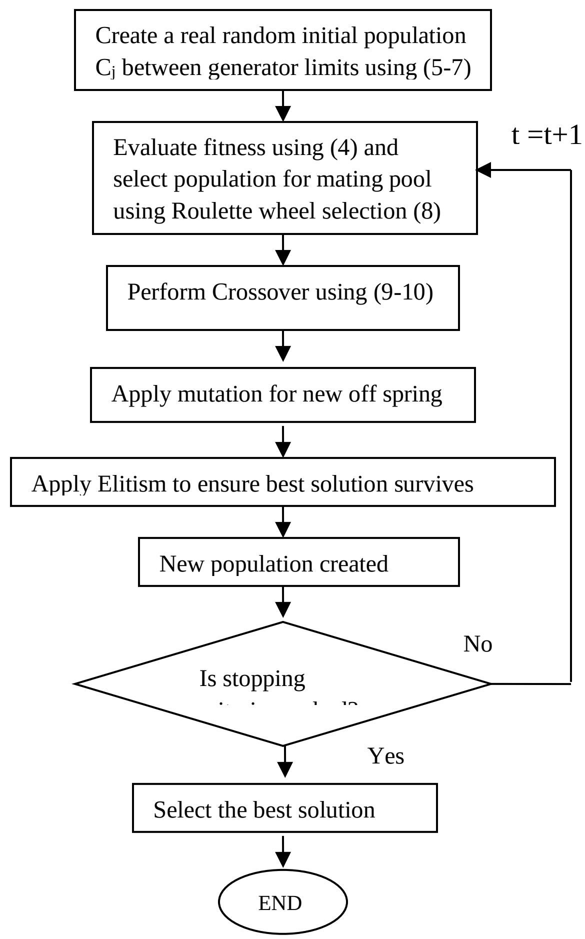


Fig. 1. Flowchart of real-coded genetic algorithm.

C. Fitness Function

For the implementation of ELD through RGA it is necessary that a fitness function is defined such that operating cost given by (1) is minimized while constraints given by (2) and (3) are satisfied. One of the methods for this is the popular penalty function method. In this method, t penalty function composed of squared or absolute violations, which are incorporated in the fitness function, and are set to reduce the fitness of the string according to the magnitude of the violation. Large values for penalty parameters ill condition the penalty function while very small values do not allow the constraint violations to contribute effectively in penalizing a string. Hence, the penalty parameters, are chosen such that an infeasible solution is awarded fitness worse than the weakest feasible string. Since two infeasible strings are not treated equally, the string further away from the feasibility boundary, is more heavily penalized. Thus, a constrained optimization problem is converted to unconstrained optimization problem

The problem objective function is

$$\min \sum_{i=1}^{N} F_i(P_i) + \alpha\left[\sum_{i=1}^{N} P_i - (P_D + P_L)\right]^2 \quad (4)$$

where α is the penalty function for not satisfying load demand and β represents the penalty function for a unit loading falling within a prohibited operating zone. If no unit output in a solutions falls within prohibited zone, the second term in (4) becomes zero.

The fitness function is obtained by transforming the minimization into maximization.

D. RGA for generators with prohibited zones

The objective of economic dispatch is to minimize fuel costs while satisfying unit and system constraints defined by (2) and (3). The system constraint to be satisfied is that of matching the load demand and reserve requirements with power generation. The unit minimum and maximum loading limits are taken care of by following a transformation process which restricts the solutions to lie between these values [29]. Then the only other constraints to be considered are the unit prohibited operating zones. A penalty function approach [12,6] is used to handle theses constraints. Another popular approach is to set the solutions at the nearest upper or lower limit of the prohibited zone which is being violated.

The following steps describe how GA steers through the wide solution space and achieves solutions that are very near to global minimum.

Step I: Generation of initial population

A population of M chromosomes is randomly generated in which each generator output P_i is constrained to lie within $P_i^{\min}$ and $P_i^{\max}$ [29]. The bounded constraints are handled as unbounded constraints by transformation of variables.

Let A= ($P_i^{\min}$ + $P_i^{\max}$)/2

B = ($P_i^{\max}$ - $P_i^{\min}$)/2 (5)

Then the transformed variable p^t is found

$$P^t = (A + BCos(r\pi)) \quad (6)$$

The j[th] chromosome in the initial population can be represented as

$$C_j(t) = \left[P_1^t, P_2^t, \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots P_N^t\right]_j \quad (7)$$

where j represents the population size M.

