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This report has been submitted to the Department of Electrical and Information Engineering University of Nairobi with my approval as supervisor:

........................................

Prof. Nicodemus Abungu Odero

Date:........................................
DEDICATION

To my parents and brothers, for always wishing me the best in life.
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First and foremost, I wish to appreciate the Almighty God for His amazing grace throughout my academic life. His love and guidance has propelled me to get this far.

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ABSTRACT

Power plants in a practical power system are not located at the same distance from the centre of loads and their fuel costs are different under normal operating conditions the generation capacity is more than the total load demand and losses. However the fundamental requirements of a system should be secure, economical and reliable.

Economical operation is very important for a given power system to return a profit on the capital invested power companies are always under constant pressure to achieve maximum possible efficiency due to the rates fixed by the regulatory bodies and the importance of conservation of fuel. The maximum efficiency refers to minimized cost per kilowatt hour to the consumer and the cost of the company delivering that power regardless of the constantly rising prices of labour, fuel, supply and maintenance.

Basically in economic operation in power generation is divided to economic load dispatch which deals with scheduling the outputs of generating units by allocating them the generating levels hence it aims at economizing the whole generation process to meet the system load demand and losses. This entails proper allocation of power output among the generating units when the cost of production is minimized by satisfying the unit constraints. Many advanced approaches have been developed towards solving the economic dispatch problem. Among the conventional methods include quadratic programming (QP), interior point method (IP) and gradient method while the search methods include genetic algorithm anti-colony optimization method, particle swarm optimization (PSO) and Tabu search (TS).

In this project other optimization methods have been discussed but genetic algorithm has been applied to solve the economic dispatch problem in hydrothermal plant and satisfying the system constraints to minimize the cost of power generated. The viability of the method is to analyze for its accuracy and rate of convergence. The hydrothermal system in this project is made up of two Hydro generators and three Thermal generators

In this project the problem is overcome by accessing the variation of the error between the total power generated and the sum of demand and power losses with the solution at a given time. The genetic algorithm is implemented using MATLAB code standard IEEE 14 bus data is used. The results obtained are then compared with those obtained from a Thermal system. The power demand loads used for analysis in both systems are 400MW and 550MW. Hydrothermal system is found to be the most suitable method for power generation.
CHAPTER 1
INTRODUCTION

1.1 WHAT IS ECONOMIC DISPATCH?

Economic dispatch (ED) is the short term determination of optimal output of power generation facilities to basically meet the system load at the lowest possible cost, while serving power to the demand in a robust and reliable manner [18,20].

1.1.1 WHAT IS HYDROTHERMAL ECONOMIC DISPATCH?

Hydrothermal Economic dispatch (HTED) is the determination of economic Hydro and Thermal generation levels that satisfy both the physical and operational constraints. The traditional HTED algorithms are largely static since the problem is decomposed by time period and the solutions are co-ordinate over the time horizon using heuristics. In addition they do not account for the important network constraints. The multi period (HTED) is a dynamic problem that determines the optimal Hydro and Thermal generation settings over a given time horizon [6].

1.1.2 WHAT IS OPTIMIZATION?

Optimization can be defined as the maximization or minimization of a given function with some defined constraints. In engineering perspective the techniques, methodology and procedures are used to decide on the specific solution in a defined set of possible alternatives that will be most suitable to satisfy a selected problem [5]. The main objective of optimization is to obtain the best results subject to restrictions or constraints that are imposed [4].

1.1.3 SOLUTION OF ECONOMIC DISPATCH PROBLEM

To solve ED problem different kinds of constraints and multiple objectives have been incorporated using various optimization techniques. In traditional ED problem, the cost function for each generator has been expressed by a simple quadratic function that is solved by conventional methods which include, Newton Raphson method, Lambda Iteration method, Base point and Participation factor method, in the modern units the input and output characteristics are highly nonlinear with valve point effects and rate limits are having multiple local minimum points in the cost function. In consideration of highly non-linear characteristics of the units requires high robust algorithms to avoid getting stuck at the local optima. These algorithms belong to the larger class of guided random search technique which
include Particle Swarm Optimization[PSO], Tabu Search(TS), Differential Evolution(DE), Ant Colony Optimization(ACO) and Genetic Algorithm(GA).

1.2 SURVEY OF EARLIER WORK

Several optimization methods have been developed to help solve the economic dispatch problem. The various methods have been discussed below:

1.2.1 PARTICLE SWARM OPTIMIZATION (PSO)

Particle swarm optimization (PSO) is an intelligent search optimization technique first developed by Kennedy and Eberhart. It is inspired by social dynamics and the behavior emergent from socially organized populations known as swarms e.g. flocks of birds or schools of fish. The individuals are referred to as particles. The particles change their positions by flying around in a multi-dimensional search space until a relatively unchanged position has been encountered, or until computational limitations are exceeded [7]. A swarm of potential solutions are called particles. A particle bases its search not only on its personal experience but also by the information given by the neighbors in the swarm. Each particle keeps track of its co-ordinates in the problem space, which is associated with the best solution fitness it has achieved so far. The fitness value is also stored and it is called pbest. Another best value that is tracked by the particle swarm optimizer is the location lbest value, obtained from any particle in the neighbours of the particle [16]. When a particle takes the whole population as its topological neighbours, the best value is a global best and is called gbest [3, 7]. A PSO system combines local search methods with global search methods. It has the problems of dependency on initial point and parameters, difficulty in finding their optimal design parameters, and the stochastic characteristic of the final outputs [8]. The main advantages of PSO are; easy implementation, simple concept, robustness to control the parameters and less computational time compared to other optimization methods.

1.2.2 SIMULATED ANNEALING (SA)

Annealing refers to the physical process of heating up a solid and then cooling it down slowly until it crystallizes. At high temperatures, the atoms have high energies and have more freedom to arrange themselves. As the temperature is reduced, the atomic energies decrease. A crystal with regular structure is obtained at the state where the system has minimum energy. If the cooling is carried out very quickly (rapid quenching), widespread irregularities and defects are seen in the crystal structure. The system does not reach the minimum energy state and ends in a polycrystalline state which has a higher energy [3].
In the analogy of optimization problem and the Annealing process, the solid states represent solutions of the optimization problem, the energies of the states correspond to the values of the objective function computed at those solutions, the minimum energy state corresponds to the optimal solution to the problem and rapid quenching can be viewed as local optimization.

Hence SA algorithm is a probabilistic method for global optimization problems emulating the process of Annealing. Starting from an initial point, the algorithm takes a step and the function is evaluated. Since the algorithm makes very few assumptions regarding the function to be optimized, it is quite robust with respect to non-quadratic surfaces. In EDP, it’s used for determination of the global or near global optimization dispatch solution. Its main disadvantage of SA is that it is very slow. Also the method cannot tell whether it has found an optimal solution [6, 9].

1.2.3 TABU SEARCH (TS)

The TS Algorithm is a general heuristic optimization approach devised for finding optimal solution of optimization problems. This method is characterized by the use of a flexible memory, it is able to eliminate local minima and to search areas beyond a local minimum. Therefore, it has the ability to find the global minimum of a multimodal search space. The process with which Tabu search overcomes the local optimality problem is based on an evaluation function that chooses the highest evaluation solution.

