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Investigation of Transmission Expansion Planning Using Genetic Algorithm

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***Abstract*— This paper presents a cost effective solution to static transmission planning problem in the deregulated power system environment under non-random uncertainties. It is proposed to develop the methodology using Genetic Algorithm (GA).The methodology so developed shall be applied to Graver's six-bus network to check its effectives. The methodology then shall be applied to the problem by including losses in transmission line expansion. The major contribution of this thesis is optimized cost and improves efficiency static transmission power system like Graver six-bus network under Deregulated environment (handling only non-random uncertainties) by using Genetic Algorithm**

Index Terms*— Transmission system, Transmission expansion planning, Genetic Algorithm, Power flow.

I. INTRODUCTION

Electricity is backbone for almost all economic activities in present times and it is a proven fact that access of this precious perishable commodity to people bears direct impact on pace of development of the country. The power system is the interconnection of generating unit to the load pass through high voltage electric transmission line and in general it's controlled by a mechanical system. The power system can be divided into several parts like generation, substation and distribution. Generation part is the main source that supply to the load. In this area the value of voltage is about 132 kV and above. While the substation make a function like medium channel. It's used transmits the power from the generation to the load. At this area the value of voltage that used is about 11kV and 66 kV. Then the distribution part is the load. The voltage flow is 240V for the single phase and 415V for three phases. Transmission lines that also interconnect neighboring utilities permit economic power dispatch across regions during normal conditions as well as the transfer of power between regions during emergency. Over the past few decades, the amount of electric power energy to be transferred from generation sites to major load areas has been growing dramatically. Due to increasing costs and the essential need for reliable electric power systems, suitable and optimal design methods for different sections of the power system are required. Transmission systems are a major part of any power system therefore they have to be accurately and efficiently planned. With rapid industrialization and increasing population the demand for electricity is increasing day by day.

Existing power system is expanding due to increased demand and becoming more complex with different types of loads and generation from varied and distributed resources and with new technology and restructuring of electrical power system adds to the complexity of the modern power system. In this research, electric power transmission systems are studied with regard to optimizing the transmission expansion planning (TEP) problem. Expansion of power system along with restructuring and deregulation the complexity of system is increasing continuously.

The remaining part of the paper is organized as follows. Section II Treatment of the Transmission Expansion Planning and DC Power flow. Section III represent the overview about Genetic Algorithm Optimization Technique. Section IV presents the Application of GA for Transmission Network Expansion Planning. Section V presents the Case Study. Results is presented in Section VI. Finally conclusion is drawn in Section VII.

II. TREATMENT OF THE TRANSMISSION EXPANSION PLANNING AND DC POWER FLOW

A. Treatment of the Transmission Expansion Planning

Based on the treatment of planning horizon, transmission expansion planning can be traditionally classified into two categories, namely static (single-stage) and dynamic (multi-stage) planning. In static planning, only a single time period is considered as a planning horizon. In contrast, dynamic planning considers the planning horizon by separating the period of study into multiple stages [1]. For static planning, the planner searches for an appropriate number of new circuits that should be added into each branch of the transmission system and in this case, the planner is not interested in scheduling when the new lines should be constructed and the total expansion investment is carried out at the beginning of the planning horizon [2]. Many research works regarding the static TEP are presented in [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13] that are solved using a variety of the optimisation techniques.

In contrast, time-phased or various stages are considered in dynamic planning while an optimal expansion schedule or strategy is considered for the entire planning period. Thus, multistage transmission expansion planning is a larger-scale and more complex problem as it deals with not only the optimal quantity, placement and type of transmission expansion investments but also the most suitable times to carry out such investments. Therefore, the dynamic transmission expansion planning inevitably considers a great number of variables and constraints that consequently require enormous computational effort to achieve an optimal solution, especially for large-scale real-world transmission systems. Many research work regarding the dynamic TEP [14, 15, 16, 17, 18, and 19] are presented some of the dynamic models that have been developed.

B. DC Power Flow

For a long-term TEP study, some assumptions are made and introduced for solving such planning problem, for example, a consideration of the reactive power allocation is neglected in the first moment of the planning. In this stage, the main concern is to identify the principal power corridors that probably will become part of the expanded system. There are several types of the mathematical model employed for representing the transmission network in the TEP study; AC power flow model, DC power flow model, transportation model, hybrid model, and disjunctive model [4].

