MULTIOBJECTIVE OPTIMAL POWER DISPATCH USING WEIGHTING METHOD

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CERTIFICATE

This is to certify that the project work that is being presented in this dissertation entitled **"Multiobjective Optimal Power Dispatch (MOPD) Using Weighting Method"** has been carried out by **Mamta** (University Roll No. 8455), a student of Delhi College of Engineering, University of Delhi. This work was completed and carried out under our supervision and forms a part of the Master of Engineering (control & instrumentation) course. She has completed her work with utmost sincerity.

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ABSTRACT

Economic load dispatch problem allocates loads to plants at minimum cost while meeting the constraints. It is done by an optimization problem which minimizes the total fuel cost of all committed plants while meeting the demand and losses.

There are various objectives of power system- cost of generation, transmission losses and environment pollution etc. In this work the cost of generation and transmission losses have been considered as objectives for optimization.

The multiobjective optimal power dispatch (MOPD) problem is formulated using weighting method and a number of noninferior solutions are generated in 2D space by varying weights for IEEE 5, 14 and 30 bus systems.

Ideal Point (IP) is one where all the objectives are minimum and it is impossible to achieve this point because of conflicting nature of the objectives therefore an attempt is made to minimize the Euclidean distance between the Ideal Point (IP) and set of noninferior solutions. This gives the **Target Points (TP)** or the best compromise solution for all these system in 2D space.

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INTRODUCTION

1.1 Overview

The optimal power system operation is achieved when are various objectives of power system -cost of generation, system transmission losses and environmental pollution etc. are simultaneously attained. But these objectives are conflicting in nature and cannot be handled by conventional single objective optimization techniques. Single objective optimization techniques give optimal solution in respect of a single aspect, i.e. they give the best value of the objective function under consideration. The values of other objectives at such a solution may be intolerably bad. But there is no other solution to facilitate the decision making process. The way out, therefore, lies in the multiobjective approach [27, 28] to problem solving.

Multiobjective optimization (or programming), [18, 19, 20] also known as multi-criteria or multi-attribute optimization, is the process of simultaneously optimizing two or more conflicting objectives subject to certain constraints. The solution of multiobjective optimization gives us a number of solutions called noninferior solution.

The multiobjective considered for optimal power dispatch are – cost of generation (F_C) and transmission losses (F_L). In economic load dispatch, cost of generation is considered as the objective function is to be minimized while satisfying load demand.

A feasible solution to a multiobjective programming problem is noninferior if there exists no other feasible solution that will yield an improvement in one objective without causing degradation in at least one of other objectives [18, 24]. A given noninferior solution or may not be acceptable to the decision maker. However, it is important to note that, it is one of these noninferior solutions for which decision maker looks for.

The ideal situation where one would like to operate the power systems is one where all the objectives are minimizing. But this is not feasible due to conflicting nature of objectives. Therefore, one can achieve a point which is non-inferior and at the minimum distance from the ideal point. Such a point is known as the **Target Point (TP) or the best compromise solution.**

There are various techniques for generating noninferior solutions- weighting method [23], constraint method and NIES method etc. In this thesis; the MOPD problem has been formulated using weighting method and has been solved by GA tool of MATLAB. This gives us noninferior noninferior solutions in 2D space for IEEE 5, 14, and 30 bus systems. Such analysis, the power system operation point can be determined. The distance of all the feasible operating points (noninferior solutions) from the ideal power system operation point is calculated by minimum distance method and the optimal power system operation is one for which this distance is minimum. This method directly gives the best compromise solution.

1.2 Objective and Methodology

Our objective in this work is to solve multiobjective optimal power dispatch (MOPD) problem by using minimum distance method with the help of GA tool. GA (Genetic Algorithm) is based on the technique of natural selection. Genetic algorithms are often applied as approaches to solve global optimization problems.

1.2.1 Tool (GA tool) in MATLAB

Genetic algorithm software extends the optimization capabilities in MATLAB optimization toolbox. GA tool use these algorithms for problems that are difficult to solve with traditional optimization techniques, including problems that are not well defined or are difficult to model Mathematically.GA is also used when computation of the objective function is discontinuous, highly nonlinear, stochastic, or has unreliable or undefined derivatives.

The Genetic Algorithm Toolbox is closely integrated with MATLAB and the Optimization toolbox. We can use the genetic algorithm and pattern search to find adept Starting points and then use the Optimization Toolbox solvers or MATLAB routines to further refine optimization. Solvers are available for both constrained and unconstrained optimization problems.

GA Toolbox complements other optimization methods, helps to find best fitness value and minimum point of the objective function. GA tool varies on various optional parameters like population, selection, fitness scaling, crossover, mutation, stopping criteria, plot function and output function, display to command window for finding the best fitness value. It's important to understand that the functioning of such an algorithm does not guarantee success. It has been shown that the genetic algorithm finds the best fitness.

1.2.2 Executing constrained and unconstrained minimization

The various problem constrained and unconstrained minimization of functions both single variable and multi variable. The analysis of results and accuracy are checked by varying the various stopping criterion.

1.3 Literature Survey

The literature of the economic dispatch problem and its solution methods are surveyed in [2] and [22]. Recently, a global optimization technique known as genetic algorithm which is a kind of the probabilistic heuristic algorithm has been studied to solve the power system optimization problems. Sheble, *et al.* [10, 12] used GA to solve the economic dispatch problem and presented the results for three units. Bakirtzis *et al* [11] have proposed a simple genetic algorithm solution to the economic dispatch problem. The operation cost obtained from GA was slightly higher than the optimum cost. Chang and Chen [13] have presented a genetic algorithm for solving economic dispatch problem. The proposed method can take into account network losses, ramp rate and valve point zone. A fuzzy logic controlled genetic algorithm has been applied to environmental – economic dispatch by Song *et al.* [14] Song and Chou [15] have proposed a hybrid GA that is combination strategy involving local search algorithms and genetic algorithm.

The analysis of multiobjective programming has evolved over the last years, in the areas of operations research, economies and psychology, applied mathematics and engineering. The theoretical work of Kuhn and Tucker [16] provided the basis for later algorithmic developments of mathematical programming. Gass and Satty [17] provided the first approach to multiobjective programming problems. They generated noninferior solutions in two – objective problems by parametrically varying the coefficients of objective function.

Chen and Chen [29] solved the multiobjective power dispatch (MPD) problem with line flow constraints consisting of minimization of cost of generation and system transmission losses using the fast Newton-Raphson approach.

Abido and Al-Ali [31] presented a Multiobjective Differential Evolution (MODE) based approach to solve the optimal power flow (OPF) problem. OPF problem has been treated as a true multiobjective constrained optimization problem. Different objective functions and different operational constraints have been considered in the problem formulation. A clustering algorithm is applied to manage the size of the Pareto set. Also, an algorithm based on fuzzy set theory is used to extract the best compromise solution. Simulation results on IEEE-30 bus test system show the effectiveness of the proposed approach in solving true multi-objective OPF and also finding well distributed Pareto solutions.

Wadhwa and Jain [23] formulated the multiobjective OPF problem using Weighting method as weighted sum of the cost of generation (F_C) and system transmission (FL). Detailed studies are carried out on three standard systems [1, 3] by considering various values of weights for cost of generation and system transmission losses. The final operating point or Target Point is chosen to be the one for which percentage saving in cost of generation and system transmission losses are same.

Jain and Wadhwa [26] considered three aspects of optimal load flow (OLF) problem- cost of generation, system transmission loss and pollution. The multiobjective optimal power flow is formulated using weighting method as the weighted sum of the objective functions. Numerous multiobjective optimal power flow studies are carried out on 5 bus system with various values of weights attached to three objective functions. The distance of each of the feasible point from the ideal point the point which has coordinates (F_{Cmin}, F_{Lmin}, F_{Emin})) is calculated and the point with the minimum distance from the ideal point is chosen to be the Target Point.

Nangia, Jain and Wadhwa [30] formulated the Multiobjective optimal load flow based on ideal distance minimization in 3D space. Three objectives of Multiobjective optimal load flow (MOLF) problem- cost of generation; system transmission loss and pollution- are considered. The MOLF problem is formulated as a Multiobjective optimization problem using weighting method and a number of noninferior solutions are generated in 3D space. The optimal power system operation is attained by ideal distance minimization Euclidean distance between Ideal Point (IP) and set of noninferior solutions. This method has been applied to three IEEE standard systems.

1.4 Object of dissertation

The scope of the thesis work is summarized as follows:

1. Main objective of project is to solve multiobjective optimal power dispatch (MOPD)- consisting of cost of generation and system transmission loss.
2. Use global search techniques like GA (Genetic Algorithm) to find the optimal solution.
3. MOPD problem has been formulated using weighting method. The noninferior set is generated by varying the weights and solving the problem using GA. The Target Point (TP) is determined using minimum distance method.

CHAPTER-2

Economic Load Dispatch

2.1 Introduction

Electrical energy can not be stored but is generated from natural sources and delivered as the demand raises. A transmission system is used for the delivery of bulk power over considerable distances. The power system consist of three parts, generator, which produces electricity, transmission line, which transmits it to far away places and load, which uses it. This configuration is applicable to all the interconnected networks but the number of elements may vary. The transmission networks are interconnected through tie lines so that utilities may interchange power, share reserve and render assistance to one another at the time of need. Since the sources of energy are so diverse, so the choice of the required sources is made on economic, technical and geographical basis. As there are few facilities to store electrical energy, the net production of a utility must clearly track its total load. For an interconnected system, it is necessary to minimize the expenses. The economic load dispatch (ELD) is used to define the production level of each plant, so that the total cost of generation and transmission is minimum for a prescribed schedule of load or ELD may also be defined as the process of allocating generation levels to the generating units in the mix, so that the system load may be supplied entirely and most economically.

2.2 Load Dispatching

Nowadays operation of a modern power system has become very complex. It is necessary to maintain frequency and voltage within limits, which is done by matching the generation of active and reactive power with the load demand. In addition, for ensuring reliability of power system it is mandatory to put additional generation capacity into the system in the event of outage of generating equipment at some station. Above all cost of electric supply should be ensured at minimum. The total interconnected network is controlled by the load dispatch centre which allocates the MW generation to each grid depending upon the prevailing MW demand in that area. Each load dispatch centre controls load and frequency of its own by matching generation in various generating stations with total required MW demand plus MW losses. Therefore, the task of load control centre is to keep the exchange of power between various zones and system frequency at desired values.

2.3 Economics of Power Generation of Thermal Plant

In all engineering works, the question of cost is of first importance. The electrical power supplier is required to supply power to a large number of consumers to meet their requirements. While designing electrical power generating stations and other systems efforts are made to achieve overall economy so that per unit cost of generation is the lowest possible. This will enable the supplier to supply electrical energy to its consumer at reasonable rates. The cost depends on the number of hours the plant is in operation or upon the number of units of electrical energy generated i.e. the operating cost is approximately proportional to units generated. Total annual cost incurred in the power generation is represented by the expression (2.1).

$$C_i (P_i (t)) = \Sigma(a_i P_i^2 + b_i P_i + C_i) \quad (2.1)$$

Where (i=1,2,.......,Ng)

Ng = number of generators

The factors influencing power generation at minimum cost are operating efficiencies of generators, fuel cost and transmission losses. The most efficient generator in the system does not guaranteed minimum cost as it may be located in an area where fuel cost is high. Also, if the plant is located far from the load centre, transmission losses may be considerably higher and hence, the plant may be overly uneconomical. Hence, the problem is to determine the generation of different plants such that the total operating cost is minimum. The operating cost plays an important role in the economic scheduling.

The cost of fuel used for economic of power generation is specified by the input-output curve of a generating unit. The input to the thermal plant is generally measured in BTU/hr and the output is measured in MW. A simplified input output curve of the thermal unit known as heat rate curve is given in following fig. 2.1(a). The Converting the ordinate of heat rate curve from BTU/hr to Rs/hr. results in the fuel cost curve shown in fig. 2.1(b)

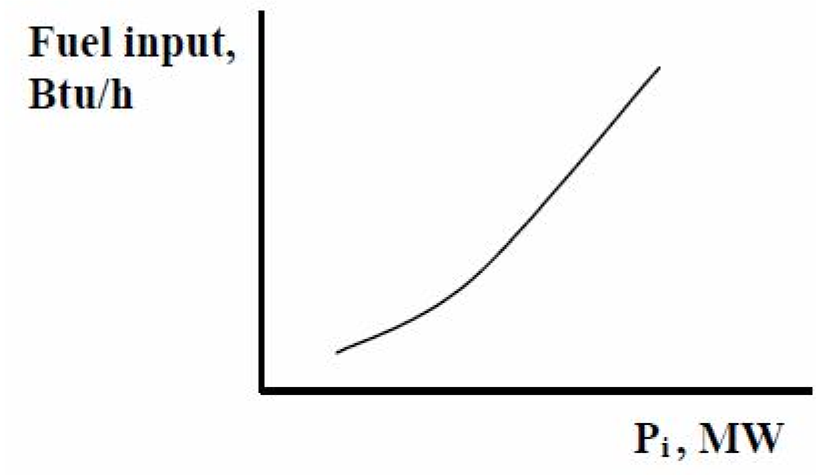


Fig. 2.1(a) Heat-rate curve

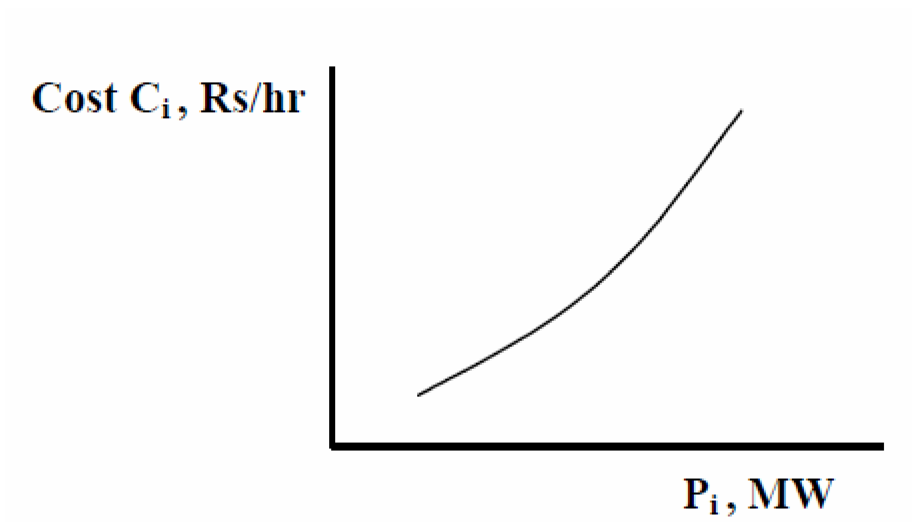


Fig 2.1(b) Fuel-rate curve

In all practical cases, the fuel cost of generator *i* can be represented as a quadratic function of real power generation from equation (2.1).An important characteristic is obtained by plotting the derivative of fuel cost curve vs. real power. This is known as the incremental fuel cost curve shown in fig. 2.1(c).

$$dC_i/dP_i = 2a_i P_i + b_i \qquad (2.2)$$

The incremental fuel cost curve is measure of how costly it will be to produce the next increment of power. The total operating cost includes the fuel cost, and the cost of labor, supplies and maintenance. These costs are assumed to be a fixed percentage of the fuel cost and are generally included in the incremental fuel cost curve.