This refers to moving to the best admissible solution in the neighborhood of the current solution in terms of the objective value and Tabu restrictions. The evaluation function selects the move that produces the most improvement or the least deterioration in the objective function. A Tabu list is employed to store the characteristics of accepted moves so that these characteristics can be used to classify certain moves as Tabu (i.e. to be avoided) in later iterations. The Tabu list determines which solutions may be reached by a move from the current solution. Since moves not leading to improvements are accepted in Tabu search, it is possible to return to already visited solutions. This might cause a cycling problem to arise. The Tabu list is used to overcome this problem. The forbidding strategy is used to control and update the Tabu list to avoid previously visited paths thus allowing exploration of new areas. An aspiration criterion is used to make a Tabu solution free if this solution is of sufficient quality thus preventing cycling [3]. Its main advantage is that it permits back tracking to the previous solution hence can lead to a better solution.
1.2.4 GENETIC ALGORITHM (GA)

Basically GA is an Evolutionary Algorithm (EA) which is also population-based optimization process. This search technique is based on principles inspired from the genetic and evolution mechanism observed in natural systems and population of living things. Its basic principle is the maintenance of a population of solutions to a given problem (Genotypes). It does not differentiate the cost function and the constraints and has a probability of convergence to a global optimum of one. It utilizes the operators of selection, crossover and mutation. It combines survival of the fittest among string structures with a structured, yet random, information exchange. In every generation, a new set of artificially developed strings is produced using elements of the fittest of the old, an occasional new element is experimented for enhancement[10]. A starting population is built with random gene values and it evolves through several generations in which selection, crossover and mutation are repeated until a satisfactory solution has been found or a maximum number of iterations have been reached[6]. The algorithm identifies the individuals with the optimizing fitness values, and those with lower fitness will naturally get discarded from the population. However, GA cannot assure constant optimization response times thereby limiting its application in real-time applications. Genetic algorithm is reviewed in detail in the next chapter of this project since it’s the core optimization method used in this project.

1.2.5 ANT COLONY OPTIMIZATION (ACO)

ACO was inspired by the behavior of ants in their natural habitat. A colony of ants is able to succeed in a task to find the shortest path between the nest and the food source by depositing a chemical substance trail, called pheromone on the ground as they move. This pheromone can be observed by other ants and motivates them to follow the path with a high probability. This optimization technique is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trail which serve as distributed, numerical information, which the ants use to probabilistically construct solutions to the problem. This is adapted by the ants during the algorithm’s execution to reflect their search experience. In this way, the best solution has more intensive pheromone and higher probability to be chosen. The described behavior of real ant colonies can be used to solve combinational optimization problems by simulation, using artificial ants searching the solution space by transiting from nodes to nodes. The
artificial ants’ moves are usually associated with their previous action, stored in the memory with a specific data structure. The pheromone consistencies of all paths are updated only after the ant finishes its tour from the first node to the last node. Every artificial ant has a constant amount of pheromone stored in it when the ant proceeds from the first node. The pheromone that is stored will be distributed average on the path after artificial ants finished their tour. The quantity of pheromone will be high if artificial ants finished their tour with a good path. The pheromone of the routes progressively decreases by evaporation in order to avoid artificial ants stuck in local optima [6]. ACO is advantageous since it can be used in dynamic systems also its positive feedback leads rapid discovery of good solutions.

1.2.6 DIFFERENTIAL EVOLUTIONARY (DE)

The Differential Evolution is a population-based, stochastic function optimizer using vector differences for perturbing the population. The DE is used to solve the economic dispatch problem with transmission loss by satisfying the linear equality and inequality constraints. DE obtains solutions to optimization problems using three basic operations: Mutation, Crossover and Selection. The mutation operator generates noisy replicas (mutant vectors) of the current population inserting new parameters in the optimization process. The crossover operator generates the trial vector by combining the parameters of the mutant vector with the parameters of a parent vector selected from the population. In the selection operator the trial vector competes against the parent vector and the one with better performance advances to the next generation. This process is repeated over several generations resulting in an evolution of the population to an optimal value [1].

1.2.7 HYBRID METHODS/HYBRID ALGORITHMS

These is a combination of two or more optimization methods with the aim of taking advantage of the pros of each method used in the mix while reducing on computation time hence speeding up convergence and/or better the quality of the solution. Examples include Expert System SA (ESSA). This seeks to use an expert system consisting of several heuristic rules to find a local optimal solution, which will be employed as an initial starting point of the second stage. This method is insensitive to the initial starting point, and so the quality of the solution is stable. It can deal with a mixture of continuous and discrete variables [6].

1.3 PROBLEM STATEMENT

The main objective of this project is to understand economic dispatch in a power system by studying theory behind Hydrothermal power generation and the most economical way to
generate power. It will involve the formulation of the hydrothermal economic dispatch problem and generate a solution using genetic algorithm. GA operators are to be understood well and will be used to write a C++ code in MATLAB software package hence will be used to solve the economic dispatch problem [21].

Thus the main objectives of this project are:

a) To find a solution to the Hydrothermal economic dispatch problem so that the total cost is minimized
b) To understand Genetic Algorithm and use it to find the optimal solution for the case of economic dispatch.

1.4 ORGANIZATION OF REPORT

The project report has been organized into five chapters as follows;

**Chapter 1**, The ED problem is introduced other optimization techniques have been discussed, objectives have also been stated.

**Chapter 2**, A literature review of Hydrothermal economic dispatch has been discussed, Genetic Algorithm has also been discussed in preparation for solution of the problem.

**Chapter 3**, Implementation of GA in solving Hydrothermal economic dispatch problem in power system is discussed

**Chapter 4**, It covers analysis of the results obtained from Hydrothermal system together with the results obtained from Thermal system.

**In Chapter 5**, Contains the conclusions and recommendations for further work.
2.1 INPUT CHARACTERISTIC OF THERMAL UNITS

The generating unit fuel consumption function or operating cost function for the thermal units are also called the input-output characteristics. The unit of the generator fuel consumption function is Btu per hour heat input to the unit (or MBtu/h). The fuel cost rate times Btu/h is the $ per hour ($/h) input to the unit of fuel. In addition to the fuel consumption cost, the operating cost of a unit includes labour cost, maintenance cost, and fuel transportation cost. It is difficult to express these costs directly as a function of the output of the unit, so these costs are included as a fixed portion of the operating cost. The Thermal unit system generally consists of the boiler, the steam turbine, and the generator. The input of the boiler is fuel, and the output is the volume of steam.

\[ P_{G \text{ min}} \leq P_G \leq P_{G \text{ max}} \] \[2.1\]

Where \( P_G \) represents the power output of the generating unit

\[ F = aP_G^2 + bP_G + c \] \[2.1a\]

Where \( a, b, \) and \( c \) are the coefficients of the input-output characteristic. The constant \( c \) equivalent to the fuel consumption of the generating unit operation without output.