Basically, the DC power flow model is widely employed to the TEP problem and it is frequently considered as a reference because in general, networks synthesized by this model satisfy the basic conditions stated by operation planning studies. The planning results found in this phase will be further investigated by operation planning tools such as AC power flow analysis, transient and dynamic stability analysis and short-circuit analysis [20]. In the simulation of this research, the DC power flow model is considered as it is widely used in transmission expansion planning [3, 4, 10, and 11].

The formulation of DC power flow is obtained from the modification of a general representation of AC power flow, which can be illustrated by the following equations.

$$Pi= | V_i | \sum_{k=0}^{n} 1 | V_k | \, [G_{ik} \cos(\Theta_i - \Theta_k) + B_{ik} \sin(\Theta_i - \Theta_k)] \quad \ldots (1)$$

$$Qi= | V_i | \sum_{k=0}^{n} 1 | V_k | \, [G_{ik} \cos(\Theta_i - \Theta_k) - B_{ik} \sin(\Theta_i - \Theta_k)] \quad \ldots\ldots(2)$$

Where P_i and Q_i are real and reactive power of bus i respectively. V_i and i are voltage magnitude and votage phase angle of bus i respectively. V_k is voltage magnitude at bus k. G_{ik} and B_{ik} are real and imaginary parts of element (i,k) of bus admittance matrix respectively. N is total number of buses in the system.

To modify AC power flow model to the DC power flow based model, the following assumptions are normally considered [22]:

- Bus voltage magnitude at each bus bar is approximate one per unit (Vi = 1 p.u. for all i buses);
- Line conductance at each path is neglected (G_{ik} = 0), or on the other hand only line susceptance (B_{ik}) is considered in the DC model;
- Some trigonometric terms of AC model in equations (1) and (2) can be
  $\sin(\theta_i - \theta_k) \approx (\theta_i - \theta_k)$ and $\cos(\theta_i - \theta_k) \approx 1$

Given these assumptions, the AC power flow equation in (1) is therefore simplified to yield the DC power flow equation as follows:

$$P_i = \sum_{k=0}^{n} B_{ik} \, Sin(\theta_i - \theta_k) \qquad (3)$$

Where B_{ik} is the line susceptance between bus i and k.

III. GENETIC ALGORITHM

A Genetic Algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. Genetic algorithms are categorized as global search heuristics. Genetic algorithms are a particular class of Evolutionary Algorithms (EA) that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover.

Genetic algorithms are implemented in a computer simulation in which a population of abstract representations (called chromosomes or the genotype of the genome) of candidate solutions (called individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. Traditionally, solutions are represented in binary as strings of 0s and 1s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population. If the algorithm has terminated due to a maximum number of generations, a satisfactory solution may or may not have been reached.

Genetic algorithms find application in bioinformatics, phylogenetics, computational science, engineering, economics, chemistry, manufacturing, mathematics, physics and other fields.

A typical genetic algorithm requires:

1. A genetic representation of the solution domain,
2. A fitness function to evaluate the solution domain.

A standard representation of the solution is as an array of bits. Arrays of other types and structures can be used in essentially the same way. The main property that makes these genetic representations convenient is that their parts are easily aligned due to their fixed size, which facilitates simple crossover operations. Variable length representations may also be used, but crossover implementation is more complex in this case. Tree-like representations are explored in genetic programming and graph-form representations are explored in evolutionary programming.

The fitness function is defined over the genetic representation and measures the *quality* of the represented solution. The fitness function is always problem dependent. For instance, in the knapsack problem one wants to maximize the total value of objects that can be put in a knapsack of some fixed capacity. A representation of a solution might be an array of bits, where each bit represents a different object, and the value of the bit (0 or 1) represents whether or not the object is in the knapsack. Not every such representation is valid, as the size of objects may exceed the capacity of the knapsack. The *fitness* of the solution is the sum of values of all objects in the knapsack if the representation is valid or 0 otherwise. In some problems, it is hard or even impossible to define the fitness expression; in these cases, interactive genetic algorithms are used.

Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover, inversion, and selection operators.