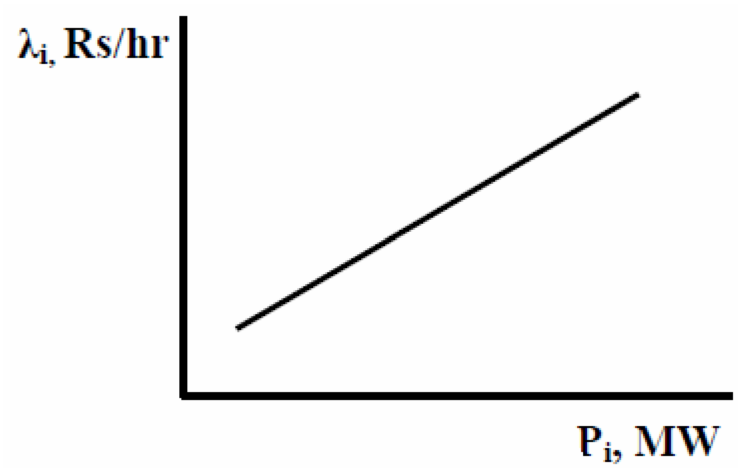


Fig. 2.1(c) Incremental fuel-cost curve

2.4 Transmission Losses

When transmission distances are very small and load density is very high, transmission losses may be neglected and the optimal dispatch of generation is achieved with all plants operating at equal incremental production cost. However, in a large inter connected network where power is transmitted over long distances with low load density areas, transmission losses are major factor and affect the optimum dispatch of generation. One common practice for including the effect of transmission losses is to express the total transmission loss as a quadratic function of the generator power outputs. The simplest quadratic form is

$$P_L = \Sigma\Sigma P_i B_{ij} P_j \qquad (i, j = 1, 2, \ldots, N_g) \qquad (2.3)$$

Where i=j= number of generating units or plants i.e. i=j=1,2,3,….,Ng

Where Ng = number of generators.

A more general formula containing a linear term and a constant term, referred to the

Kron's loss formula, is

$$P_L = \Sigma\Sigma P_i B_{ij} P_j + \Sigma B_{0i} P_i + B_{00} \qquad (2.4)$$

The coefficients B_{ij} are called *loss coefficients* or B-coefficients. These B coefficients for a given system are assumed to remain constant, and reasonable accuracy can be expected provided the actual operating conditions are close to the base case where the B constants are computed. There are various ways of arriving at a loss equation.

2.5 ELD Formulation

The economic dispatching problem is to minimize the overall generating cost which is the function of plant output given by

$$C_i (P_i (t)) = \Sigma a_i P_i^2 + b_i P_i + C_i \qquad (i=1,2,\ldots,N_g) \qquad (2.5)$$

Subject to the constraints that generation should equal total demand plus losses, i.e.

$$\Sigma P_i = P_D + P_L \tag{2.6}$$

Satisfying the inequality constraints, expressed as follows:

$$P_{i(max)} \leq P_i \leq P_{i(min)} \qquad (i=1,2,\ldots\ldots,Ng) \tag{2.7}$$

Where $P_{i(min)}$ and $P_{i(max)}$ are the minimum and maximum generating limits, respectively, for plant i.

CHAPTER-3

Genetic Algorithm

3.1 Introduction

A global optimization technique known as genetic algorithm (GA) has emerged as a candidate due to its flexibility and efficiency for may optimization applications. Genetic Algorithm is a stochastic searching algorithm. The Darwinian Survival of the fittest principle with genetic operation, abstracted from nature to form a robust mechanism that is very effective at finding optimal solution to complex-real world problems. Evolutionary computing is an adaptive search technique based on the principles of genetics and natural selection. They operate on string structures. The string is a combination of binary digits representing a coding of the control parameters for a given problem. Many such string structures are considered simultaneously, with the most fit of these structures receiving exponentially increasing opportunities to pass on genetically important material to successive generation of string structures. Genetic algorithms search for many points in the search space at ones, and yet continually narrow the focus of the search to the areas of the observed best performance. The basic elements of genetic algorithms are reproduction, crossover, and mutation.

The first step is the coding of control variables as string in binary numbers. In reproduction, the individuals are selected based on their fitness values relative to those of the population. In the crossover operation, two individual strings are selected random from the mating pool and a crossover site is selected at random along the string length. The binary digits are interchanged between two strings at the crossover site. In mutation, an occasional random alteration of a binary digit is done.

3.2 Algorithm: Genetic Algorithm

1. Code the problem variables into binary strings.
2. Randomly generate initial population strings. Tossing of a coin can be used.
3. Evaluate fitness values of population members.
4. Is solution available among the population? If ‘yes’ then GOTO step9.
5. Select highly fit strings as parents and produce off springs according to their fitness.
6. Create new strings by mating current off spring. Apply crossover and mutation
7. Operators to introduce variations and form new strings.
8. New strings replace existing one.
9. GOTO step 4 and repeat.
10. Stop

GA differs from more traditional optimization techniques as

- Genetic algorithms use objective function information to guide the search, not derivative or other auxiliary information. Evolution of a given function uses the
- Parameters, encoded in the string structures.
- Genetic algorithms use a coding of the parameters used to calculate the objective function in guiding the search, not the parameters themselves.

- Genetic algorithms search through many points in the solution space at one time, not a single point.
- Genetic algorithms use probabilistic rules, not deterministic rules, in moving from one set of solution (a population) to the next.

3.3 Fitness Function

GA is usually suitable for solving maximization and minimization problems [7]. Minimization problems are usually transformed into maximization problems by some suitable transformation. In general, fitness function F(x) is first derived from the objective function and used in successive genetic operations.

Certain genetic operators require that fitness function be non-negative, although certain operators do not have this requirement. Consider the following transformation

$F(x) = f(x)$ for maximization problem

$F(x) = 1/f(x)$ for minimization problem, if $f(x) \neq 0$

$F(x) = 1/(1+f(x))$, if $f(x) = 0$

A number of such transformations are possible. The fitness function value of the string is known as string's fitness.

3.4 Example

Two uniform bars are connected by pins at A and B and supported at A. A horizontal force P acts at C. knowing the force, length of bars and its weight determined the equilibrium configuration of the system if friction at all joints are neglected (see Fig.)

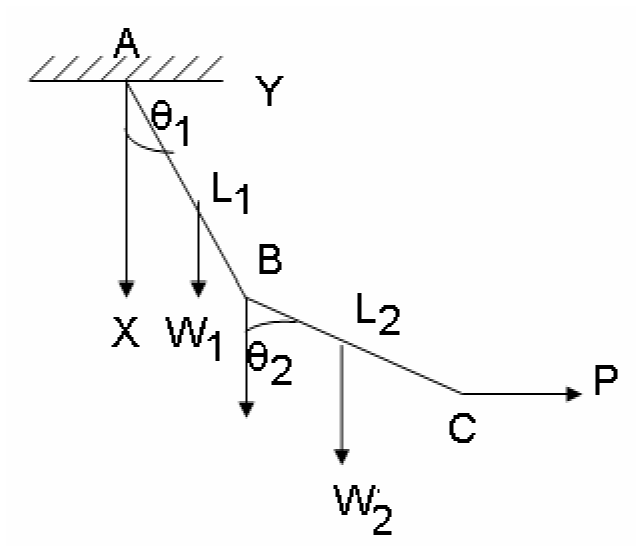


Fig 3.1 Two bar pendulum

Given $P=W_1=W_2=L_1=L_2=2$

The total potential for two bar pendulum is written as

$$\prod = -P[L_1 \,Sin(\theta_1) + L_2 \,Sin(\theta_2)]-(W_1L_1/2)Cos(\theta_1)-W_2[(L_2)/2 \,Cos(\theta_2)+L_1Cos(\theta_1)] \quad (3.1)$$

Putting the values for P, W_1, W_2 and L_1, L_2

$$\prod(\theta_1, \theta_2) = -4Sin(\theta_1)-6Cos(\theta_1)-4Sin(\theta_2)-2Cos(\theta_2) \quad (3.2)$$

$$0\leq\theta_1, \theta_2\leq 90 \quad (3.3)$$

Equilibrium configuration is the one which makes $\prod$ a minimum.

Solution:

$\delta\prod = 0$, for $\prod$ to be maximum or minimum

$$\delta\prod = (d\prod/d\theta_1) + (d\prod/d\theta_2) = 0 \qquad (3.4)$$

d_1, d_2 are arbitrary, therefore we get,

$$d\prod/d\,\theta_1 = 4Cos(\theta_1) - 6Sin(\theta_1) = 0 \qquad (3.5)$$

$$d\prod/d\,\theta_2 = 4Cos(\theta_2) - 2Sin(\theta_2) = 0 \qquad (3.6)$$

from equation (5) & (6),

$\tan\theta_1 = 2/3$, $\theta_1 = 33.7°$ (0.588 radians)

$\tan\theta_2 = 2$, $\theta_2 = 63.43°$ (1.107 radians)

for which $\prod = -11.68$

Since there are two unknowns and in this problem, we will use 4 bit binary string for each unknown.

$$\text{Accuracy} = (X^n - X^a) / (2^2 \times 2^2 - 1) = 90/15 = 6°$$

Hence the binary coding and the corresponding angles are given as

$$X_¡ = (X_¡^a) + [(X_¡^n - X_¡^a) / (2^2 \times 2^2 - 1)]\, S_¡$$

Where, S¡ is the decoded value of the ¡th chromosome. The binary coding and the corresponding angles are given in Table-3.1.

Table-3.1 Binary coding and the corresponding angles

S. NO.	Binary coding	Angle
1	0000	0
2	0001	6º
3	0010	12º
4	0011	18º
5	0100	24º
6	0101	30º
7	0110	36º
8	0111	42º
9	1000	48º
10	1001	54º
11	1010	60º
12	1011	66º
13	1100	72º
14	1101	78º
15	1110	84º
16	1111	90º

Since the objective function is negative, instead of minimizing the function ‘f’ let us maximize –f=f’. The maximum value of f = 8 when θ_1, θ_2 are zero. Hence the fitness function F is given as

F = f’ – 7 = -f – 7

First randomly generate eight populations with 8-bit strings as shown in Table-3.2

Table-3.2 Computation of fitness function

Population No.	population	Angles θ_1	θ_2	F =(-f-7)
1	0000 0000	0	0	1
2	0010 0001	12(0.209rad)	6(0.104rad)	2.1
3	0001 0101	6(0.104rad)	30(0.523rad)	3.11
4	0010 1000	12(0.21rad)	48(0.8377rad)	4.01
5	0110 1010	36(0.628rad)	60(1.047rad)	4.66
6	1110 1000	84(1.466rad)	48(0.8377rad)	1.91
7	1110 1101	84(1.466rad)	78(1.36rad)	1.93
8	0111 1100	42(0.733rad)	72(1.256rad)	4.55

The objective function of the problem is given in equation (3.2). The contours of the objective function as well as the 2D plot are shown in Fig.3.2

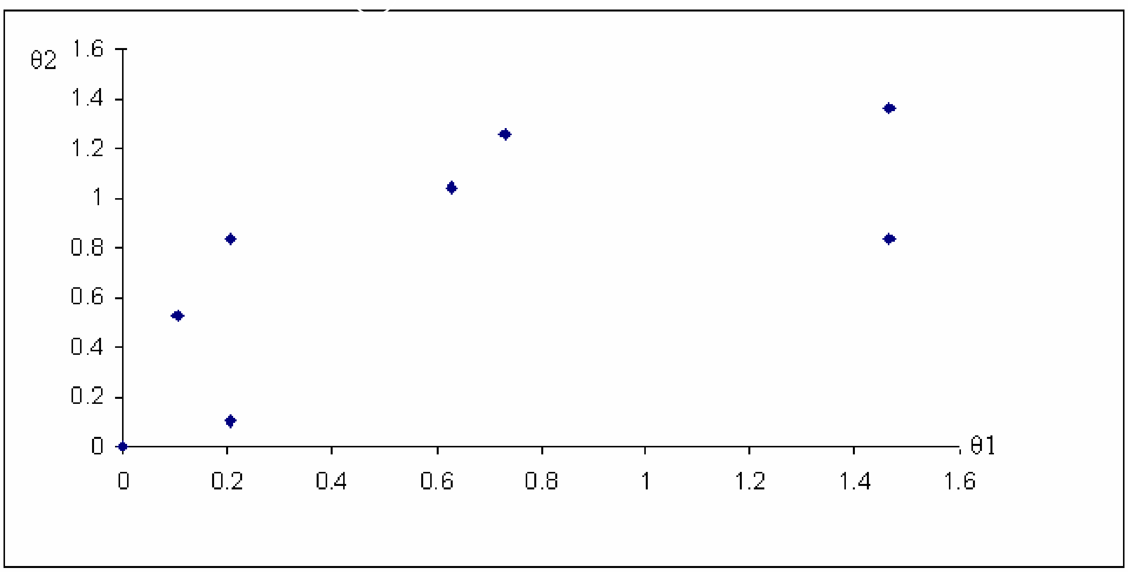


Fig 3.2 Contours of equal objective function

3.5 Reproduction

Reproduction is usually the first operator applied on population. Chromosomes are selected from the population to be parents to crossover and produce offspring. According to Darwin's evolution theory of survival of the fittest, the best ones should survive and create new offspring. That is why reproduction operator is sometime known as the selection operator. The various method of selecting chromosome for parents to crossover is roulette-wheel selection, tournament selection, rank selection and elitism.