Let \((F_k, P_k)\) be obtained from the statistical data, where \( k = 1, 2 \ldots n \), and the fuel curve will be a quadratic function. To determine the coefficients \( a, b, \) and \( c \), the error for each data pair \((F_k, P_k)\) was computed as follows:

\[ \Delta F = (aP_G^2 + bP_G + c) - F_k \] \[2.1b\]

According to the principle of least squares the objective function is formed as follows:

\[ J = (\Delta F)^2 = \sum_{k=1}^{n} (aP_G^2 + bP_G + c - F_k)^2 \] \[2.1c\]

By obtaining necessary conditions for an extreme value of the objective function when the first derivative of the above function \( J \). This is in respect to the independent variables \( a, b, \) and \( c \) and the derivatives are set equal to zero:
\[ \frac{\partial J}{\partial a} = \sum_{k=1}^{n} 2P_{k}^{2}(aP_{k}^{2} + bP_{k} + c - F_{k}) = 0 \quad \ldots \ldots \ldots \quad [2.1d] \]

\[ \frac{\partial J}{\partial a} = \sum_{k=1}^{n} 2P_{k}(aP_{k}^{2} + bP_{k} + c - F_{k}) = 0 \quad \ldots \ldots \ldots \quad [2.1e] \]

\[ \frac{\partial J}{\partial a} = \sum_{k=1}^{n} 2(aP_{k}^{2} + bP_{k} + c - F_{k}) = 0 \quad \ldots \ldots \ldots \quad [2.1f] \]

In order to get the coefficients, from the equations above the following equations are obtained:

\[ \left( \sum_{k=1}^{n} P_{k}^{2} \right) a + \left( \sum_{k=1}^{n} P_{k} \right) b + nc = \sum_{k=1}^{n} F_{k} \quad \ldots \ldots \ldots \quad [2.1g] \]

\[ \left( \sum_{k=1}^{n} P_{k}^{3} \right) a + \left( \sum_{k=1}^{n} P_{k}^{2} \right) b + \left( \sum_{k=1}^{n} P_{k} \right) c = \sum_{k=1}^{n} (F_{k}P_{k}) \quad \ldots \ldots \quad [2.1h] \]

\[ \left( \sum_{k=1}^{n} P_{k}^{4} \right) a + \left( \sum_{k=1}^{n} P_{k}^{3} \right) b + \left( \sum_{k=1}^{n} P_{k}^{2} \right) c = \sum_{k=1}^{n} (F_{k}P_{k}^{2}) \quad \ldots \ldots \quad [2.1i] \]

By solving the equations [2.1g], [2.1h] and [2.1i] simultaneously, the coefficients a, b and c are obtained respectively.
The input - output curve of a hydroelectric plant with variable head is represented in the graph below. This type of characteristic occurs whenever the variation in the pond and/or after bay elevations is a fairly large percentage of the overall net hydraulic head is constant.

Fig. 2.1 input-output curve of a hydroelectric plant

### 2.2 HYDROTHERMAL SYSTEM ECONOMIC DISPATCH

Hydrothermal system economic dispatch is usually more complex than the economic dispatch of an all-thermal generation system. All hydro-systems are different. The reasons for the differences are the natural differences in the watersheds, the differences in the manmade storage and release elements used to control the water flows and the very many different types of natural and manmade constraints imposed on the operation of hydroelectric systems.

A hydrothermal plant involves the scheduling of water release. Depending on the water release, a Hydro system can be divided into short range (one day, one week) and long range (one month, one year) scheduling. Assuming $P_T, F(T)$ is the power output and input - output characteristic of a thermal plant, and let $P_H, W (P_H)$ be the power output and input - output characteristic of a hydro-electric plant. The hydrothermal system economic dispatch problem can be expressed as:
\[
min F_\Sigma = \int_0^T F[P_T(t)] dt \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2a]
\]

Where: \( F_\Sigma \) = the total fuel cost for the hydrothermal plant

\[P_H(t) + P_T(t) - P_D(t) = 0 \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2b]\]

\[
\int_0^T W[P_H(t)] dt - W_\Sigma = 0 \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2c]
\]

Dividing the operation period (T) into \( S \) stages

\[T = \sum_{k=1}^{S} \Delta t_k \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2d]\]

At any time stage, suppose that the power output of the hydro plant and the thermal plant as well as load demand are constant. Then equations (2.2b) and (2.2c) are becomes:

\[P_{Hk} + P_{Tk} - P_{Dk} = 0, \quad k = 1, 2, \ldots, s \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2e]\]

\[
\sum_{k=1}^{S} W(P_{Hk}) \Delta t_k - W_\Sigma = \sum_{k=1}^{S} W_k \Delta t_k - W_\Sigma = 0 \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2f]
\]

The objective function from equation (1) becomes:

\[F_\Sigma = \sum_{k=1}^{S} F(P_{Tk}) \Delta t_k = \sum_{k=1}^{S} F_k \Delta t_k \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2g]\]

### 2.2.1 CONSIDERING NETWORK LOSSES

When the generators are connected towards the bus bars power is lost, hence when analyzing economic dispatch, real power losses (P_L) are incorporated. With \( m \) Hydro plants and \( n \) Thermal plants. The system load is given in the time period (T). The given water consumption of Hydro plant \( j \) is \( W_{\Sigma j} \). Then economic dispatch with network loss can be expressed as shown:

\[
min F_\Sigma = \sum_{i=1}^{n} \int_0^T F_i[P_{Ti}(t)] dt \quad \ldots \quad \ldots \quad \ldots \quad \ldots \quad [2.2.1a]
\]
\[
\sum_{j=1}^{m} P_{Hj}(t) + \sum_{i=1}^{n} P_{Ti}(t) - P_L(t) - P_D(t) = 0 \quad \text{.................................................}[2.2.1b]
\]
\[
\int_{0}^{T} W_j[P_{Hj}(t)] dt - W_\Sigma j = 0 \quad \text{.................................................}[2.2.1c]
\]

Dividing the operation period \( T \) into \( s \) time stages
\[
T = \sum_{k=1}^{s} \Delta t_k \quad \text{.................................................}[2.2.1d]
\]

Then the other equations become:
\[
F_\Sigma = \sum_{i=1}^{n} \sum_{k=1}^{s} F_{ik}(P_{Ti,k}) \Delta t_k \quad \text{.................................................}[2.2.1e]
\]
\[
\sum_{j=1}^{m} P_{Hjk} + \sum_{i=1}^{n} P_{Ti,k} - P_{Lk} - P_{Dk} = 0, \quad k = 1,2, ..., s \quad \text{.................................................}[2.2.1f]
\]
\[
\sum_{k=1}^{s} W_{jk}(P_{Hjk}) \Delta t_k - W_\Sigma j = 0, \quad j = 1,2, ..., m \quad \text{.................................................}[2.2.1g]
\]

Hence the Lagrange Function becomes:
\[
L = \sum_{i=1}^{n} \sum_{k=1}^{s} F_{ik}(P_{Ti,k}) \Delta t_k - \sum_{k=1}^{s} \lambda_k \left[ \sum_{j=1}^{m} P_{Hjk} + \sum_{i=1}^{n} P_{Ti,k} - P_{Lk} + P_{Dk} \right] \Delta t_k \\
+ \sum_{j=1}^{m} \gamma_j \left[ \sum_{k=1}^{s} W_{jk}(P_{Hjk}) \Delta t_k - W_\Sigma j \right] \quad \text{.................................................}[2.2.1h]
\]

The necessary conditions for the extreme value of the Lagrange function are[17]:
\[
\frac{\partial L}{\partial P_{Hjk}} = \gamma_j \frac{dW_{jk}}{dP_{Hjk}} \Delta t_k - \lambda_k \left[ 1 - \frac{\partial P_{Lk}}{\partial P_{Hjk}} \right] \Delta t_k = 0, \quad j = 1,2, ..., m; \quad k = 1,2, ..., s \quad [2.2.1i]
\]
\[
\frac{\partial L}{\partial P_{Tik}} = \frac{dF_{ik}}{dP_{Tik}} \Delta t_k - \lambda_k \left[ 1 - \frac{\partial P_{Lk}}{\partial P_{Tik}} \right] \Delta t_k = 0, \quad i = 1,2,\ldots,n; \quad k = 1,2,\ldots,s \quad \text{[2.2.1j]}
\]

\[
\frac{\partial L}{\partial \lambda_k} = - \left[ \sum_{j=1}^{m} P_{Hjk} + \sum_{i=1}^{n} P_{Tik} - P_{Lk} + P_{Dk} \right] \Delta t_k = 0, \quad k = 1,2,\ldots,s \quad \text{[2.2.1k]}
\]

\[
\frac{\partial L}{\partial \gamma_j} = \sum_{k=1}^{s} W_{jk} \Delta t_k - W_{j\Sigma} = 0 \quad j = 1,2,\ldots,m \quad \text{[2.2.1l]}
\]