Step II: Evaluation of fitness function

The objective of ELD is to minimize operating cost while demand and other constraints are satisfied. RGA works through the population to maximize fitness, hence the fitness function is evaluated as reciprocal of the function (4). Therefore, for each chromosome in the generated population, the fitness function is evaluated using the inverse of the objective function given by (4)

Step III: Evolution of population to next generation

The initial population evolves using the basic three genetic operators of selection, crossover and mutation. For this, chromosomes from the parent population are copied into the mating pool with a probability proportional to their fitness to form the offspring population using Roulette-Wheel [28].

The probability of selection of the *i*[th] string is given by

$$\rho_i = \frac{F_i}{\sum_{j=1}^{M} F_j} \quad (8)$$

Where M is the population size.

Step IV: Creation of offspring through crossover operator

So far, the strings were only getting replicas without any new addition. The crossover operation is used to create new individuals with higher fitness. In binary GA a part of the parents is exchanged with each other at randomly selected sites; the crossover probability controls the frequency of crossover in a generation. This is achieved by swapping of two parent strings at randomly selected locations. For continuous real coded GA if two chromosomes $C_1(t)$ and $C_2(t)$ are randomly selected from the population for crossover, then the two off springs C_3 (t) and C_4 (t) are evaluated as

$$C_3(t+1) = r\,C_1(t) + (1-r)\,C_2(t) \quad (9)$$

$$C_4(t+1) = r\,C_2(t) + (1-r)\,C_1(t) \quad (10)$$

Where t represents generation and r is a random positive number; $r \in [0,1]$.

Step V: Mutation operation

The above two operators, crossover and reproduction efficiently recombined existing chromosomes but no new genetic information is added to the pool. The mutation operator changes the alleles (individual members in the chromosome, i.e. outputs of generators) at random. If the i^{th} variable of the m^{th} chromosome is randomly selected from a population of M for mutation, then the new chromosome produced will be

$$C_m^{'}(t+1) = \left[P_1^t, P_2^{'}..............P_m^{t-}, ...P_N^t \right]$$

such that P_m^{t-} lies between P_m^{Max} and P_m^{Min}

A simple RGA treats mutation as a secondary operator. The mutation operator introduces new genetic structures in the population by randomly modifying some of its building blocks. It helps the search algorithm to escape from the local minima.

The probability of crossover and mutation occurring in an execution is selected suitably. These parameters have a dramatic effect on RGA convergence.

Step VI: Elitism for preserving the best solutions

While the population moves through the search space, guided by the genetic operators, it is likely that the best solution strings, i.e. strings with high fitness values may be lost. Elitism ensures that a few best strings of previous generations are copied to the new generation without alteration.

Step VI: Stopping criteria

The RGA algorithm is applied on the randomly generated population for maximizing the fitness function. The stopping criteria used is either a after a predetermined number of generations or when the ratio of minimum to maximum fitness in a population approaches one, indicating saturation.

X. RESULTS

TABLE I

Generator operating limits and cost coefficients

Generator / variable	Ai	Bi	ci	Pimax	Pimin
Unit 1	0.008	7	200	10	85
Unit 2	0.009	6.3	180	10	80
Unit 3	0.007	6.8	140	100	70

$$[B] = \begin{pmatrix} 0.0218 & 0 & 0 \\ 0 & 0.0228 & 0 \\ 0 & 0 & 0.0179 \end{pmatrix}$$

TABLE II

Solution by conventional method

Lambda	P1(MW)	P2(MW)	P3(MW)	Delambda
8.0000	51.3136	78.5292	71.1575	-0.3155
7.6845	35.3730	64.3822	52.8017	-0.0054
7.6790	35.0965	64.1369	52.4834	-0.0001
7.6789	35.0908	64.1319	52.4768	0.0000

Result after 4 iterations

Total cost = 1592.7

TABLE III

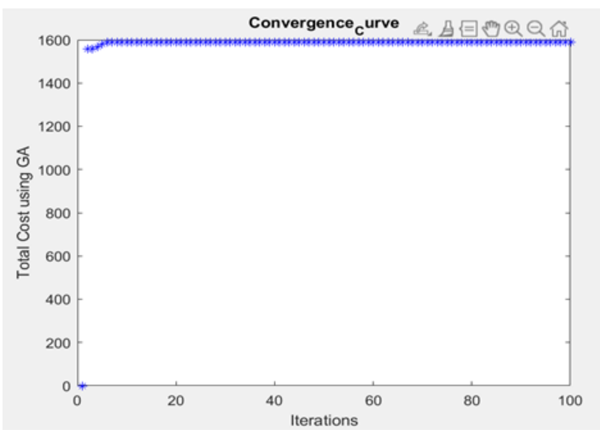
Simulation parameter in GA

method / parameter	GA1	GA2	GA3	GA4	GA5
Population	10	10	10	50	100
Generation	50	50	50	100	100
Crossover probability	0.74	0.69	0.89	0.8	0.8