3.6.1 Roulette-wheel selection

The commonly used reproduction operator is the proportionate reproductive operator where a string is selected from the mating pool with a probability proportional to the fitness. Thus, ith string in the population is selected with a probability proportional to Fi where Fi is the fitness value for that string. Since the population size is usually kept fixed in simple GA, the sum of the probability of each string being selected for the mating pool must be one. The probability of the ith selected string is

$$P_i = \frac{F_i}{\sum_{j=1}^{n} F_j}$$

Where 'n' is the population size. For the example problem discussed in 3.5 Example the probability values of each string are given in Table-3.3

Table-3.3 Probability of individual string

Population no.	population	F= -f-7	P_i
1	0000 0000	1	0.0429
2	0100 0001	2.1	0.090
3	0001 0101	3.22	0.1336
4	0010 1000	4.01	0.1723
5	0110 1010	4.66	0.200
6	1110 1000	1.91	0.082
7	1110 1101	1.93	0.0829
8	0111 1100	4.55	0.1955
		$\overline{F}$ =2.908	

One way to implement this selection scheme is to imagine a roulette-wheel with its circumference for each string marked proportionate to string's fitness (see Fig-3.3).

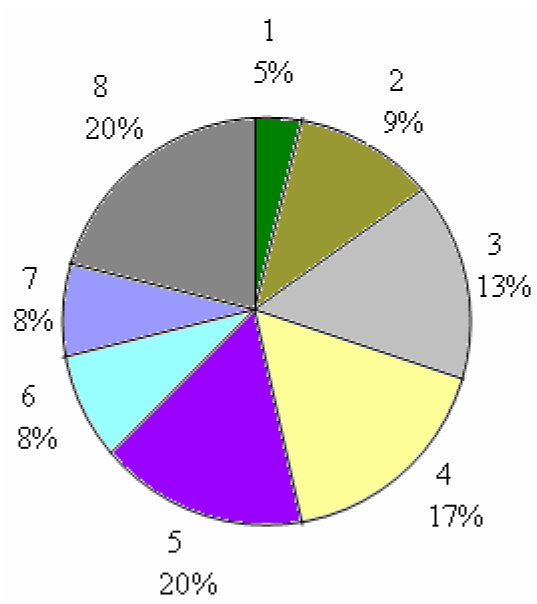


Fig-3.3 Roulette-wheel marked for eight individuals according to fitness

The fitness of the population is calculated as roulette wheel is spun ‘n’ times, each time selecting an instance of the string chosen by the roulette-wheel pointer. Since the circumference of the wheel is marked according to a string’s fitness. The roulette-wheel mechanism is expected to make $F/\overline{F}$ copies of ith string of the mating pool

The average fitness

$$\overline{F} = \sum_{j=1}^{n} (F_j)/n$$

Fig-3.3 shows a Roulette-wheel for eight individuals having different fitness values. Since the fifth individual has a higher fitness than any other, it is expected that the Roulette-wheel section will choose the fifth individual more than any other individual.

3.6 Crossover

The basic operator for producing new chromosome is crossover. In this operator, information is exchanged among strings of matting pool to create new strings. The aim of the crossover operator is to search the parameter space. Crossover is a recombination operator, which proceeds in three steps. First, the reproduction operator selects at random a pair of two individual string for mating, then a crossover site is selected at random along the string length and the position values are swapped between two string following the cross site. Single point crossover, Two point crossover, Multi point crossover, Uniform crossover, Matrix crossover etc. In the single point crossover, two individual strings are selected at random from the matting pool. Next, a crossover site is selected randomly along the string length and binary digits (alleles) are swapped between the two strings at crossover site. Suppose site 3 is selected at random. It means starting from the 4th bit and onwards, bits of strings will be swapped to produce offspring which is given in Example-1.

Example-1 Single point crossover operation

Parent 1: X_1 = { 0 1 0 **1 1 0 1 0 1 1** }

Parent 2: X_2 = { 1 0 0 **0 0 1 1 1 0 0** }

Offspring 1: X_1 = { 0 1 0 **0 0 1 1 1 0 0** }

Offspring 2: X_2 = { 1 0 0 **1 1 0 1 0 1 1** }

In a two point crossover operator, two random sites are chosen and the contents bracketed by these sites are exchanged between two mated parents. If the cross site 1 is three and cross site 2 is six, the strings between three and six are exchanged which is shown in Example-2. In a multipoint crossover, again there are two cases. One is even no of cross sites and other is odd no of sites. For even no of sites the string is treated as a string and cross sites are selected around the circle uniformly at random.

Example-2 Two point crossover operation

Parent 1: X_1 = {0 1 0 **1 1 0** 1 0 1 1}

Parent 2: X_2 = {1 0 0 **0 0 1** 1 1 0 0}

Offspring 1: X_1 = {0 1 0 **0 0 1** 1 0 1 1}

Offspring 2: X_2 = {1 0 0 **1 1 0** 1 1 0 0}

Sites are selected around the circle uniformly at random if the number of cross sites is odd, then a different cross point is always assumed at the string beginning.

3.7 Mutation

The final genetic operator in the algorithm is mutation. In general evolution, mutation is a random process where one allele of a gene is replaced by another to produce a new genetic structure. Mutation is an important operation, because newly created individuals have no new inheritance information and the number of alleles is constantly decreasing. This process results in the contraction of the population to one point, which is wished at the end of convergence process. Diversity is one goal of the learning algorithm to search always in regions not viewed before. Therefore, it is necessary to enlarge the information contained in the population. One way to achieve this goal is **mutation**. The role of mutation is often seen as providing a guarantee that the probability of searching any given string will never be zero and acting as safety net to recover good genetic material that may be lost through the action of selection and crossover. In GA's mutation is randomly applied with low probability in the range of 0.001 & 0.01 and modifies elements in the chromosome. Here, binary mutation flips the value of the bit at the loci selected to be the mutation point. Given that mutation is applied uniformly to an entire population of strings, it is possible that a given string may be mutated at more than one point.

Example-3 Mutation operation

Offspring X_1: 1 1 **1** 1 0 1 0

New offspring X_2: 1 1 **0** 1 0 1 0

3.9 Minimize a fitness function using GA toolbox

This is a demonstration of how to create and minimize fitness function of unconstraint problem with the help of genetic algorithm (GA).

3.9.1 Unconstrained Minimization Problem

Here we want to minimize a objective function of two variables

$$\min_{x} \quad f(x1, x2) = -4Sin(x1)-6Cos(x1)-4Sin(x2)-2Cos(x2)$$

since the objective function is negative, instead of minimizing the function 'f' let us maximize –f=f'.

3.9.2 Coding the Fitness Function

We create an M-file named fitness_2bp.m with the following code in it:

```
function y = fitness_2bp(x)
y = -4*sin(x(1))-6*cos(x(1))-4*sin(x(2))-2*cos(x(2));
```

The Genetic Algorithm solver assumes the objective function will take one input x, where x is a row vector with as many elements as number of variables in the problem. The fitness function computes the value of the function and returns that scalar value in its one return argument y.

3.9.3 Maximizing Using GA

To maximize our objective function using the GA function, we need to pass in a function handle to the objective function as well as specifying the number of variables in the problem.

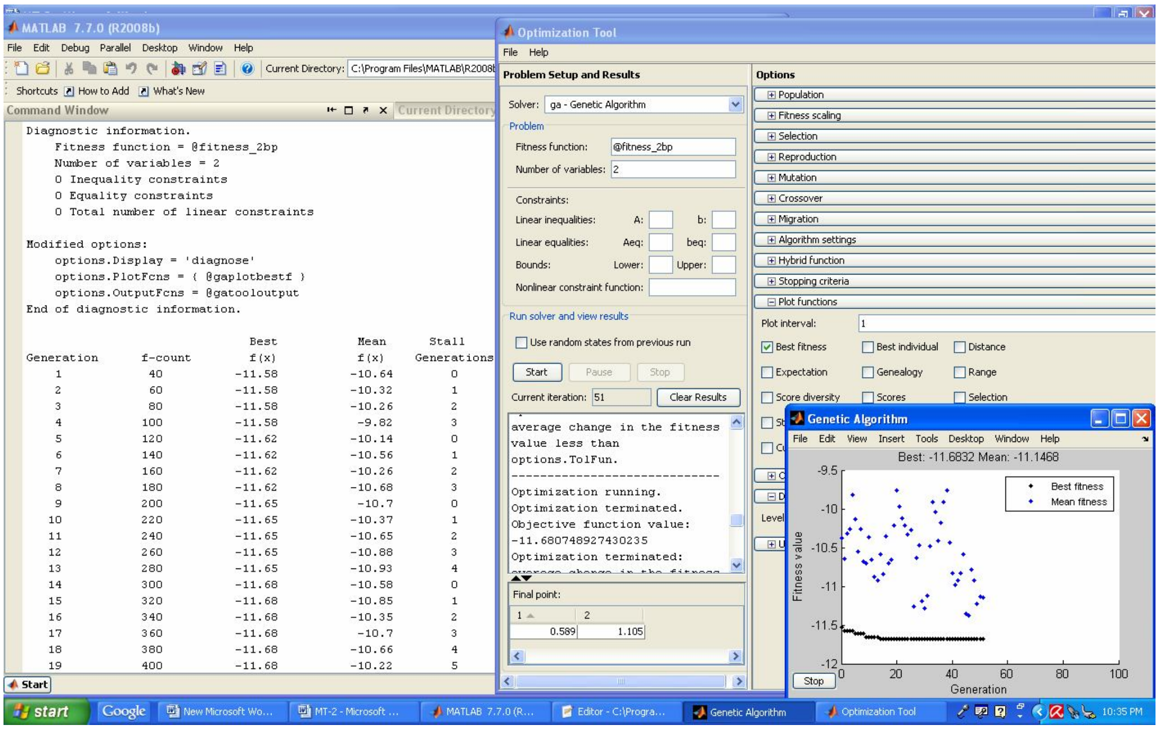
```
FitnessFunction = @fitness_2bp;
numberOfVariables = 2;
[x,fval]=ga(@fitness_2bp,2)

Optimization terminated: average change in the fitness value less than options. TolFun.
x =
   0.5717    1.1076


   fval = -11.6823
```

3.9.4 Maximizing unconstraint problem using gatool

In fitness function box we have mentioned the name toolbox and saved M-file with starting character as @fitness_2bp and number of variable box we have to mention the below toolbox (no. of variables present in the given fitness function). We have to select plot function (at least 1) to show the plot. By default display to command window is off so it is required to choose an option other than off. When we click the start button, we get the best fitness point and minimum point of the fitness function.

FitnessFunction = @fitness_2bp;

numberOfVariables = 2;



Optimization terminated: average change in the fitness value less than options. TolFun.

x =

0.589 1.105

fval = -11.6832

3.10 Advantages of GA

Advantages of GA's are given below as discussed in [5, 27].

- Simple to understand and to implement, and early give a good near solution
- Optimizes with continuous or discrete variables.
- Doesn't require derivative information.
- Simultaneously searches from a wide sampling of the cost surface.
- Deals with a large number of variables.
- Is well suited for parallel computers.
- Optimizes variables with extremely complex cost surfaces (they can jump out of a local minimum).
- Provides a list of optimum variables, not just a single solution.
- Can encode the variables so that the optimization is done with the encoded variables.
- Works with numerically generated data, experimental data, or analytical encoded variables.
- Works with numerically generated data, experimental data, or analytical functions. Therefore, works on a wide range of problems.
- For each problem of optimization in GAs, there are number of possible encodings.

These advantages are intriguing and produce stunning results where traditional optimization approaches fail miserably. Due to various advantages as discussed above, GAs is used for a number of different application areas. In power system, the GAs has been used in following areas:

- Loss reduction using Active Filter
- Power system restoration planning
- Controllers
- Optimal load dispatch
- Voltage stability

3.11 Disadvantages of GA

In spite of its successful implementation, GA does posses some weaknesses leading to

- Longer computation time.
- Less guaranteed convergence, particularly in case of epistemic objective function containing highly correlated parameters [6, 8].
- Premature convergence of GA is accompanied by a very high probability of entrapment into the local optimum [9].
- GAs tends to fail with the more difficult problems and need good problem knowledge to be tuned.
- Need much more function evaluations than linearized methods.
- No guaranteed convergence even to local minimum [9].
- Have to discretize parameter space [6, 8].