From the Lagrange equations above the following expressions are obtained:

\[
\frac{dF_k}{dP_{Tk}} = \gamma \quad \frac{dW_k}{dP_{Hk}} = \lambda_k \quad k = 1,2,\ldots,s \quad \text{[2.2.1m]}
\]

If the time stage is very short it becomes:

\[
\frac{dF}{dP_T} = \gamma \quad \frac{dW}{dP_H} = \lambda \quad \text{[2.2.1n]}
\]

The above equation (2.2.1n) defines the incremental principle of a hydrothermal system economic dispatch. When the thermal unit increases power output \( \Delta P \), the incremental fuel consumption will be:

\[
\Delta F = \frac{dF}{dP_T} \Delta P \quad \text{[2.2.1o]}
\]

When hydro unit increases power output \( \Delta P \), the incremental water consumption becomes:

\[
\Delta W = \frac{dW}{dP_H} \Delta P \quad \text{[2.2.1p]}
\]

From the equations (2.2.1n), (2.2.1o) and (2.2.1p) above the following relationship is obtained:

\[
\gamma = \frac{\Delta F}{\Delta W} \quad \text{[2.2.1q]}
\]

Where \( \gamma \) defines the coefficient that converts water consumption to fuel

\[
\Delta F = \gamma \Delta W \quad \text{[2.2.1r]}
\]
2.3 LITERATURE REVIEW ON GENETIC ALGORITHMS

These are search algorithms based on the process of biological evolution. In genetic algorithms, the mechanics of natural selection and genetics are emulated artificially. The search for a global optimum to an optimization problem is conducted by moving from an old population of individuals to a new population using genetics-like operators. Each individual represents a candidate to the optimization solution[19]. An individual is modeled as a fixed length string of symbols, usually taken from the binary alphabet i.e. a series of 1s and 0s. Then an evaluation function, called fitness function, assigns a fitness value to each individual within the population. The fitness value is measure for the quality of a given individual. The basic optimization procedure involves nothing more than processing highly fit individuals in order to produce better individuals as the search progresses. A typical genetic algorithm cycle involves four major processes of fitness evaluation, selection, recombination and creation of a new population [11].

2.3.1 BIOLOGICAL INSPIRATION – GENETICS

A chromosome is a long, complicated thread of DNA (deoxyribonucleic acid). Hereditary factors that determine particular traits of an individual are strung along the length of these chromosomes, like beads on a necklace. Each trait is coded by some combination of DNA. There are four bases; A (Adenine), C (Cytosine), T (Thymine) and G (Guanine). Meaningful combinations of the bases produce specific instructions to the cell. Changes occur during reproduction. The chromosomes from the parents exchange randomly by a process called crossover. Therefore, the offspring exhibit some traits of the father and some traits of the mother. A rarer process called mutation also changes some traits [14]. Living beings evolve through natural selection; only those which are strong enough to survive till the reproductive age and that win the struggle to mate can propagate their genetic heritage. In other words those which have a high fitness can proliferate and their offspring have a high probability of inheriting good characters after the partial mixing (crossover) of the sexed reproduction.
Table 2.1: Comparison between natural evolution and genetic algorithm

<table>
<thead>
<tr>
<th>Natural Evolution</th>
<th>GA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chromosome</td>
<td>String/solution</td>
</tr>
<tr>
<td>Genes(bits)</td>
<td>Part of the solution</td>
</tr>
<tr>
<td>Locus</td>
<td>Position of gene</td>
</tr>
<tr>
<td>Alleles</td>
<td>Value of gene</td>
</tr>
<tr>
<td>Genotype</td>
<td>Structure or coded string/solution</td>
</tr>
<tr>
<td>Phenotype</td>
<td>Parameter set, a decoded structure/solution</td>
</tr>
</tbody>
</table>

2.3.2 GENETIC ALGORITHM PROCESS

GA is a global search technique based on the mechanics of natural selection and genetics. GA searches from population/generation. It deals with coded parameters rather than the real parameters themselves. Hence computation is basically made easy, GA process consists of the following issues:

1. The parameters should be represented
2. The fitness function should also be represented
3. Creation of the initial population of possible solutions
4. Selection of appropriate genetic operators
5. Finally the design of an interface between the problem and Genetic Algorithm

The mechanics of GA are extremely simple only involving copying strings and swapping partial strings. A simple classic GA that produces satisfactory results in many applications requires the following:

- Population initialization
- Solution coding
- Fitness function
- Genetic operators
- Parameter setting
2.3.2.1 POPULATION INITIALIZATION

These are randomly generated with the population size dependent on nature of the problem but allowing entire range of possible solutions. There are two methods of choosing the initial population. One uses randomly generated solutions created by a random number generator and is preferred for problems where no prior knowledge exists. The second method is used where prior knowledge of the problem exists and therefore requirements are set that solutions have to meet to be part of the initial solution. This has the advantage of faster convergence.

2.3.2.2 SOLUTION CODING

The main parameters to be optimized are usually represented in a string form since genetic operators are suitable for this type of representation. Different representation schemes might cause different performances in terms of accuracy and computation time. There are two common methods used for representation of optimization problems i.e. binary representation and real number/integer representation. When a binary representation scheme is employed, an important issue is to decide the number of bits used to encode the parameters to be optimized. Each parameter should be encoded with the optimal number of bits covering all possible solutions in the solution space. When too few or too many bits are used the performance can be adversely affected. GA works on the encoding of a problem, not on the problem itself. This access will allow more freedom and resolution for modifying the parameter features to arrive at the optimal solution [3, 12].

2.3.2.3 FITNESS EVALUATION

This is as an interface between the GA and the optimization problem. The GA assesses solutions for their quality according to the information produced by this unit and not by using direct information about their structure. The quality of a proposed solution is usually calculated depending on how well the solution performs the desired functions and satisfies the given constraints since the GA is a search technique and must be limited to exploring a reasonable region of variable space. Generally fitness is applied to maximization, however since most optimization problem involve cost then they become minimization problems. In this case therefore, the fittest individuals will have the lowest value of the associated objective function. The fitness function is normally used to transform the objective function value into a measure of relative fitness [3, 12].
2.3.2.4 GENETIC OPERATORS

There are three main genetic operators i.e. Selection, Crossover and Mutation. However others such as inversion and elitism are sometimes applied. The main function of these operators is to maintain genetic diversity and combine existing solutions into new ones.

The operators are discussed below:

2.3.2.4.1 Selection

This refers to the choosing of parent chromosomes from a population to be used to form off-springs. After random generation of the initial population, selection is done before reproduction to ensure more fit individuals are used to generate off-springs which will hopefully be fitter. For each new generation, selection is done in the previous population to ensure perpetual improvement in fitness as the algorithm advances. As GA imitates the natural selection’s principle of survival for the fittest, and the fitness of each individual has been evaluated, the selection is done in a way that the ones with higher fitness values have a greater chance of being selected. The degree of bias to selection of fitter individuals is known as selection pressure. There greater it is, the more the fitter individuals are favored in selection thus improving the fitness of successive generation. The basic Selection methods include random selection, the roulette wheel selection, tournament selection, and rank selection etc [15].