Mutation probability	0.3	0.3	0.3	0.35	0.45

TABLE IV
Simulation result for different simulation of GA

method	**P1(MW)**	P2(MW)	P3(MW)	P_L(MW)	Total Cost
GA1	82	15	45	1.879607	1564.492
GA2	13	71	66	1.965914	1584.313
GA3	58	63	28	1.77862	1581.421
GA4	26	72	52	1.813336	1580.192
GA5	58	77	11	2.106823	1567.02



Cost optimization for ELD by Genetic Algorithm

TABLE V
Results with different load demands

P_D	method	P_{G1}(MW)	P_{G2}(MW)	P_{G3}(MW)	P_L(MW)	Cost(Rs/h)
500	classical	*107.33	200.27	219.481	27.092	26165.89
	GA	144.190	196.45	181.291	21.92	26024.00
600	classical	132.514	237.53	269.70	39.746	31406.42
	GA	177.82	134.57	314.442	26.84	31361.00
700	classical	*163.71	276.60	315	55.32	36983.41
	GA	210	217.87	315	42.87	36639.00

TABLE VI
Results of generation allocation without valve point loading

P_D	method	P_{G1}(MW)	P_{G2}(MW)	P_{G3}(MW)	P_L(MW)	Cost(Rs/h)
750	Classical	329.63	295.11	142.78	17.54	7451.30
	GA	367.4	288.66	113.35	19.412	7462.60
850	Classical	377.59	381.28	113.76	22.64	8406.80
	GA	430.09	321.84	122.04	23.959	8411.62
950	Classical	504.13	400	70.96	25.10	9397.70
	GA	456.55	380.44	144.34	31.957	9407.00

TABLE VII
Performance of GA with valve point loading

P_D	Method	P_{G1}(MW)	P_{G2} (MW)	P_{G3} (MW)	PL (MW)	Cost (Rs/h)
750	GA	398.78	245.79	125.88	20.44	7667.50
850	GA	481.99	245.66	149.33	26.99	8681.20
950	GA	517.64	317.72	147.61	36.52	9682.00

TABLE VIII
Effect of population size on GA performance

Demand (MW)	Population Size	Method	Cost (Rs/h)	CPU Time (Sec)
750	20	GA	7465	0.0961
750	40	GA	7467	0.1061
750	60	GA	7460	0.112
750	80	GA	7450	0.117
750	100	GA	7443	0.142

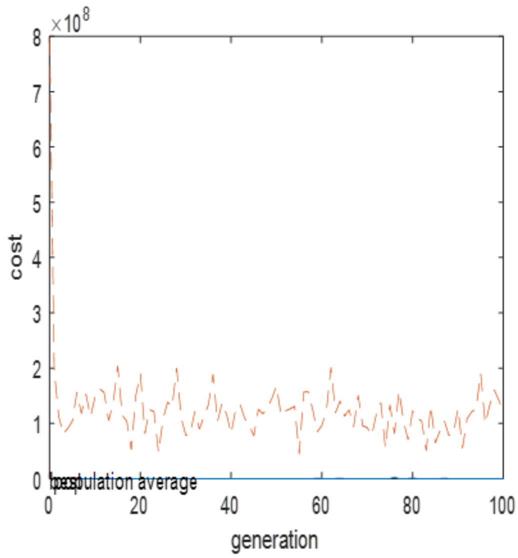


Table I shows the cost coefficients and constraints of a 3 unit generating systems. Table II shows the solution of 3 generating units by using conventional lamda iteration method. Table III shows the parameters of GA which is used for the solution of 3 unit system. Table IV shows the different simulation of GA. Table V shows the comparison of conventional method with GA by taking a different load demands and table VI shows the comparison of conventional and GA without taking the valve point loading effect. Table VII shows the result of GA by considering valve point effects and non linearity's. Table VIII shows that the effect of population size on the cost coefficients and the graph which shows the variation of cost with respect to the population size.

CONCLUSION

In this paper describes the genetic algorithms and their associations with the economic load dispatch. Due to its attractive properties, the GA has become very popular for use in various power system applications, including ELD. Many papers on the use of GA for solving the ELD problem have been reviewed. ELD problems of varying complexity have been investigated in the literature using GA with satisfactory results. Economic load dispatch (ELD) is a process of finding optimal generation scheduling of available generators in an interconnected power system to meet the demand of the system, at the lowest possible cost, while satisfying various operational constraints on the system. More just, the soft computing method has received supplementary concentration and was used in a quantity of successful and sensible applications. Here, we find when we solve the ELD problems by the help of GA, we always find a minimum cost in compare with the conventional method and hence we say that GA is more economical and efficient to use.

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