3.12 Multiobjective optimization using GA

Being a population-based approach, GA is well suited to solve multiobjective optimization problems. A generic single objective GA can be modified to find a set of multiple non-dominated solutions in a single run. The ability of GA to simultaneously search different regions of a solution space makes it possible to find a diverse set of solutions for difficult problems with non-convex, discontinuous, and multi-modal solutions spaces. The crossover operator of GA may exploit structures of good solutions with respect to different objectives to create new non dominated solutions in unexplored parts of the Pareto front. In addition, most multiobjective GA do not require the user to prioritize, scale, or weight objectives. Therefore, GA has been the most popular heuristic approach to multiobjective design and optimization problems.

CHAPTER- 4

Multiobjective Optimal Power Dispatch (MOPD) Using Weighting Method

4.1 Introduction

The optimization Process consists of three basic components: an objective function, variables, and constraints. It finds the value of the variables that minimize or maximizes the objective function while satisfying the constraints. The problem relies on many variables and therefore various combinations of values of the variables have to be explored to obtain the optimized objective function [33]. Confliction criteria such as cost, capacity performance and reliability are to be considered simultaneously and most suitable one is selected. This is also called a multi objective optimization problem (MOOP).

If a multiobjective problem is well formed, there should not be a single solution that simultaneously minimizes each objective to its fullest. In each case we are looking for a solution for which each objective has been optimized to the extent that if we try to optimize it any further, then the other objective(s) will suffer as a result. Finding such a solution, and quantifying how much better this solution is compared to other such solutions (there will generally be many) is the goal when setting up and solving multiobjective optimization problem.

Optimal economic dispatch in electric power systems has gained increasing importance as the cost associated with generation and transmission of electric energy keeps on increasing. The procedure involves the allocation of total generation requirements among the available generating units in the system in such a manner that the constraint imposed on different system variables are adequately satisfied and the achieved overall cost associated with it is a minimum.

4.2 Formulation of multiobjective problem

In mathematical terms, the multiobjective problem can be written as:

Minimize

$$[Z_1(x), Z_2(x) \ldots\ldots\ldots Z_n(x)]^T$$

S.t.

$$g(x) \leq 0$$

$$x \geq 0$$

$$h(x) = 0$$

Where $[Z_1(x), Z_2(x), \ldots\ldots, Z_n(x)]$ is the multi objective function, g and h are the inequality and equality constraints, respectively, and *x* is the vector of optimization or decision variables.

Multiobjective Optimal power dispatch (MOPD) studies have been carried out on IEEE 5, 14 and 30 bus systems in 2D space. The data of IEE 5, 14 and 30 bus systems is given in Appendix-

II. In 2D space, two objectives i.e. cost of generation and system transmission Losses are considered.

The ideal situation where one would like to operate the power systems is one where all the objectives i.e. cost of generation and system transmission losses are minimum. Such a point is called the ideal point. In 2D space, it is represented by (F_{Cmin}, F_{Lmin}). Therefore, while considering multiobjective optimal power dispatch problem, a strategy has to be adopted by the power systems analyst or operator to achieve optimum values as per his satisfaction level and requirements. The operating point so obtained is called the **Target Point** (TP) or the best compromise solution.

4.3 Weighting Method

The weighting method identify the noninferior set, which the best compromise solution lies [33], also known as the parametric approach, has been the most common method used for solving multiobjective problems until recently. Multiobjective problem is converted in this method into scalar optimization as given below:

$$\text{Minimize} \quad \sum_{i=1}^{G} w_i f_i(x) \tag{4.1}$$

$$\text{Subject to} \quad x \in X \tag{4.2}$$

$$\sum_{i=1}^{G} w_i = 1 \qquad w_i \geq 1 \qquad (i=1,2,\ldots\ldots,G) \tag{4.3}$$

Where Wi is the weighting coefficients.

The approach yields meaningful results to the decision maker only when solved many times for different values of wi (i=1,2,……..,G). Though very little is usually known about the values of weighting coefficient, the DM still choose them, presumably on the basis of his institution. The weighting coefficients do not reflect proportionally the relative importance of the objectives but are only factors which, when varied, locate points in the noninferior set.

3.4 Formulation of MOPD Problem

Two aspects of the optimal power dispatch (OPD) problem considered in 2D space are:

1- To minimize the cost of generation.

2- To minimize the system transmission losses.

The objective function to minimize the cost of generation is given as,

$$F_C = \Sigma\, F[Ci(Pgi)] \qquad (i=1,2,\ldots,NG) \qquad (4.6)$$

Where Pgi is the power generation at the ith generator, Ci is the cost of generation for ith generator and NG is the total number of generators in the system.

$$P_L = \Sigma\Sigma\, P_i\, B_{ij}\, P_j \qquad (i, j=1, 2,\ldots,N_g) \qquad (4.7)$$

Where i=j= number of generating units or plants i.e. i=j=1,2,3,….,Ng

Where Ng = number of generators.

In 2D space, the multiobjective function comprises of cost of generation and system transmission losses i.e.

$$F = [\ F_C, F_L] \tag{4.4}$$

To generate the noninferior solution of multiobjective optimization problem, the weighting method is used. In this method the problem is converted into a scalar optimization problem as

Minimize

$$F = F_C F_C + W_L F_L \tag{4.5}$$

Where,

F_C is the cost of generation and

W_C is the Weight attached cost of generation.

F_L is the System transmission loss

W_L is the weight attached system transmission losses.

The multiobjective optimal power dispatch (MOOPD) problem is subjected to inequality and equality constraints are given as.

4.5 Ideal distance minimization method

This method [30] employs the concept of an 'Ideal Point' (IP) scalarize the problems having multiple objectives and minimizes the Euclidean distance between the IP and the set of feasible or non inferior solutions.

The ideal situation where one would like to operate the power system is the one where both objectives namely cost of generation (Fc) and system transmission loss ($F_{L)}$ are minimum. In order to locate the target points in 2D space, the following distance functions are proposed:

In 2D space, it is defined as:

Distance = $[(Fc - F_{Cmin})^2+(F_L-F_{Lmin})^2]^{½}$ (4.8)

Where

F_{Cmin} – The value of cost of generation obtained by individually minimizing Fc.

F_{Lmin} – The value of system transmission losses obtained by individually minimizing F_L.

This represents the distance of any feasible point from the ideal point. The Target Point to be selected is one for which the distance from the ideal point is minimum.

CHAPTER-5

Results and discussion

5.1 Introduction

The distance function as defined by eq. (4.8) is formulated for multiobjective optimal power dispatch (MOPD) in 2D space respectively to locate the target points. This method also gives the target points in three steps only, for 5, 14 and 30 bus system in 2D space. The non inferior set generate in 2D by varying the weights attached to the objective functions.

5.2 IEEE 5-bus system in 2D space

The objective function minimizes with respect to weights. Problem has been formulated as shown below.

Minimize

$$F = W_1 F_C + W_2 F_L$$

Where $F_C = C_1 + C_2$

Where, C_1 and C_2 are the cost characteristic as given in APPENDIX-II.

Subject to inequality constraint

$$30 \leq P_i \leq 120 \qquad \text{for } i=1, 2.$$

And equality constraint

$P_{Generation} - P_{Demand} - P_{Loss} = 0$

$P_{Loss} = \Sigma\Sigma P_i B_{ij} P_j$ (i, j=1, 2,……,N_g)

Where i=j= number of generating units or plants i.e. i=j=1,2,3,….,Ng

Where Ng = number of generators.

5.2.1 M-File for IEEE 5- bus dispatch problem

Objective function file

```
function z = objective_5bus(x)

z=W1*((50*(x(1)/100)*(x(1)/100))+(351*(x(1)/100))+44.4+(50*(x(2)/100)*(x(2)/100))+(38
 9*(x(2)/100))+40.6)+W2*((0.00035336*x(1)*x(1))+2*0.0000103196*x(1)*x(2)+0.0003689
92*x(2)*x(2));
```

Constraint function file

```
function [c,ceq]=constraint_5bus(x)

c=[-x(1)+30;x(1)-120;-x(2)+30;x(2)-120];

ceq=(x(1)+x(2)-0.00035336*x(1)*x(1)-2*0.0000103196*x(1)*x(2)-
0.000368992*x(2)*x(2)-160);
```

Run the above program with the help of GA tool from the results. We will obtain P_1 and P_2 values when these values are substituted in cost (F_C) and loss (F_L) function then between Ideal Point (IP) and Target Point (TP) will be found.

Table-5.1 Results of MOPD studies with varying weights in 2D space

(IEEE 5-bus system)

S.no.	W_C	W_L	F_C	F_L	Distance
1	0	1	763.1833	5.0582	0.022323
2	1	0	760.951	5.1812	0.0246
3	1	0.01	760.9597	5.1811	0.02458
4	1	0.05	760.9628	5.1805	0.02446
5	1	0.1	760.9614	5.1798	0.02432
6	1	0.5	760.9595	5.1745	0.02326
7	1	1	760.9644	5.1684	0.02204
8	1	10	761.2431	5.1088	0.010533
9	**1**	**20**	**761.57**	**5.0856**	**0.008267**
10	1	30	761.8217	5.0753	0.009355
11	1	40	762.0106	5.0699	0.010851
12	1	50	762.1547	5.0667	0.012156
13	1	60	762.2672	5.0647	0.013226
14	1	70	762.3545	5.0633	0.014072
15	1	80	762.4329	5.0623	0.014842
16	1	90	762.4886	5.0615	0.1539
17	1	100	762.5433	5.061	0.015933
18	10	0.01	760.9597	5.1811	0.02458

19	10	0.05	760.9597	5.1811	0.02458
20	10	0.1	760.9601	5.181	0.02456
21	10	0.5	760.9604	5.181	0.02456
22	10	1	760.9615	5.1797	0.0243
23	10	10	760.9644	5.1684	0.02204
24	10	20	760.984	5.1577	0.019903
25	10	30	761.0039	5.1483	0.018028
26	10	40	761.0321	5.1403	0.01644
27	10	50	761.0637	5.1333	0.016459
28	10	60	761.0982	5.1271	0.013858
29	10	70	761.1353	5.1217	0.012833
30	10	80	761.1704	5.1169	0.011943
31	10	90	761.2036	5.1126	0.011169
32	10	100	761.2392	5.1087	0.010503

Table-5.2 Active power of two generation of IEEE 5-bus system

S.no	W_1	W_2	P_1	P_2
1	0	1	96.568	68.6
2	1	0	97.248	67.933
3	1	0.01	97.253	67.928
4	1	0.05	97.218	67.963
5	1	0.1	97.182	67.998
6	1	0.5	96.901	68.273
7	1	1	96.568	68.6
8	1	10	92.625	72.484
9	1	20	90.439	74.646
10	1	30	89.169	75.906
11	1	40	88.339	76.731
12	1	50	87.753	77.314
13	1	60	87.318	77.747
14	1	70	86.982	78.081
15	1	80	86.715	78.348
16	1	90	86.497	78.564
17	1	100	86.316	78.745
18	10	0.01	97.253	67.928
19	10	0.05	97.252	67.929

20	10	0.1	97.249	67.932
21	10	0.5	97.246	67.935
22	10	1	97.181	67.999
23	10	10	96.568	68.6
24	10	20	95.953	69.205
25	10	30	95.396	69.752
26	10	40	94.891	70.249
27	10	50	94.43	70.703
28	10	60	94.007	71.12
29	10	70	93.619	71.503
30	10	80	93.261	71.856
31	10	90	92.929	72.183
32	10	100	92.621	72.487

Noninferior set for IEEE 5-bus has been shown in graph of fig 5.1, graph has been plotted from table 5.1 between transmission loss function (as X- axis) and cost of generation function (Y-axis), IP shows the Ideal Point which is feasible and TP shows the Target Point or best compromise solution which is at minimum distance from Ideal Point, From graph Red point indicates Ideal Point (F_{Cmin}, F_{Lmin}) and Blue point indicates Target Point (F_C,* F_L*)) of noninferior set.

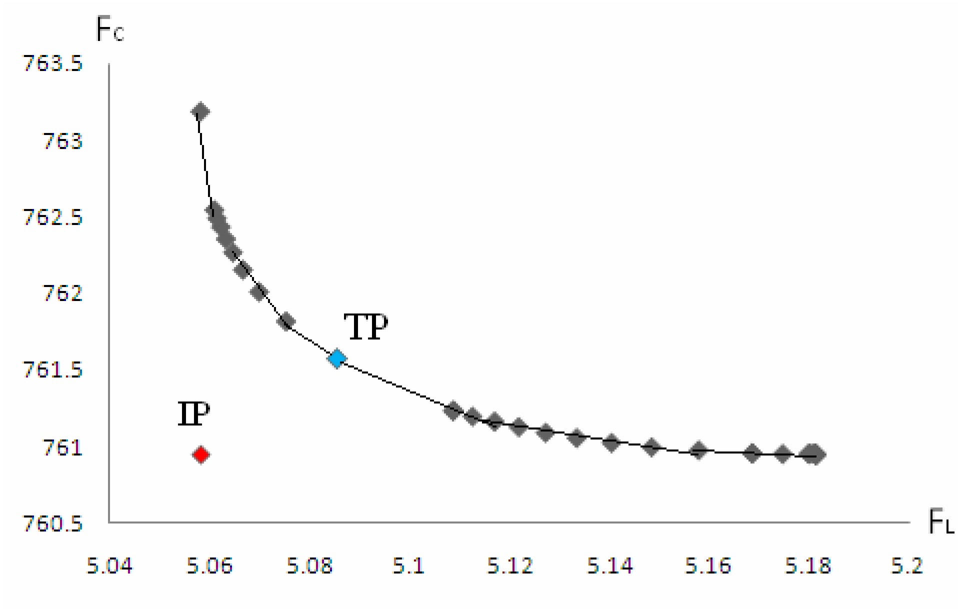


Fig 5.1 2D plot between cost of genration and trnsmission losses

Observation ;

Cost of generation obtained F_C* = 761.57 $/hr

Transmission loss obtained F_L* = 5.0856 MW

Hence the target point is (F_C,* F_L*) or (761.57, 5.0856) and the minimum distance from ideal point (760.9515, 0.0582) to target point (761.57, 5.0856) is 0.008265.