A. Initialization

Initially many individual solutions are randomly generated to form an initial population. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions. Traditionally, the population is generated randomly, covering the entire range of possible solutions (the *search space*). Occasionally, the solutions may be "seeded" in areas where optimal solutions are likely to be found.

B. Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a *fitness-based* process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. Certain selection methods rate the fitness of each solution and preferentially select the best solutions. Other methods rate only a random sample of the population, as this process may be very time-consuming.

Most functions are stochastic and designed so that a small proportion of less fit solutions are selected. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection

C. Reproduction

population of solutions from those selected through genetic operators: crossover (also called recombination), and/or mutation.

For each new solution to be produced, a pair of "parent" solutions is selected for breeding from the pool selected previously. By producing a "child" solution using the above methods of crossover and mutation, a new solution is created which typically shares many of the characteristics of its "parents". New parents are selected for each new child, and the process continues until a new population of solutions of appropriate size is generated. Although reproduction methods that are based on the use of two parents are more "biology inspired," some research suggests more than two "parents" are better to be used to reproduce a good quality chromosome.

These processes ultimately result in the next generation population of chromosomes that is different from the initial generation. Generally the average fitness will have increased by this procedure for the population, since only the best organisms from the first generation are selected for breeding, along with a small proportion of less fit solutions, for reasons already mentioned above

D. Termination

This generational process is repeated until a termination condition has been reached. Common terminating conditions are:

- A solution is found that satisfies minimum criteria
- Fixed number of generations reached
- Allocated budget (computation time/money) reached
- The highest ranking solution's fitness is reaching or has reached a plateau such that successive iterations no longer produce better results
- Manual inspection
- Combinations of the above

Simple generational genetic algorithm pseudo code

1. Choose the initial population of individuals
2. Evaluate the fitness of each individual in that population
3. Repeat on this generation until termination: (time limit, sufficient fitness achieved, etc.)
   a) Select the best-fit individuals for reproduction
   b) Breed new individuals through crossover and mutation operations to give birth to offspring
   c) Evaluate the individual fitness of new individuals

Replace least-fit population with new individuals

IV. Application of GA for Transmission Network Expansion Planning

GA's theory has been extensively presented in several papers in recent years covering a number of applications in power systems. It is a robust optimization technique that works above a set of candidate solutions (individuals) named population and performs a number of operations based on genetic mechanical. Such operators recombine the information contained in the individuals to create new populations.

GA uses a selection mechanism whose main objective is to select 'good' individuals from the current population and inserting them into a mating pool.

Besides the well-known basic GAs operating principles, several modifications and improvements, considered critical to the performance of the optimization process, have been applied with success as a way to make possible the solution of the different problems.

A. The Representation

The most natural representation to adopt for the STNEP, but not the only one, is assigning one *gene* for each transmission route along the power system, whether existing or candidate. Such type of representation could be called as *Decimal representation*. An *allele* corresponds to the number of additions in a specific transmission route as shown in Figure 1, where only circuits 29–32 are presented. According to this representation, an individual with all genes equal to zero represents the existing transmission network.

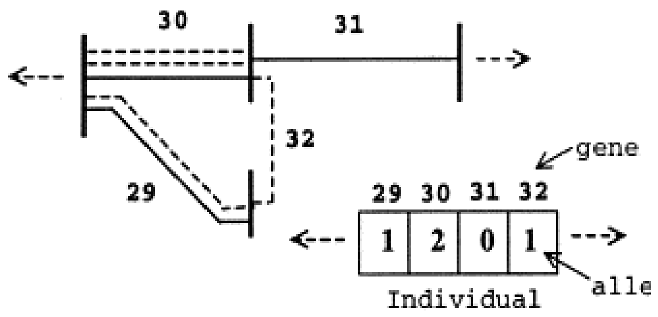

Figure 1 Individual representing a transmission system

B. The Fitness Function

This function is responsible for measuring the quality of the individuals and is completely related to the objective function *f*. The lower the objective function value evaluated for an individual, the higher its quality. Several fitness functions *F* may be used, depending on the problem. The two fitness functions most frequently used are $F=K_1/f$; usually $K_1=1$ and, $F=K_2-f$; K_2 must be large enough for *F* to be positive. Tests performed indicated that there is no significant difference between the GA's performance using either one of the two fitness functions. As was stated before, the objective function is composed of two terms, corresponding to the investment and loss of load costs. The first term may be calculated easily, but the second one requires the solution of a liberalized optimum power flow (problem (2)), so that the respective loss of load for a particular configuration can be evaluated. This value must be then multiplied by the current value of the penalty factor α.