Random selection

In this method, the parents are randomly selected from the population of possible solutions.

Roulette wheel selection

This is a selection whereby, the individuals in a population are marked on a roulette wheel with each occupying a slice whose size is proportionate to its fitness value. The wheel is then spin for as many times as the number of individual and after each spin the selected individual on the wheel is pooled for generation of the next population.

Tournament selection

In this method, the individuals compete and the fittest is selected and pooled for reproduction, the process is repeated till enough parent chromosomes have been selected.
Rank selection

Here the individuals are ranked in a way that each is assign a rank matching its fitness i.e. the fittest chromosome is ranked number 1 and the weakest is ranked last. Then selection is done like in tournament selection.

2.3.2.4.2 Crossover

This basically refers to the process of exchanging information between two parents to generate new off-springs. The main objective of doing this is to try and create off-springs which are fitter than their parents. It basically contains the genetic information that already exists in the parent chromosomes [15]. In this project, it involves exchange of bits since binary encoding is used and each bit in a chromosome/string contains information about the solution represented by that chromosome. The crossover methods include:

❖ One point crossover

This is a crossover operator that randomly selects a crossover point within a given chromosome then interchanges the two parent’s chromosomes at this point to produce two off springs.

❖ Two point crossover

This is a crossover operator that randomly selects two crossover points within a chromosome then interchanges the two parent chromosomes between these points to produce two new off springs

❖ Uniform crossover

This uses a fixed mixing ratio between two parents. Unlike one- and two-point crossover, the uniform crossover enables the parent chromosomes to contribute the gene level rather than the segment level. If the mixing ratio is 0.5, approximately half of the genes in the offspring will come from parent 1 and the other half will come from parent 2.

❖ Three parent crossover

This involves three parents which are randomly selected. Then comparison is done between two parent chromosomes and for a similar bit, that bit is copied to the offspring else the corresponding bit from the third chromosome is copied.
**Heuristic crossover**

It produces a linear extrapolation of the two individuals as given by the equation below where the variables are defined as those for arithmetic crossover [3].

\[
\text{Offspring} = \beta (P_{mn} - P_{dn}) - P_{mn}
\]

Where ‘\(\beta\)’ is a random weighting in the interval and

\(P_{mn}\) and \(P_{dn}\) are the \(n^{th}\) variables in the mother and father chromosomes respectively [12].

**Arithmetic crossover**

This is a crossover operator that linearly combines two parent chromosome vectors to produce two new offspring variables according to the following equations:

- \(\text{Offspring}_1 = \beta P_{mn} + (1 - \beta) P_{dn}\)
- \(\text{Offspring}_2 = (1 - \beta) P_{mn} + \beta P_{dn}\)

The variables are also defined as those of heuristic crossover

### 2.3.2.4.3 Mutation

This process is performed on the off-springs after crossover. This is because crossover does not introduce new genetic material to the new population. It is for this reason that mutation is important. It achieves this by random alteration of the genes/bits in the off-springs. Mutation is a way of minimizing the problem of local optima convergence and also ensures no loss of genetic information. Mutation probability defines the rate at which or how often mutation is done. Frequent mutation in GA makes it to become a random search hence it should have a low probability. [15] the various types of mutation include;

**Bit flipping mutation**

This involves using mutation mask chromosomes and inverting the selected bits(changing 1s and 0s and vice versa)

**Interchanging mutation**

This involves exchanging the bits of two randomly selected positions in the offspring.
_reverse mutation_

This mutation is performed by choosing a random point and then reversing the bits after that point.

2.3.2.5 CONTROL PARAMETERS
The important control parameters of GA include the population size (number of individuals in the population), number of iterations, crossover rate and mutation rate. The algorithm should run iteratively until the convergence criterion is achieved.
CHAPTER 3
SOLUTION OF HYDROTHERMAL ECONOMIC DISPATCH USING GA

3.1 PROBLEM FORMULATION
In the Hydrothermal system period is a key factor for the analysis. For a certain period of Time T depending on, the storage of reservoir at the beginning and at the end of the period is specified water inflow to the reservoir is also defined. The problem is to determine the water discharge rate \( q(t) \) so as to minimize the cost of thermal generation.

3.1.1 CONSTRAINTS
The main constraints that are taken into consideration for the hydro part of the hydrothermal system are:

- \( X^o \) – initial water storage
- \( X^N \) – final water storage
- \( J \) – Inflow
- \( P_D \) - power demand
- \( q \) - Control variable (discharge)
- \( T \) – Period

The main objective is to minimize the overall cost which is given by the following equation:

\[
\text{Minimizing cost } C_T = \int_0^T C'(P_{GT}(t)) dt \quad \text{[3.1.1a]}
\]

(i) Meeting the load demand

In order to meet the load demand the load demand equation should balance as follows:

\[
P_H(t) + P_T(t) - P_L(t) - P_D(t) = 0; \quad te = [0, t] \quad \text{[3.1.1b]}
\]

This is known as the power balance equation.
(ii) Water availability

Hydro-generators generate power from water that is used to turn the turbines. Hence water availability can be expressed as follows:

\[ X'(T) - X'(0) - \int_0^T J(t) \, dt + \int_0^T q(t) \, dt = 0 \quad \ldots \,
\]

where \( J(t) \) is the water inflow (rate), \( X'(t) \) water storage, and \( X(0), X(T) \) are specified water storages at the beginning and at the end of the optimization interval.

(iii) Hydro Generation

The hydro generation \( PH \) is a function of hydro discharge and water storage (or head), i.e.

\[ PH(t) = f(X'(t), q(t)) \quad \ldots \]

Through discretization the optimization intervals divided into \( M \) intervals of \( \Delta T \) over each interval the variables remain fixed

\[ \min_q q^m (m = 1, 2, \ldots, M) \Delta T \sum_{m=1}^M C'(P_{GT}^m) = \min_q q^m (m = 1, 2, \ldots, M) \sum_{m=1}^M C(P_{GT}^m) \quad \ldots \]

3.1.2 UNDER THE FOLLOWING CONSTRAINTS

Under the above mentioned constraints in a hydroelectric generator. The following can be obtained

(i) Power balance equation

The power balance for a hydrothermal system considering all the network losses is given as follows:

\[ P_T^m + P_H^m - P_L^m - P_D^m = 0 \quad \ldots \]

Where

- \( P_T \) = Thermal generation in the \( m^{th} \) interval
- \( P_H \) = Hydro generation in the \( m^{th} \) interval
- \( P_L \) = Transmission loss in the \( m^{th} \) interval
- \( P_D \) = Load demand in the \( m^{th} \) interval
The real power losses within the generators can be expressed as follows:

\[ P_L = \sum_{i=1}^{N} \sum_{j=1}^{N} P_{ij} B_{ij} + \sum_{i=1}^{N} B_{ii} P_i + B_{00} \cdots \cdots \cdots \cdots \cdots [3.1.2b] \]

Where \( B_{ij} \) represents coefficients of losses.

(ii) Water continuity equation

\[ X'(m) - X'(m-1) - J^m \Delta T + q^m \Delta T = 0 \cdots \cdots \cdots \cdots \cdots \cdots [3.1.2c] \]

Where:

\( X^m \) = water storage at the end of the \( m^{th} \) interval

\( J^m \) = water inflow (rate) in the \( m^{th} \) interval

\( q^m \) = water discharge (rate) in the \( m^{th} \) interval

Hence the above equation (3.1.2c) becomes:

\[ X'(m) - X'(m-1) - J^m + q^m = 0; m = 1,2,\ldots , M \cdots \cdots \cdots \cdots \cdots \cdots \cdots [3.1.2d] \]

(iii) Hydro Generation

The Hydro generation at any subinterval can be expressed as:

\[ P_{GH}^m = h_0 \left( 1 + 0.5e(X'(m) - X'(m-1)) \right)(q^m - \rho) \cdots \cdots \cdots \cdots [3.1.2e] \]

Where: \( h_0 \) = basic water head (head corresponding to dead storage)

\( (q^m - \rho) \) = effective discharge in \( m^3/s \).