5.3 IEEE 14- bus system in 2D space

The objective function is minimizing with respect the weights. We have formulated the problem in the following manner:

Minimize

$$F = W_1 F_C + W_2 P_{Loss}$$

Where $F_C = C_1 + C_2 + C_6$

Where, C_1, C_2 and C_6 are the cost characteristic as given in APPENDIX-II.

Subject to inequality constraint

$50 \le Pi \le 150$ for i=1, 2, 6.

And equality constraint

$$P_{Generation} - P_{Demand} - P_{Loss} = 0$$

$$P_{Loss} = \Sigma\Sigma\, P_i\, B_{ij}\, P_j \quad (i, j=1, 2,\ldots\ldots,Ng)$$

Where i=j= number of generating units or plants i.e. i=j=1,2,3,….,Ng

Where Ng = number of generators.

5.3.1 M-File for IEEE 14- bus dispatch problem

Objective function file

```
function z = objective_14bus(x)

z=W1*(((50*(x(1)/100)*(x(1)/100))+(245*(x(1)/100))+105+(50*(x(2)/100)*(x(2)/100))+(351
*(x(2)/100))+44.4+(50*(x(3)/100)*(x(3)/100))+(389*(x(3)/100))+40.6))+W2*(100*(((x(1)/1
00)*(x(1)/100)*0.0231)+(2*(x(1)/100)*(x(2)/100)*0.0078)+(2*(x(1)/100)*(x(3)/100)*(0.000
7))+((x(2)/100)*(x(2)/100)*0.0182)+(2*(x(2)/100)*(x(3)/100)*0.0022)+((x(3)/100)*(x(3)/10
0)*0.0329)));
```

Constraint function file

```
function [c,ceq]=constraint_14bus(x)

c=[-x(1)+50;x(1)-150;-x(2)+50;x(2)-150;-x(3)+50;x(3)-150];

ceq=(x(1)+x(2)+x(3)-259-
(100*(((x(1)/100)*(x(1)/100)*0.0231)+(2*(x(1)/100)*(x(2)/100)*0.0078)+(2*(x(1)/100)*(x(3
)/100)*(0.0007))+((x(2)/100)*(x(2)/100)*0.0182)+(2*(x(2)/100)*(x(3)/100)*0.0022)+((x(3)/
100)*(x(3)/100)*0.0329))));
```

Run the above program with the help of GA tool from the results. We will obtain P_1, P_2 and P_3 values when these values are substituted in cost of generation (F_C) and transmission losses (F_L) function then between Ideal Point (IP) and Target Point (TP) will be found.

Table-5.3 Results of MOPD studies with varying weights in 2D space (IEEE 14-bus system)

S.no.	W_C	W_L	F_C	F_L	Distance
1	0	1	1189	7.4	51.5
2	1	0	1137.5	8.7	45.5
3	1	0.01	1137.5	8.7	45.5
4	1	0.05	1137.5	8.7	45.5
5	1	1	1137.8	8.6	42.0011
6	1	5	1137.8	8.6	42.0011
7	1	10	1139.6	8.4	35.0629
8	1	20	1142.1	8	22.1678
9	1	25	1144.6	7.9	19.8648
10	**1**	**40**	**1152.8**	**7.7**	**18.5564**
11	1	55	1157.5	7.6	21.1896
12	1	60	1158.8	7.6	22.4207
13	1	90	1164.8	7.5	27.5234
14	1	95	1165.6	7.5	28.3171
15	10	0	1137.5	8.7	45.5
16	10	1	1137.5	8.7	45.5
17	10	0.01	1137.5	8.7	45.5
18	10	0.05	1137.5	8.7	45.5
19	10	0.1	1137.5	8.7	45.5

20	10	0.5	1137.5	8.7	45.5
21	10	1	1137.5	8.7	45.5
22	10	5	1137.5	8.7	45.5
23	10	10	1137.5	8.7	45.5
24	10	15	1137.5	8.7	45.5
25	10	20	1137.5	8.7	45.5
26	10	25	1137.5	8.7	45.5
27	10	30	1137.5	8.7	45.5
28	10	35	1137.5	8.7	45.5
29	10	45	1137.7	8.6	42.0005
30	10	50	1137.8	8.6	42.0011
31	10	55	1137.9	8.6	42.0019
32	10	60	1138	8.6	42.003
33	10	65	1138.1	8.6	42.0043
34	10	70	1138.2	8.5	38.513
35	10	75	1138.5	8.5	38.5064
36	10	80	1138.7	8.5	38.5187
37	10	85	1138.9	8.5	38.5254
38	10	90	1139.2	8.4	35.0413
39	10	95	1139.4	8.4	35.0515
40	10	100	1139.6	8.4	35.0629

Table-5.4 Active power of three generation of IEEE 14- bus system

S.no	W_1	W_2	P_1	P_2	P_3
1	0	1	81.59	109.108	75.733
2	1	0	150	67.692	50
3	1	0.01	150	67.692	50
4	1	0.05	150	67.692	50
5	1	1	147.675	69.944	50
6	1	5	147.675	69.944	50
7	1	10	140.707	73.905	52.769
8	1	20	129.446	78.524	59.068
9	1	25	125.341	80.48	61.113
10	1	40	116.463	85.186	65.096
11	1	55	110.627	88.614	67.406
12	1	60	109.098	89.555	67.972
13	1	90	102.512	93.796	70.235
14	1	95	101.711	94.833	70.726
15	10	0	150	67.692	50
16	10	1	150	67.692	50
17	10	0.01	150	67.692	50
18	10	0.05	150	67.692	50
19	10	0.1	150	67.692	50
20	10	0.5	150	67.692	50

21	10	1	150	67.692	50
22	10	5	150	67.692	50
23	10	10	150	67.692	50
24	10	15	150	67.692	50
25	10	20	150	67.692	50
26	10	25	150	67.692	50
27	10	30	150	67.692	50
28	10	35	150	67.692	50
29	10	45	148.314	69.324	50
30	10	50	147.675	69.444	50
31	10	55	147.049	70.551	50
32	10	60	146.437	71.144	50
33	10	65	145.838	71.725	50
34	10	70	145.252	72.294	50
35	10	75	144.478	72.611	50.932
36	10	80	143.683	72.873	50.932
37	10	85	142.09	73.134	51.417
38	10	90	142.156	73.393	51.884
39	10	95	141.422	73.65	52.335
40	10	100	140.707	73.905	52.769

Noninferior set for IEEE 5-bus has been shown in graph of fig 5.2, graph has been plotted from table 5.1 between transmission loss function (as X- axis) and cost of generation function (Y-axis), IP shows the Ideal Point which is feasible and TP shows the Target Point or best compromise solution which is at minimum distance from Ideal Point, From graph Red point indicates Ideal Point (F_{Cmin}, F_{Lmin}) and Blue point indicates Target Point (F_C,* F_L*)) of noninferior set.

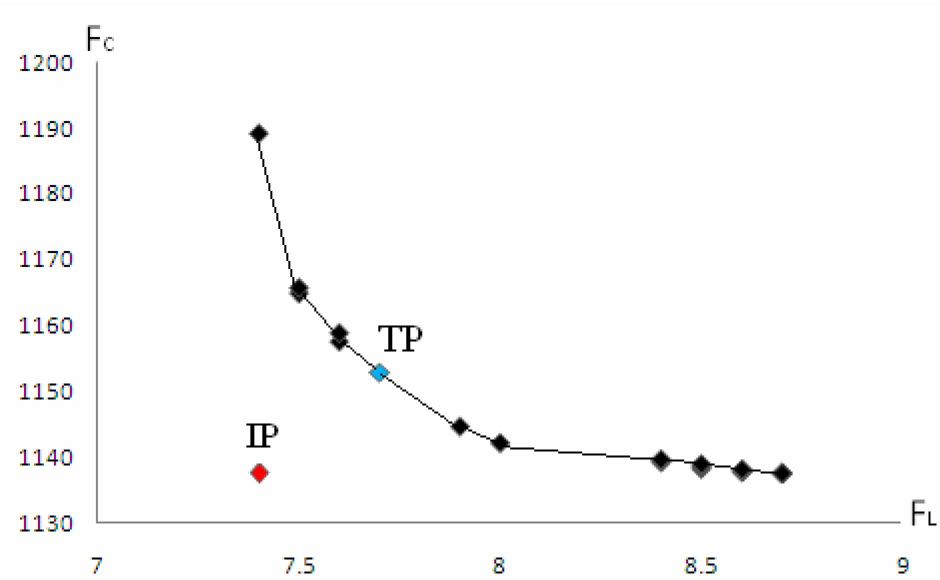


Fig 5.2- 2D plot between cost of generation and transmission losses

Observation ;

Cost of generation obtained F_C* = 1152.8 $/hr

Transmission loss obtained F_L* = 7.7 MW

Hence the target point is (F_C,* F_L*) or (1152.8, 7.7) and the minimum distance from ideal point (1137.5, 7.4) to target point (1152.8, 7.7) is 18.5564.

5.4 IEEE 30- bus system in 2D space

The objective function is minimizing with respect the weights. We have formulated the problem in the following manner:

Minimize

$$F = W_1 F_C + W_2 P_{Loss}$$

Where $F_C = C_1 + C_2 + C_8$

Where, C_1, C_2 and C_3 are the cost characteristic as given in appendix.

Subject to inequality constraint

$$50 \leq Pi \leq 150 \qquad \text{for i=1, 2, 8.}$$

And equality constraint

$$P_{Generation} – P_{Demand} – P_{Loss} = 0$$

$$P_{Loss} = \Sigma\Sigma\ P_i\ B_{ij}\ P_j \quad (i, j=1, 2,\ldots\ldots,Ng)$$

Where i=j= number of generating units or plants i.e. i=j=1,2,3,….,Ng

Where Ng = number of generators.

5.4.1 M-File for IEEE 30- bus load dispatch problem

Objective function file

```
function z=objective_30bus(x)
z=W1*(50*(x(1)/100)*(x(1)/100)+245*(x(1)/100)+105+50*(x(2)/100)*(x(2)/100)+351*(x(2)
/100)+44.4+50*(x(3)/100)*(x(3)/100)+389*(x(3)/100)+40.6)+W2*(100*(((x(1)/100)*(x(1)/1
00)*0.0307)+(2*(x(1)/100)*(x(2)/100)*0.0129)+(2*(x(2)/100)*(x(3)/100)*0.0002)+((x(2)/10
0)*(x(2)/100)*0.0152)+(2*(x(2)/100)*(x(3)/100)*(-0.0011))+((x(3)/100)*(x(3)/100)*0.0190)));
```

Constraint function file

```
function [c,ceq]=constraint_30bus(x)
c=[-x(1)+50;x(1)-150;-x(2)+50;x(2)-150;-x(3)+50;x(3)-150];
ceq=(x(1)+x(2)+x(3)-283.4-
(100*(((x(1)/100)*(x(1)/100)*0.0307)+(2*(x(1)/100)*(x(2)/100)*0.0129)+(2*(x(2)/100)*(x(3
)/100)*0.0002)+((x(2)/100)*(x(2)/100)*0.0152)+(2*(x(2)/100)*(x(3)/100)*(-
0.0011))+((x(3)/100)*(x(3)/100)*0.0190))));
```

Run the above program with the help of GA tool from the results. We will obtain P_1, P_2 and P_3 values when these values are substituted in cost of generation (F_C) and transmission losses (F_L) function then between Ideal Point (IP) and Target Point (TP) will be found.