\( \rho \) = non effective water discharge.

\( e \) = water head correction factor.
3.2 GA APPLIED TO HYDROTHERMAL ECONOMIC DISPATCH

A simple Genetic Algorithm is an iterative procedure, which maintains a constant size population $P$ of candidate solutions. During each iteration step (generation) three genetic operators (reproduction, crossover, and mutation) are performed to generate new populations (offspring), and the chromosomes of the new populations are evaluated via the value of the fitness which is related to cost function. Based on these genetic operators and evaluations, better new populations of candidate solution are formed.

3.2.1 GA PSEUDO CODE

In GA, it is not required to put the generating units within the constraints. The generated value automatically remains within the constraints. The sequential steps of solving the given problem using GA are as follows:

**Step 1:** Conducting a study on the IEEE 14-bus network, since it is used

**Step 2:** Read data i.e. cost coefficients, Genetic Algorithm parameters, power demand, generation unit minimum power, maximum power and losses

**Step 3:** Generate the initial population of chromosomes randomly in real code.

**Step 4:** Calculate the cost for the various values of the chromosomes

**Step 5:** Calculate the fitness of each chromosome according to the fitness function and sort. Those with the lowest cost function are selected for the next generation. The average fitness of the population is also calculated.

**Step 6:** Selection is done based on reproduction followed by crossover with embedded mutation to create the new population for the next generation.

**Step 7:** The fitness of the new offspring is calculated and they are sorted in the ascending order. The lowest value of the objective function means better fitness. Therefore the fittest are selected for the next generation.

**Step 9:** Stop criteria. If the number of iterations reaches maximum, go to step 10. Otherwise go back to step 4.
3.2.2 STOPPING CONDITIONS FOR THE ALGORITHM
The genetic algorithm uses the following conditions to determine when to stop [15]:

**Generations:** The algorithm stops when the number of generations reaches the value of generations defined.

**Population Convergence:** GA will stop when much of the population converges to a single solution.

**Deviation:** The algorithm stops if the mean deviation in performance of individuals in the population falls below a specified threshold (when genetic diversity has become small).

**Time limit:** The algorithm stops after running for an amount of time in seconds equal to the time limit.

**Fitness limit:** The algorithm stops when the value of the fitness functions for the best point in the current population is less than or equal to fitness limit.

**Stall generations:** The algorithm stops if there is no improvement in the objective function for a sequence of consecutive generations of length Stall generations.

**Stall time limit:** The algorithm stops if there is no improvement in the objective function during an interval of time in seconds equal to stall time limit.
3.2.3 FLOWCHART

Fig 3.1: Flowchart for GA based on economic dispatch
4.1 TEST NETWORK

The IEEE-14 bus system is used as the test network in this project due to availability of data on it and its simplicity in analysis as compared to an actual network such as the Kenyan network. This system has 14 buses, 20 lines, 2 generators and 3 synchronous condensers.

Fig 4.1: One line diagram of IEEE 14 -bus system [4]
Table 4.1: IEEE 5-Machines 14-Bus System Generator’s Cost Curves coefficients

<table>
<thead>
<tr>
<th>Bus</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>e</th>
<th>f</th>
<th>P_{min}</th>
<th>P_{max}</th>
<th>Q_{min}</th>
<th>Q_{max}</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.0</td>
<td>2.00</td>
<td>0.00375</td>
<td>15.0</td>
<td>0.06283</td>
<td>50</td>
<td>250</td>
<td>-40</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>0.0</td>
<td>1.75</td>
<td>0.0175</td>
<td>10.0</td>
<td>0.08976</td>
<td>20</td>
<td>160</td>
<td>-40</td>
<td>50</td>
</tr>
<tr>
<td>3</td>
<td>0.0</td>
<td>1.00</td>
<td>0.0625</td>
<td>10.0</td>
<td>0.14784</td>
<td>15</td>
<td>100</td>
<td>0</td>
<td>40</td>
</tr>
<tr>
<td>6</td>
<td>0.0</td>
<td>3.25</td>
<td>0.00834</td>
<td>5.0</td>
<td>0.20944</td>
<td>10</td>
<td>70</td>
<td>-6</td>
<td>24</td>
</tr>
<tr>
<td>8</td>
<td>0.0</td>
<td>3.00</td>
<td>0.025</td>
<td>5.0</td>
<td>0.25133</td>
<td>10</td>
<td>60</td>
<td>-6</td>
<td>24</td>
</tr>
</tbody>
</table>

Table 4.2: Transmission Loss Coefficients IEEE 14 bus Test Systems

<table>
<thead>
<tr>
<th>Test System</th>
<th>B-Coefficients</th>
</tr>
</thead>
<tbody>
<tr>
<td>IEEE 14-Bus 5-Machines System</td>
<td>$[B] = \begin{bmatrix} 0.0212 &amp; 0.0085 &amp; 0.0069 &amp; 0.0002 &amp; 0.0002 \ 0.0085 &amp; 0.0188 &amp; -0.0062 &amp; 0.0051 &amp; 0.0002 \ 0.0069 &amp; -0.0062 &amp; 0.4817 &amp; -0.1333 &amp; -0.1604 \ 0.0002 &amp; 0.0051 &amp; -0.1333 &amp; 0.2180 &amp; -0.0251 \ 0.0002 &amp; 0.0002 &amp; -0.1604 &amp; -0.0251 &amp; 0.1406 \end{bmatrix}$</td>
</tr>
</tbody>
</table>

4.3 RESULTS

The hydrothermal system consists of two hydroelectric generators and three thermal generators. On the other hand the thermal system consists of all thermal generators. The optimal generations obtained for the two systems after optimization are represented in tables 4.4, 4.5, 4.6 and 4.7. The two cases of power demand used for analysis are 400MW and 550MW.

Table 4.3: GA Parameters Used

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>500</td>
</tr>
<tr>
<td>Number of generations( iterations)</td>
<td>500</td>
</tr>
<tr>
<td>Number of units</td>
<td>5</td>
</tr>
<tr>
<td>Time limit</td>
<td>100</td>
</tr>
<tr>
<td>Stall time limit</td>
<td>200</td>
</tr>
</tbody>
</table>
4.3.1 CASE 1
In this case both systems were analyzed with a power load demand of 400MW; the analytical results obtained for Hydrothermal and Thermal system were represented in table 4.4 and 4.5 respectively.

**Table 4.4: Optimal Generations for Hydrothermal ED using GA**

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>P(Minimum)</th>
<th>P(Generated)</th>
<th>P(Maximum)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1 (Hydro)</td>
<td>12</td>
<td>112.5056</td>
<td>126</td>
</tr>
<tr>
<td>PG2 (Hydro)</td>
<td>20</td>
<td>180</td>
<td>180</td>
</tr>
<tr>
<td>PG3 (Thermal)</td>
<td>50</td>
<td>50.0794</td>
<td>200</td>
</tr>
<tr>
<td>PG4 (Thermal)</td>
<td>40</td>
<td>43.5968</td>
<td>170</td>
</tr>
<tr>
<td>PG5 (Thermal)</td>
<td>30</td>
<td>32.077</td>
<td>215</td>
</tr>
<tr>
<td>Total Generation(MW)</td>
<td><strong>152</strong></td>
<td><strong>418.2595</strong></td>
<td><strong>891</strong></td>
</tr>
<tr>
<td>Total real power losses(MW)</td>
<td></td>
<td><strong>18.2595</strong></td>
<td></td>
</tr>
<tr>
<td>Total generation costs($)</td>
<td></td>
<td><strong>516.6631</strong></td>
<td></td>
</tr>
</tbody>
</table>

**Table 4.5: Optimal Generations for Thermal ED using GA**

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>P(Minimum)</th>
<th>P(Generated)</th>
<th>P(Maximum)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1</td>
<td>50</td>
<td>187.6998</td>
<td>250</td>
</tr>
<tr>
<td>PG2</td>
<td>20</td>
<td>160</td>
<td>160</td>
</tr>
<tr>
<td>PG3</td>
<td>15</td>
<td>63.6278</td>
<td>100</td>
</tr>
<tr>
<td>PG4</td>
<td>10</td>
<td>11.6127</td>
<td>70</td>
</tr>
<tr>
<td>PG5</td>
<td>10</td>
<td>10.773</td>
<td>60</td>
</tr>
<tr>
<td>Total Generation(MW)</td>
<td><strong>105</strong></td>
<td><strong>433.7133</strong></td>
<td><strong>640</strong></td>
</tr>
<tr>
<td>Total real power losses(MW)</td>
<td></td>
<td><strong>33.7133</strong></td>
<td></td>
</tr>
<tr>
<td>Total generation costs($)</td>
<td></td>
<td><strong>789.2799</strong></td>
<td></td>
</tr>
</tbody>
</table>
4.3.2 CASE 2
In this case both systems were analyzed with a power load demand of 550MW, the analytical results obtained for Hydrothermal and Thermal system were represented in table 4.6 and 4.7 respectively.

Table 4.6: Optimal Generations for Hydrothermal ED using GA

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>P(Minimum)</th>
<th>P(Generated)</th>
<th>P(Maximum)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1 (Hydro)</td>
<td>12</td>
<td>125.6903</td>
<td>126</td>
</tr>
<tr>
<td>PG2 (Hydro)</td>
<td>20</td>
<td>180</td>
<td>180</td>
</tr>
<tr>
<td>PG3 (Thermal)</td>
<td>50</td>
<td>54.7014</td>
<td>200</td>
</tr>
<tr>
<td>PG4 (Thermal)</td>
<td>40</td>
<td>82.8273</td>
<td>170</td>
</tr>
<tr>
<td>PG5 (Thermal)</td>
<td>30</td>
<td>133.4814</td>
<td>215</td>
</tr>
<tr>
<td>Total Generation(MW)</td>
<td>152</td>
<td>576.7004</td>
<td>891</td>
</tr>
<tr>
<td>Total real power losses(MW)</td>
<td></td>
<td>26.7004</td>
<td></td>
</tr>
<tr>
<td>Total generation costs($)</td>
<td></td>
<td>805.6313</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.7: Optimal Generations for Thermal ED using GA,

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>P(Minimum)</th>
<th>P(Generated)</th>
<th>P(Maximum)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1</td>
<td>50</td>
<td>249.9418</td>
<td>250</td>
</tr>
<tr>
<td>PG2</td>
<td>20</td>
<td>160</td>
<td>160</td>
</tr>
<tr>
<td>PG3</td>
<td>15</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>PG4</td>
<td>10</td>
<td>33.5415</td>
<td>70</td>
</tr>
<tr>
<td>PG5</td>
<td>10</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>Total Generation(MW)</td>
<td>105</td>
<td>603.4833</td>
<td>640</td>
</tr>
<tr>
<td>Total real power losses(MW)</td>
<td></td>
<td>53.4833</td>
<td></td>
</tr>
<tr>
<td>Total generation costs($)</td>
<td></td>
<td>1169.1</td>
<td></td>
</tr>
</tbody>
</table>
4.3.3 Plot of the best function

Fig 4.2: Convergence Characteristics for five systems

4.3.4 Score Characteristics

Fig 4.3: Score Characteristics for individuals
4.3.5 Plot of Best individual characteristics

Fig 4.4: Best individual characteristics for the system
4.4 ANALYSIS AND COMPARISON

The fuel costs and real power losses obtained for 400MW and 550 MW are compared. It has been observed that for all the power demand the hydrothermal system gives a lower fuel cost with minimal power losses compared to the thermal system. This proves that hydrothermal system is reliable method for power generation.

**Table 4.8: Comparison between Hydrothermal and Thermal system**

Power Demand = 400MW

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>Power generated(MW) (Hydrothermal)</th>
<th>Power Generated(MW) (Thermal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1</td>
<td>(Hydro) 112.5056</td>
<td>(Thermal) 187.6998</td>
</tr>
<tr>
<td>PG2</td>
<td>(Hydro) 180</td>
<td>(Thermal) 160</td>
</tr>
<tr>
<td>PG3</td>
<td>(Thermal) 50.0794</td>
<td>(Thermal) 63.6278</td>
</tr>
<tr>
<td>PG4</td>
<td>(Thermal) 43.5968</td>
<td>(Thermal) 11.6127</td>
</tr>
<tr>
<td>PG5</td>
<td>(Thermal) 32.077</td>
<td>(Thermal) 10.773</td>
</tr>
</tbody>
</table>

Total Generation(MW) 418.2595 433.7133
Total real power losses(MW) 18.2595 33.7133
Total generation costs($) 516.6631 789.2799

**Table 4.9: Comparison between Hydrothermal and Thermal system**

Power Demand = 550MW

<table>
<thead>
<tr>
<th>Generator No.</th>
<th>Power generated(MW) (Hydrothermal)</th>
<th>Power Generated(MW) (Thermal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>PG1</td>
<td>(Hydro) 125.6903</td>
<td>(Thermal) 249.9418</td>
</tr>
<tr>
<td>PG2</td>
<td>(Hydro) 180</td>
<td>(Thermal) 160</td>
</tr>
<tr>
<td>PG3</td>
<td>(Thermal) 54.7014</td>
<td>(Thermal) 100</td>
</tr>
<tr>
<td>PG4</td>
<td>(Thermal) 82.8273</td>
<td>(Thermal) 33.5415</td>
</tr>
<tr>
<td>PG5</td>
<td>(Thermal) 133.4814</td>
<td>(Thermal) 60</td>
</tr>
</tbody>
</table>

Total Generation(MW) 576.7004 603.4833
Total real power losses(MW) 26.7004 53.4833
Total generation costs($) 805.6313 1169.1
4.4.1 Plot of Fuel Cost against demand for the two systems

![Fuel Cost against demand](image)

Fig 4.5: Variation of Fuel Cost with Power demand

4.4.2 Plot of Real power loss against demand for the two systems

![Real power loss against demand](image)

Fig 4.6: Variation of Real power losses with Power demand
**Fig 4.5** shows the variation of optimal cost with power demand for both a hydrothermal system and a thermal system. From the figure, it is observed that the cost of generation increases with increase in power demand. Also the cost of generation with all thermal generators is higher than the cost of generation for the hydrothermal plant. This is so because in a hydrothermal plant hydroelectric generators are used combined with the thermal generators. The hydroelectric generators use water to generate power, since water is available for free this lowers the fuel cost. While the thermal generators use coal which is expensive hence a high cost of generation. As the power demand increases the cost increases.