Table-5.5 Results of MOPD studies with varying weights in 2D space (IEEE 30-bus system)

S.no.	W_C	W_L	F_C	F_L	Distance
1	0	1	1361.2	7	1.041
2	1	0	1257.1	11.8	1.248
3	1	0.01	1257.1	11.8	1.248
4	1	0.05	1257.1	11.8	1.248
5	1	0.1	1257.1	11.8	1.248
6	1	1	1257.1	11.7	1.222
7	1	5	1260.2	10.8	0.988486
8	1	10	1267.4	9.8	0.73525
9	1	15	1275.4	9.2	0.600561
10	1	20	1283.3	8.7	0.513817
11	**1**	**25**	**1290.7**	**8.4**	**0.495371**
12	1	30	1297.6	8.1	0.495803
13	1	35	1303.9	7.9	0.52324
14	1	40	1309.8	7.8	0.561915
15	1	45	1315.2	7.6	0.601579
16	1	50	1320.1	7.5	0.643273
17	1	55	1324.7	7.4	0.683953
18	1	60	1329	7.4	0.726483

19	1	65	1333	7.3	0.762997
20	1	70	1336.6	7.3	0.798817
21	1	75	1340.1	7.2	83.1627
22	1	80	1340.1	7.2	83.1627
23	1	85	1346.3	7.1	0.892379
24	1	90	1349.1	7.1	0.920367
25	1	95	1351.8	7.1	0.947357
26	1	100	1354.3	7	0.972
27	10	0	1257.1	11.8	1.248
28	10	0.01	1257.1	11.8	1.248
29	10	0.5	1257.1	11.8	1.248
30	10	0.1	1257.1	11.8	1.248
31	10	10	1257.1	11.7	1.222
32	10	15	1257.2	11.7	1.222
33	10	20	1257.2	11.6	1.196
34	10	25	1257.6	11.5	1.170011
35	10	30	1258	11.3	1.118036
36	10	35	1258.5	11.2	1.09209
37	10	40	1259	11.1	1.066169
38	10	45	1259.8	10.9	1.014359
39	10	50	1260.2	10.8	0.988486
40	10	55	1260.8	10.7	0.962711
41	10	60	1261.5	10.6	0.937034

42	10	65	1262.9	10.4	0.885901
43	10	70	1262.9	10.3	0.859958
44	10	75	1263.6	10.2	0.834535
45	10	80	1264.3	10.1	0.809209
46	10	85	1265.1	10.1	0.80996
47	10	95	1266.6	9.9	0.759961
48	10	100	1267.4	9.8	73.525

Table-5.6 Active power of three generation of IEEE 30 bus system

S.no	W_1	W_2	P_1	P_2	P_3
1	0	1	50	114.965	125.424
2	1	0	150	82.304	62.875
3	1	0.01	150	82.286	62.893
4	1	0.05	150	82.213	62.964
5	1	0.1	150	82.121	63.051
6	1	1	150	80.525	64.583
7	1	5	139.523	80.351	74.317
8	1	10	125.262	83.511	84.43
9	1	15	114.217	86.727	91.612
10	1	20	105.339	89.818	96.946
11	1	25	98.008	92.718	101.046
12	1	30	91.83	95.407	104.282
13	1	35	86.537	97.894	106.893
14	1	40	81.944	100.185	109.039
15	1	45	77.915	102.197	110.829
16	1	50	74.348	104.246	112.342
17	1	55	71.164	106.048	113.635
18	1	60	68.304	107.717	114.752
19	1	65	65.714	109.266	115.73

20	1	70	63.169	110.707	116.58
21	1	75	61.224	112.049	117.335
22	1	80	59.258	113.302	118.007
23	1	85	57.447	114.475	118.608
24	1	90	55.775	115.574	119.149
25	1	95	54.226	116.606	119.149
26	1	100	52.784	117.577	120.082
27	10	0	150	82.304	62.876
28	10	0.01	150	82.303	62.878
29	10	0.5	150	82.295	62.885
30	10	0.1	150	82.286	62.893
31	10	10	150	80.525	64.583
32	10	15	150	79.677	65.398
33	10	20	150	78.855	66.188
34	10	25	148.409	78.92	67.573
35	10	30	146.514	79.192	69.038
36	10	35	144.681	79.473	70.442
37	10	40	142.906	79.76	71.787
38	10	45	141.188	80.054	73.078
39	10	50	139.522	80.353	74.317
40	10	55	137.907	80.657	75.508
41	10	60	136.339	80.964	76.653
42	10	65	134.816	81.275	77.754

43	10	70	133.337	81.589	78.815
44	10	75	131.899	81.906	79.837
45	10	80	130.5	82.225	80.822
46	10	85	129.138	82.545	81.772
47	10	95	126.521	83.189	83.574
48	10	100	125.264	83.512	84.429

Noninferior set for IEEE 5-bus has been shown in graph of fig 5.3, graph has been plotted from table 5.1 between transmission loss function (as X- axis) and cost of generation function (Y- axis), IP shows the Ideal Point which is feasible and TP shows the Target Point or best compromise solution which is at minimum distance from Ideal Point, From graph Red point indicates Ideal Point (F_{Cmin}, F_{Lmin}) and Blue point indicates Target Point (F_C,* F_L*)) of noninferior set.

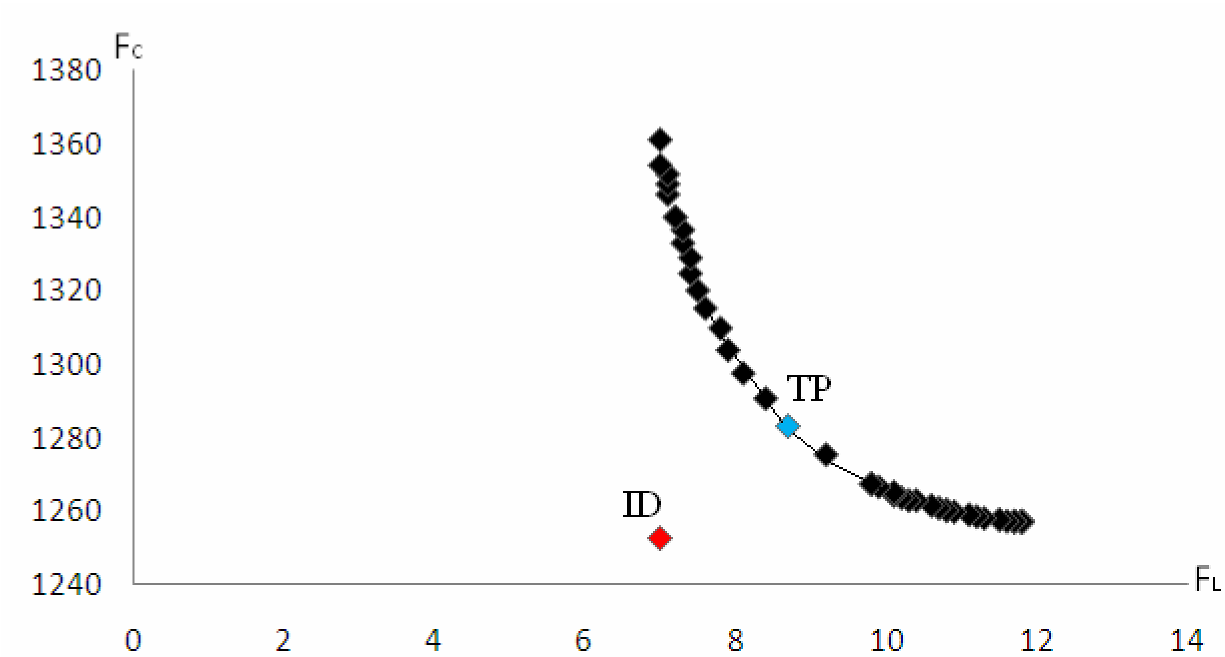


Fig 5.3 2D Plot between cost of generation and transmission losses

Observation ;

Cost of generation obtained F_C* = 1290.7 $/hr

Transmission loss obtained F_L* = 8.4 MW

Hence the target point is (F_C,* F_L*) or (1290.7, 8.4) and the minimum distance from ideal point (1257.1, 7) to target point (1290.7, 8.4) is 0.495371.

CHAPTER-6

Conclusion and future scope

6.1 Conclusion

In this work, Formulation of solution methods to obtain the optimum solution of Mutiobjective optimal power dispatch (MOPD) problem has been implemented successfully using weighting method with the help of GA tool.

The focus of this thesis work concentrates on simultaneously minimization of two objectives of power system – cost of generation and transmission loss using weighting method. Mutiobjective optimal power dispatch (MOPD) problem has been formulated by using weighting method. The noninferior set for IEEE 5, 14 and 30 bus systems obtained by parametrically varying weights attached to the objective. MOPD problem has been solved by GA tool of MATLAB and from the result Target Point (TP) or best compromise solution is obtained with minimum computational effort. Optimal weights have been derived for IEEE 5, 14 and 30 bus systems which give the Target Point (TP) in single step, thereby saving a lot of computational effort.

6.2 Scope for Future work

Present work of Multiobjective optimal power dispatch (MOPD) problem can be extended to solve using weighting method on IEEE standard system viz. 5, 14 and 30 bus systems in 3D space by varying weights. This objective function can be minimized to reach the Target Point (TP) or best compromise solution.

Multiobjective optimal power dispatch (MOPD) problem can be solved using different methods. There are various techniques for generating noninferior solutions, e.g. Constraint method, noninferior estimation (NISE) method and step method (STEM) can be using MOPD problem with the help of GA tool of MATLAB. These methods generate noninferior set in 2D and 3D space respectively for IEEE 5, 14 and 30 bus systems. Approximation of the noninferior set is the most desirable feature for practical problems.

APPENDIX - I

1. GA Problem solved by hand

Consider the example-3.5 of CHAPTER-3

Minimize

$$F(\theta_1, \theta_2) = -4Sin(\theta_1)-6Cos(\theta_1)-4Sin(\theta_2)-2Cos(\theta_2)$$

Let us choose an initial population size of 8

$0^{o} \leq \theta \leq 90^{o}$

String type used is Bit string

String size is 4.

For minimization problem

$$F = -f - 7$$

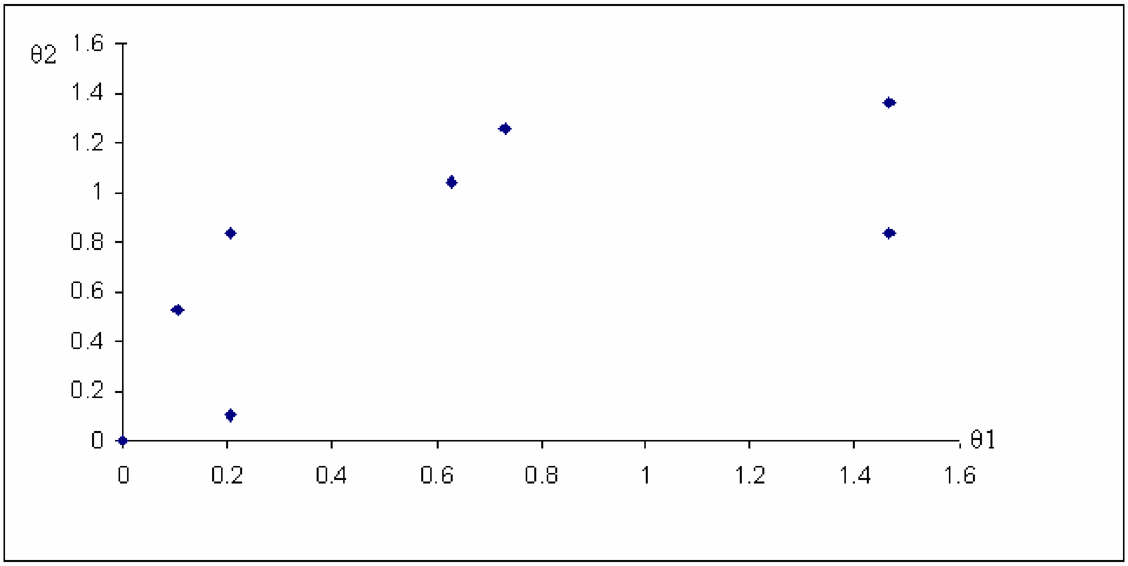
This transformation converts minimization problem to an equivalent maximization problem.

Table-1 Problem continuation (Iteration –1)

Population No.	Initial population	θvalues θ1 θ2	F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette wheel
1	0000 0000	0 0	1	0.0429	0.33	0
2	0010 0001	12 6	2.1	0.090	0.72	1
3	0001 0101	6 30	3.11	0.1336	1.064	1
4	0010 1000	12 48	4.01	0.1723	1.368	2
5	**0110 1010**	**36 60**	**4.66**	**0.200**	**1.6**	**2**
6	1110 1000	84 48	1.91	0.082	0.656	1
7	1110 1101	84 78	1.93	0.0829	0.664	1
8	0111 1100	42 72	4.55	0.1955	1.56	2
Sum			23.27			
average			2.908			

To find best fitness value, graph has been plotted form table-1 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 1. contours of equal objective function



As observed from 2-D plot that there are many fitness values so the objective function are unable to predict the best fitness value. Hence scatter points are moving to next generation for finding the best fitness value.

Selection of population for the next generation

Elite child is the one which is having the best fitness value. Its string value is **0110 1010.**

Crossover fraction is set to 0.8. Here out of 7 populations other than elite child in the first generation, the fraction of 0.8 gives 6 strings to be crossed.

Mutation fraction is set to 0.2. So, one string is to be mutated.