**Fig 4.6** shows the variation of real power losses with power demand for both the Hydrothermal and Thermal. The real power losses also increase with increase in power demand. The real power losses for the Hydrothermal case are lower than those for the Thermal case.
CHAPTER 5
CONCLUSIONS AND RECOMMENDATIONS

5.1 CONCLUSION
Genetic Algorithm approach to solving hydrothermal economic dispatch problem has been successfully implemented and tested. From the results obtained it is clear that a hydrothermal system yields better results than a thermal system. In a hydrothermal system both the fuel cost and the real power losses are reduced. This makes hydrothermal system to be the preferred system for power generation.

The reliability of the system for power generation is good. This is attributed to the use of hydroelectric generators which depend on water to turn the turbines. The cost of generation reduces since water is naturally available from large water bodies for free.

5.2 RECOMMENDATIONS FOR FURTHER WORK

- The presentation in this report has concentrated on optimum economical operation of a power system in the sense of minimization of the generation cost. This has been achieved using a Genetic algorithm approach. Another important issue that can be considered here is power system optimization in the sense of reducing active Real Power losses in the system.

- Besides reduction of power losses, another way to approach the economic dispatch problem is to develop a multi-objective Genetic Algorithm that minimizes generation cost while at the same time reducing pollution and atmospheric emissions of thermal power plants. Power plants produce gases (e.g. sulphur oxides $\text{SO}_x$ and Nitrogen Oxides) which are a potential threat to environmental safety.
REFERENCES


[7] Soliman Abdel-Hady Soliman and Abdel-Aal Hassan Mantawy, Modern Optimization Techniques with Applications in Electric Power Systems


[19] R. Behera, B.P.Panigrahi, B.B. Pati, ELD using modified GAs, Department of Electrical Engineering, I.G.I.T. Sarang, Orissa, India

[20] Hamid Bouzeboudja, Abdelkader Chaker, Ahmed Allali and Bakhta Naama, ED solution using a real-coded GA.

APPENDIX

APPENDIX A

Simple Genetic Algorithm

{
    Initialize population;
    Evaluate population;
    While termination criteria not satisfied
    {
        Select parents for reproduction;
        Perform recombination and mutation;
        Evaluate population;
    }
}
APPENDIX B

% ECONOMIC DISPATCH ALGORITHM
% The data matrix should have 5 columns of fuel cost coefficients and plant limits.
% 1.a ($/MW^2) 2. b $/MW 3. c ($) 4.lower limit(MW) 5.upper limit(MW)
% n denotes the no of generation units
% F denotes the fuel cost in dollars
% PG is the total power generated
% (PG=power demand+ power loss)

function [ F PG PL]=ed(x)
global data B Pd
x=abs(x);
N=length(data(:,1));
for i=1:n-1
    if x(i)>1;
        x(i)=1;
    else
    end
    P(i)=data(i+1,4)+x(i)*(data(i+1,5)-data(i+1,4));
end
B11=B(1,1);
B1n=B(1,2:n);
Bnn=B(2:n,2:n);
A=B11;
BB1=2*B1n*P';
B1=BB1-1;
C1=P*Bnn*P';
C=Pd-sum(P)+C1;
x1=roots([A B1 C]);
% x=.5*(-B1-sqrt(B1^2-4*A*C))/A
x=abs(min(x1));
if x>data(1,5)
    x=data(1,5);
else
end
if x<data(1,4)
x=data(1,4);
else
end
% PG is the Total Power generated
PG=[x P];
for i=1:n
    % Fuel cost equation for a generating plant
    F1(i)=data(i,1)* PG(i)^2+data(i,2)*PG(i)+data(i,3);
end
% PL represents the real power loss
PL=PG*B*PG';
lam=abs(sum(PG)-Pd-PG*B*PG');
F=sum(F1)+1000*lam;

% code representing the hydrothermal system
% case study of 14 bus bars

% HYDROTHERMAL GENETIC CODE

clear;
clc;
tic;
global data B Pd
% Economic dispatch with Bmn coefficients by Genetic Aligorithm
% The data matrix should have 5 columns of fuel cost coefficients and plant limits.
% 1.a ($/MW^2) 2. b $/MW 3. c ($) 4.lower lomit(MW) 5.Upper limit(MW)
% no of rows denote the no of generators(n)
%generator coefficients
    data=[0.00001829 0.187 1.423 12 126 %Hyrdoelectric generator
          0.0000203 0.198 1.714 20 180 %Hydroelectric Generator
          0.01 0.1 100 50 200 %Thermal Generator
          0.02 0.1 120 40 170 %Thermal Generator
          0.01 0.1 150 30 215]; %thermal Generator
% Loss coefficients it should be squarematrix of size nXn
% n denotes the no of plants
% losses in a 14 bus
B=[0.0005 0 0 0 0
   0 0.0003 0 0 0
   0 0 0.0004 0 0
   0 0 0 0.0004 0
   0 0 0 0 0.0004]
% Power Demand (MW)
Pd = 550;

% Using Genetic Algorithm toolbox of MATLAB
% setting the genetic algorithm parameters.
% Maximum number of Generations (iterations)
options = gaoptimset;
options = gaoptimset('PopulationSize', 500, 'Generations', 500, 'TimeLimit', 100, 'StallTimeLimit', 200,
'PlotFcns',{@gaplotbestf,@gaplotbestindiv,@gaplotdistance,@gaplotscorediversity });
[x ff]=ga(@ed,5,options);

% PG is the power generated from the various generators
% F is the total fuel cost of the plant it is expresses in dollars per MW
% PL represents the real power loss between the generators
[ F PG PL]=ed(x)

% Ptotal represents the total generated + the real power losses
Ptotal=sum(PG)
tic;

% *% THERMAL GA CODE*
clear;
clc;
tic;
global data B Pd

% Economic dispatch with Bmn coefficients by Genetic Algorithm
% The data matrix should have 5 columns of fuel cost coefficients and plant limits.
% 1. a ($/MW^2) 2. b $/MW 3. c ($) 4. lower limit (MW) 5. Upper limit (MW)
% no of rows denote the no of plants (n)
data=[0.0 2.0 0.00375 50 250] % Thermal Generator
0.0 1.75 0.0175 20 160 % Thermal Generator
% Thermal Generator
% Thermal Generator
% Thermal Generator
% Loss coefficients it should be square matrix of size nXn
% n denotes the no of plants
% losses in a 30 bus
B=0.01*[
0.0212 0.0085 0.0069 0.0002 0.0002
0.0085 0.0188 -0.0062 0.0051 0.0002
0.0069 -0.0062 0.4817 -0.1333 -0.1604
0.0002 0.0051 -0.1333 0.2180 -0.0251
0.0002 0.0002 -0.1604 -0.0251 0.1406
];
% Power Demand (MW)
Pd=550;
% Using Genetic Algorithm toolbox of MATLAB
% setting the genetic algorithm parameters.
% Maximum number of Generations (iterations)
options = gaoptimset;
[@gaplotbestf, @gaplotbestindiv, @gaplotdistance, @gaplotscorediversity);
[x ff]=ga(@ed, 5, options); % PG is the power generated from the various generators
% F is the total fuel cost of the plant it is expresses in dollars per MW
% PL represents the real power loss between the generators
[F PG PL]=ed(x)
Ptotal=sum(PG)
tic;
% '@gaplotbestf' plots a graph of the best fitness using genetic algorithm
% '@gaplotbestindiv' plots the best individual after fitness has been tested
% F is the total fuel cost
% P1 is the allocation of power generated by each plant.
% PL is the total transmission losss