Application of Crossover for producing next generation

Before Crossover	After Crossover
0001 0101	0010 0100
0010 1000	0001 1001
0010 1000	0011 1000
0111 1100	0110 1100
0110 1010	0111 1000
0111 1100	0110 1110

Application of Mutation for producing next generation

Before mutation the string is

1110 1000

After mutation the string becomes

1100 1010

New population for the second iteration

Elite child

0110 1010

Crossover children

0010 0110

0101 1001

0010 1010

0110 1000

0011 1000

1100 1010

Muted child

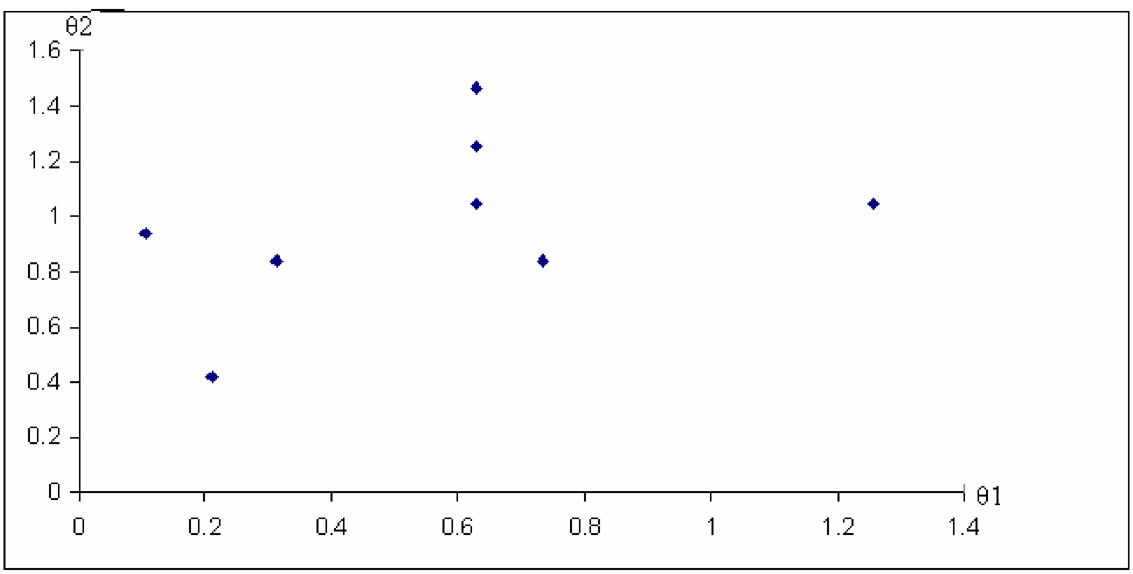
1100 1110

Table-2 Problem continuation (Iteration –2)

Population No.	Initial population	θvalues θ1 θ2	F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette wheel
1	0010 0100	12 24	3.15	0.097	0.777	0
2	0001 1001	6 54	3.79	0.116	0.935	1
3	0011 1000	18 48	4.25	0.131	1.049	1
4	0110 1100	36 72	4.62	0.142	1.140	1
5	0111 1000	42 48	4.44	0.136	1.096	1
6	0110 1110	36 84	4.39	0.135	1.083	1
7	**0110 1010**	**36 60**	**4.66**	**0.143**	**1.150**	**1**
8	1100 1010	72 60	3.12	0.096	0.770	0
Sum			32.42			
average			4.05			

To find best fitness value, graph has been plotted form table-2 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 2. Contours of equal objective function



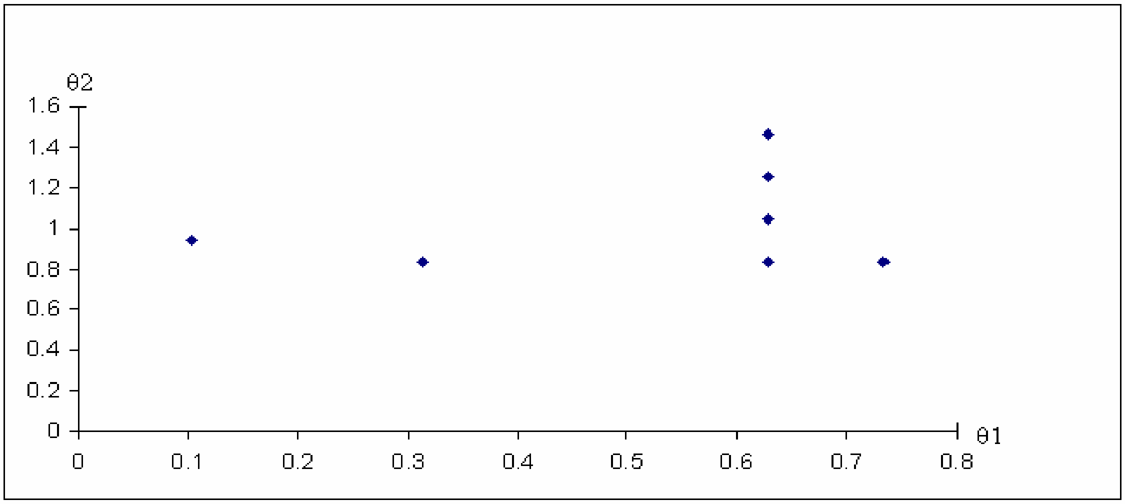
Similarly, as observe from 2-D plot that there are many fitness values so the objective function are unable to predict the best fitness value. Hence scatter points are moving to next generation for finding the best fitness value.

Table-3 Problem continuation (Iteration –3)

Population No.	Initial population	θvalues θ1 θ2		F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette wheel
1	0011 1000	18	48	4.27	0.120	0.964	0
2	0111 1000	42	48	4.44	0.125	1.096	1
3	0110 1100	36	72	4.62	0.130	1.104	1
4	0110 1110	36	84	4.39	0.124	0.992	1
5	0110 1110	36	84	4.39	0.124	0.992	1
6	0110 1000	36	48	4.51	0.127	0.997	1
7	**0110 1010**	**36**	**60**	**4.66**	**0.131**	**0.105**	**1**
8	0001 1001	6	54	3.79	0.107	0.850	0
Sum				35.4			
Average				4.425			

To find best fitness value, graph has been plotted form table-3 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 3. Contours of equal objective function



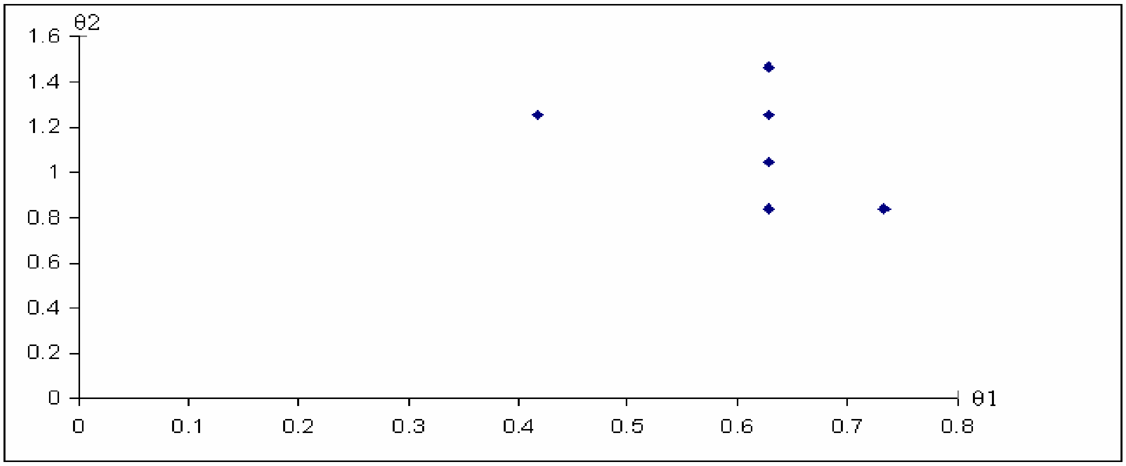
On comparing this plot again with previous, it is observed that the points are closer to each other and also that this plot is better than the previous plot. However from this too, the best fitness value cannot be predicted. Hence another generation is chosen and selection of population for the next generations similarly is done.

Table-4 Problem continuation (Iteration –4)

Population No.	Initial population	θvalues θ1 θ2		F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette Wheel
1	0110 1000	36	48	4.51	0.124	0.997	1
2	0111 1000	42	48	4.44	0.122	0.982	0
3	0110 1000	36	48	4.51	0.124	0.997	1
4	0110 1100	36	72	4.62	0.127	1.022	1
5	0110 1110	36	84	4.39	0.121	0.971	0
6	0110 1000	36	48	4.51	0.124	0.997	1
7	**0110 1010**	**36**	**60**	**4.66**	**0.128**	**1.030**	**1**
8	0100 1100	24	72	4.52	0.125	1.000	1
Sum				36.16			
average				4.52			

To find best fitness value, graph has been plotted form table-4 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 4. Contours of equal objective function



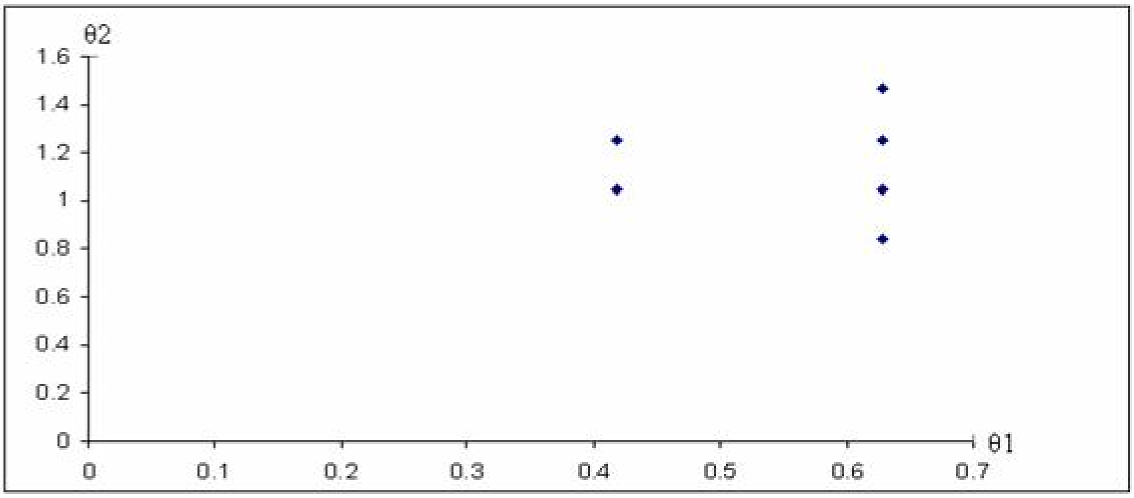
The figure shown cannot decide the best fitness value of the objective function but we get better contours of equal objective function because the scattering and diversity among points is reduced. Hence, it is required to move to next generation for finding the best fitness and similarly selection of population for the next generations.

Table-5 Problem continuation (Iteration –5)

Population No	Initial population		θvalues θ1	θ2	F= -f-7	P select (F/FΣ)	Expected Count (F/avgF)	Actual count From roulette Wheel
1	0110	1110	36	84	4.39	0.1610	0.966	0
2	0110	1000	36	48	4.51	0.1654	0.993	1
3	0110	1100	36	72	4.62	0.1694	1.107	1
4	0100	1100	24	72	4.56	0.1672	1.004	1
5	**0110**	**1010**	**36**	**60**	**4.66**	**0.1701**	**1.026**	**1**
6	0100	1010	24	60	4.52	0.1658	0.995	1
Sum					27.26			
Average					4.54			

To find best fitness value, graph has been plotted form table-5 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 5. Contours of equal objective function



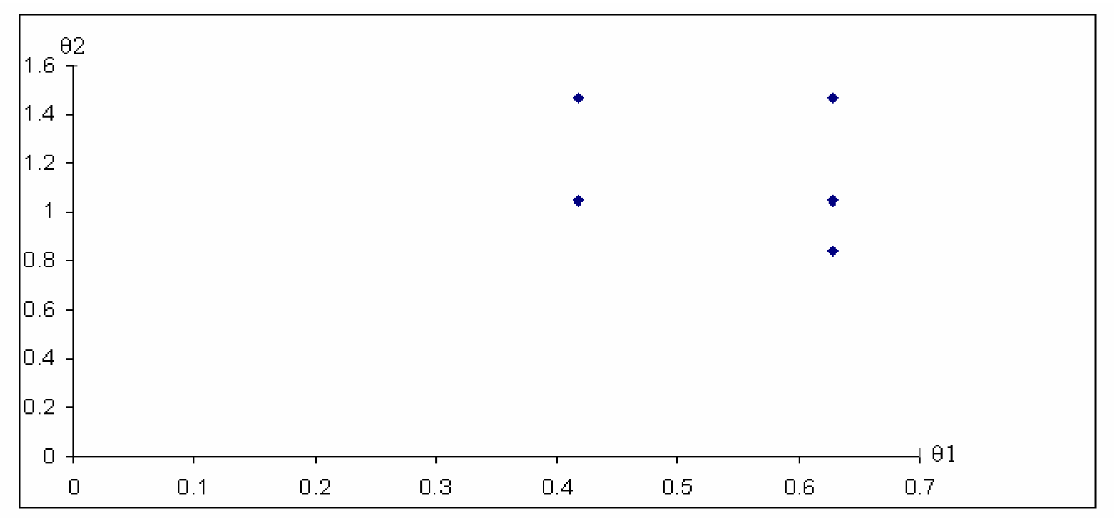
Similarly, this figure cannot decide the best fitness value of the objective function but there are better contours of equal objective function because the scattering and diversity among points is reduced. Hence, it is desirable move to next generation for finding best fitness and selection of population for the next generation

Table-6 Problem continuation (Iteration–6)

Population no	Initial population	θvalues θ1 θ2	F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette Wheel
1	0110 1110	36 84	4.39	0.163	0.979	0
2	0110 1000	36 48	4.51	0.167	1.006	1
3	0110 1000	36 48	4.51	0.167	1.006	1
4	0100 1110	24 84	4.29	0.159	0.957	0
5	**0110 1010**	**36 60**	**4.66**	**0.173**	**1.040**	**1**
6	0100 1010	24 60	4.52	0.168	1.008	1
Sum			26.88			
Average			4.48			

To find best fitness value, graph has been plotted form table-6 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 6. Contours of equal objective function



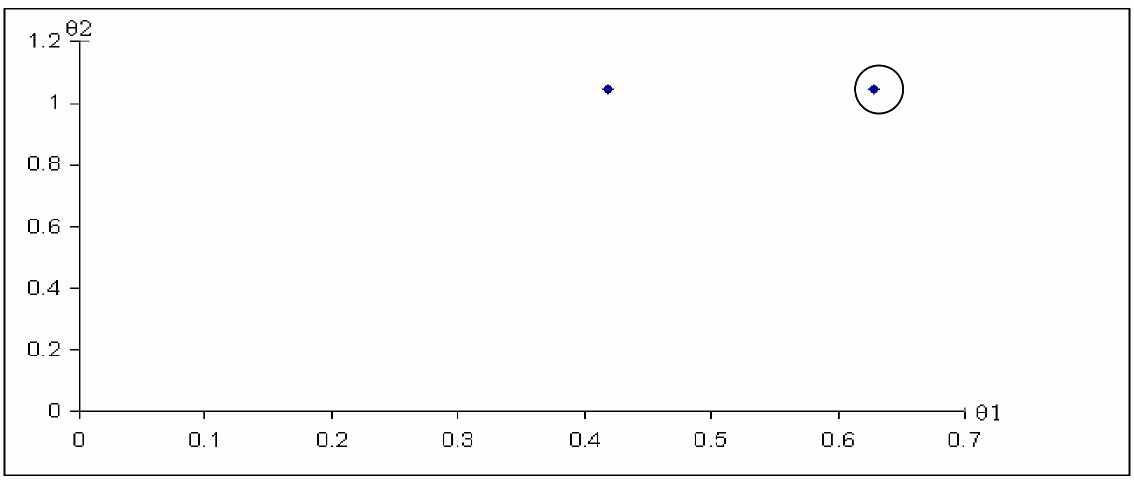
Similarly, this figure cannot decide the best fitness value of the objective function but there are better contours of equal objective function because the scattering and diversity among points is reduced. Hence, it is desirable move to next generation for finding best fitness and selection of population for the next generation.

Table-7 Problem continuation (Iteration –7)

Population no	Initial population	θvalues θ1 θ2	F= -f-7	P select (F/ΣF)	Expected Count (F/avgF)	Actual count From roulette Wheel
1 2	**0110 1010** 0100 1010	**36 60** 24 60	**4.66** 4.52	**0.508** 0.491	**1.015** 0.984	**1** 0
Sum			9.18			
average			4.59			

To find best fitness value, graph has been plotted form table-7 between population θ_1 (X-axis) and θ_2 (Y-axis).

Fig 7. Contours of equal objective function



From the above graph observation can be made that the points are reduced to two, among then best fitness value is choosen based on the column actual count from roulette wheel in table 7. If it is one then that point will choosen as best fitness value accordingly that point has been marked circle as shown in the above graph.

RESULTS

If there are numerous fitness values that are scattered far away and decision for best fitness value is difficult then we continue to next generation until decision best fitness value can be made from the graph.

APPENDIX – II

IEEE 5- Bus test system

Table-1 Impedance data

Line Destination	*R p.u.	*X p.u.	Line Charging
1-2	0.10	0.4	0.0
1-4	0.15	0.6	0.0
1-5	0.05	0.2	0.0
2-3	0.05	0.2	0.0
2-4	0.10	0.4	0.0
3-5	0.05	0.2	0.0

*The impedance are based on MVA as 100.

Table-2 Operating condition

Bus no.	Generation		Load	
	MW	Voltage magnitude	MW	MVAR
1	…	1.02	…	…
2	…	…	60	30
3	100	1.04	…	…
4	…	…	40	10
5	…	…	60	20

.

* Slack bus

Table-3 Regulated bus data

Bus no.	Voltage magnitude	Minimum MVAR capability	Maximum MVAR capability	Minimum MW capability	Maximum MW capability
1	1.02	0.0	60	30	120
2	1.04	0.0	60	30	120

The nodal load voltage inequality is $0.9 \leq |V_i| \leq 1.05$.

Cost characteristics

$C_1 = 50P_1^2+245P_1+105$ \$/hr

$C_2 = 50P_2^2+351P_2+44.4$ \$/hr

Here for the 5 bus system we have taken, the total load demand of the system is 160 MW. Maximum and minimum active power constraint on the generator bus for the given system is 120 MW and 30 MW respectively. Voltage magnitude constraint for generator bus 3 is 1.04.

B-coefficients of 5 bus system

B_{11} = 0.00035336

B_{12} = 0.0000103196

B_{21} = 0.0000103196

B_{22} = 0.000368992

IEEE 14- Bus test system

Table- 4 Impedance and line charging data

Line destination	Resistance p.u.*	Reactance p.u.*	Line charging p.u.*
1-2	0.01938	0.05917	0.0264
1-5	0.05403	0.22304	0.0246
2-3	0.04699	0.19797	0.0219
2-4	0.05811	0.17632	0.0187
2-5	0.05695	0.17388	0.0170
3-4	0.06701	0.17103	0.0173
4-5	0.01335	0.04211	0.0064
4-7	0.0	0.20912	0.0
4-9	0.0	0.55618	0.0
5-6	0.0	0.25202	0.0
6-11	0.09498	0.19890	0.0
6-12	0.12291	0.25581	0.0
6-13	0.06615	0.13027	0.0
7-8	0.0	0.17615	0.0
7-9	0.0	0.11001	0.0
9-10	0.03181	0.08450	0.0
9-14	0.12711	0.26038	0.0
10-11	0.08205	0.19207	0.0

12-13	0.22092	0.19988	0.0
13-14	0.17093	0.34802	0.0

* Impedance and line-charging susceptance in p.u. on a 100 MVA base. Line charging one-half of total charging of line.

Table-5 Operating conditions

Bus no.	Starting bus voltage Magnitude p.u.	Phase Angle deg	Generation MW	Generation MVAR	Load MW	Load MVAR
1*	1.06	0.0	0.0	0.0	0.0	0.0
2	1.0	0.0	40	0.0	21.7	12.7
3	1.0	0.0	0.0	0.0	94.2	19.0
4	1.0	0.0	0.0	0.0	47.8	-3.9
5	1.0	0.0	0.0	0.0	7.6	1.6
6	1.0	0.0	0.0	0.0	11.2	7.5
7	1.0	0.0	0.0	0.0	0.0	0.0
8	1.0	0.0	0.0	0.0	0.0	0.0
9	1.0	0.0	0.0	0.0	29.5	16.6
10	1.0	0.0	0.0	0.0	9.0	5.8
11	1.0	0.0	0.0	0.0	3.5	1.8
12	1.0	0.0	0.0	0.0	6.1	1.6

13	1.0	0.0	0.0	0.0	13.5	5.8
14	1.0	0.0	0.0	0.0	14.9	5.0

*Slack bus

TABLE-6 Regulated bus data

Bus number	**Voltage Magnitude, p.u.**	**Minimum MVAR capability**	**Maximum MVAR capabilty**
2	1.045	-40	50
3	1.010	0	40
6	1.070	-6	24
8	1.090	-6	24

Cost characteristics

$C_1 = 50P_1^2+245P_1+105$ $/hr

$C_2 = 50P_2^2+351P_2+44.4$ $/hr

$C_6 = 50P_6^2+389P_6+40.6$ $/hr

B-coefficients of 14 bus system

B_{11} = 0.0231

B_{12} = 0.0078

B_{13} = -0.0007

B_{21} = 0.0078

B_{22} = 0.0182

B_{23} = 0.0022

B_{31}= -0.0007

B_{32} = 0.0022

B_{33} = 0.0329

IEEE 30- Bus test system

Table- 7 Impedance and line charging data

Line destination	Resistance p.u.*	Reactance p.u.*	Line charging p.u.*
1-2	0.0192	0.0575	0.0264
1-3	0.0452	0.1852	0.0204
2-4	0.0570	0.1737	0.0184
3-4	0.0132	0.0379	0.0042
2-5	0.0472	0.1983	0.0209
2-6	0.0581	0.1763	0.0187

4-6	0.0119	0.0414	0.0045
5-7	0.0460	0.1160	0.0102
6-7	0.0267	0.0820	0.0085
6-8	0.0120	0.0420	0.0045
6-9	0.0	0.2080	0.0
6-10	0.0	0.5560	0.0
9-10	0.0	0.2080	0.0
9-11	0.0	0.1100	0.0
4-12	0.0	0.2560	0.0
12-13	0.0	0.1400	0.0
12-14	0.1231	0.2559	0.0
12-15	0.0662	0.1304	0.0
12-16	0.0945	0.1987	0.0
14-15	0.2210	0.1997	0.0
16-17	0.0824	0.1923	0.0
15-18	0.1070	0.2185	0.0
18-19	0.0639	0.1292	0.0
19-20	0.0340	0.0340	0.0
10-20	0.0936	0.0936	0.0
10-17	0.0324	0.0324	0.0
10-21	0.0348	0.0348	0.0
10-22	0.0727	0.0727	0.0
21-22	0.0116	0.0116	0.0

15-23	0.0100	0.1000	0.0
22-24	0.1150	0.1150	0.0
23-24	0.1320	0.1320	0.0
24-25	0.1885	0.1885	0.00.0
25-26	0.2544	0.2544	0.0
25-27	0.1093	0.1093	0.0
27-28	0.0	0.0	0.0
27-29	0.2198	0.2198	0.0
27-30	0.3202	0.3202	0.0
29-30	0.2399	0.2399	0.0
8-28	0.0636	0.0636	0.0214
6-28	0.0169	0.0169	0.0065

* Impedance and line-charging susceptance in p.u. on a 100 MVA base. Line charging one-half of total charging of line.

Table-8 Operating conditions

Bus no.	Starting bus voltage Magnitude p.u.	Phase Angle deg	Generation MW	MVAR	Load MW	MVAR
1*	1.06	0	0	0	0	0
2	1.0	0	40	0	217	12.7
3	1.0	0	0	0	2.4	1.2
4	1.0	0	0	0	7.6	1.6
5	1.0	0	0	0	94.2	19.0
6	1.0	0	0	0	0	0
7	1.0	0	0	0	22.8	10.9
8	1.0	0	0	0	30	30.0
9	1.0	0	0	0	0	0
10	1.0	0	0	0	5.8	2.0
11	1.0	0	0	0	0	0
12	1.0	0	0	0	11.2	7.5
13	1.0	0	0	0	0	0
14	1.0	0	0	0	6.2	1.6
15	1.0	0	0	0	8.2	2.5
16	1.0	0	0	0	3.5	1.8
17	1.0	0	0	0	9	5.8

18	1.0	0	0	0	3.2	0.9
19	1.0	0	0	0	9.5	3.4
20	1.0	0	0	0	2.2	0.7
21	1.0	0	0	0	17.5	11.2
22	1.0	0	0	0	0	0
23	1.0	0	0	0	3.2	1.6
24	1.0	0	0	0	8.7	6.7
25	1.0	0	0	0	0	0
26	1.0	0	0	0	3.5	2.3
27	1.0	0	0	0	0	0
28	1.0	0	0	0	0	0
29	1.0	0	0	0	2.4	0.9
30	1.0	0	0	0	10.6	1.9

*Slack bus

Table-9 Regulated bus data

Bus number	Voltage Magnitude, p.u.	Minimum MVAR capability	Maximum MVAR capabilty
2	1.045	-40	50
5	1.01	-40	40
8	1.01	-10	40
11	1.082	-6	24
13	1.071	-6	24

Table-10 Transformer Data

Transformer destination	Tap setting
4-12	0.932
6-9	0.978
6-10	0.969
28-27	0.968

Table-11 Static capacitor data

Bus no.	Susceptance* p.u.
10	0.19
24	0.043

*Susceptance in p.u. on 100 MVA base.

Cost characteristics

$C_1 = 50P_1^2+245P_1+105$ $/hr

$C_2 = 50P_2^2+351P_2+44.4$ $/hr

$C_8 = 50P_8^2+389P_8+40.6$ $/hr

B-coefficients of 30 bus system

$B_{11} = 0.0307$

$B_{12} = 0.0129$

$B_{13} = -0.0002$

$B_{21} = 0.0129$

$B_{22} = 0.0152$

$B_{23} = 0.0011$

$B_{31} = -0.0002$

$B_{32} = 0.0011$

$B_{33} = 0.0190$

APPENDIX-III

Mathematical statement of noninferiority

Single objective problems are characterized by complete ordering of their feasible solution. Any two feasible solutions X1 and X2 are comparable in terms of the objective function; i.e. either

$Z(X_1) = Z(X_2)$, $Z(X_1) > Z(X_2)$, $Z(X_1) > Z(X_2)$.

This comparison can be made for all the feasible solutions, and the solution X* for which their exists no other solution X such that Z(X) < Z(X*) is called optimal for solution for a minimization problem. But, in multiobjective problems, it is not possible to compare all the feasible solutions because the comparison on the basis of one objective function may contradict the comparison based on another objective function. Suppose there are two objective functions,

$Z(X) = [Z^1(X), Z^2(X)]$

And two solutions X1, X2. Then,

$Z(X^1) = [Z_1(X^1), Z_2(X^1)]$

$Z(X^2) = [Z_1(X^2), Z_2(X^2)]$

X^1 is better than X^2 if

$Z_1(X^1) < Z_2(X^2)$ and $Z_2(X^1) \leq Z_2(X^2)$

or

$Z_1(X^1) \leq Z_2(X^2)$ and $Z_2(X^1) < Z_2(X^2)$

But if $Z_1(X^1) < Z_2(X^2)$ and $Z_2(X^1) > Z_2(X^2)$, then nothing can be said about the two solutions - X^1, X^2, i.e. they are incomparable. This is what is meant by partial ordering. All solutions are not comparable on the basis of the values of objective functions only. Since a complete order is not available, the notion of optimality must be dropped.

The partial ordering in multiobjective problems does allow some feasible solutions to be eliminated. Inferior solutions, which are dominated by at least one feasible solution, may be dropped. Noninferior solutions are the alternatives of interest.

Mathematically, a solution X is noninferior for a minimization problem if there exists no feasible Y such that

$Z_K(Y) \leq Z_K(X)$ $\forall$ K = 1,2, ………..., h

And

$Z_K(Y) < Z_K(X)$ for at least one K= 1,2,………h

The noninferior set generally includes many alternatives, all of which obviously cannot be selected. The objectives must be traded off against other in moving from one noninferior alternative to another and a strategy has to be adopted by the analyzer to achieve optimum values as per his satisfaction level and requirements. The preferred alternative is called the Target Point or the best – compromise solution.

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