C. The Selection Mechanism

The selection or sampling mechanism begins the creation of the mating pool by selecting individuals from de current population.

A number of selection mechanisms have been implemented with success and all of them are attempts to achieve the correct balance between the population diversity and selective pressure, which are fundamental issues in the genetic exploration, since a low selective pressure makes the search ineffective, and a high selective pressure or deficient population diversity may lead to a premature convergence.

In this GA used in Paper, the *Tournament Selection* technique was used. It is a simple but efficient method of sampling that consists of randomly selecting a predefined number of individuals (tournament or window size *s*) and then, picks from this sample the one with the largest fitness value. This process is repeated *N* times (being *N* the population size). Large values of *s* increase selective pressure and, therefore, increase the chance of the GA converging prematurely to a sub-optimal solution [23]. The main advantage of this mechanism is the possibility of controlling the selective pressure, so that the tournament size is a critical parameter for the performance of the GA. Tournament Selection does not require the implementation of any scaling or ranking method because it just requires the relative differences of the fitness values between the selected individuals.

D. The Crossover Mechanism

Through this mechanism, the genetic information contained in the individuals belonging to the mating pool is exchanged. The crossover is usually not applied to all pairs of individuals, however, for the STNEP problem, it is important to stimulate a higher exchange of genetic information among the individuals by using a large crossover rate value with respect to the one used in another GA application which is about 0.5. In this work, the two-point crossover technique has been adopted. It has been referenced as a fairly suitable crossover technique [40].

E. The Mutation Mechanism

From the viewpoint of genetic diversity, this mechanism is especially important to prevent the permanent loss of any allele. After several generations, it could be possible for a given gene to have the same allele in all the individuals. The mutation mechanism might restore missed alleles, leading the search to regions possibly not yet explored, acting as a source of diversity [25] .If a given gene is selected for mutation, its respective allele is swapped to another random-chosen value. A Simulated Annealing approach, similar to the one presented in [26], has been implemented in this work in order to enhance the mutation mechanism.

F. The Stopping Criterion

There are several strategies for stopping the evolution process of a GA. In this work, the GA has stopped, when it reached a predefined number of generations or when the best individual of the population did not change within a predefined number of generations.

G. The Initial Population

The initial population is built randomly starting from a *head individual* calculated by the solution of the expansion problem (1) but using continuous variables rather than integer. Although the best individual generated is often unfeasible, the genetic quality of the population thus generated is high

V. CASE STUDY

This objective of this work is to find a cost effective and an efficient solution to static transmission planning problem in the deregulated power system environment under non-random uncertainties. The cost of loss is depending on the current flowing in network and bus. while current depend on connected load of alternative plans and arrangement of network. We have taken different current constraint for different plans according to network arrangement. The methodology so developed shall be applied to Graver's six-bus network to check its effectives and optimized the cost of loss.

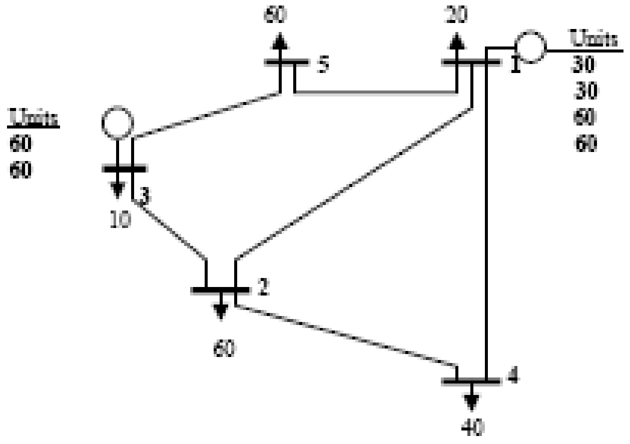

Figure 2 Existing Generation and Transmission System

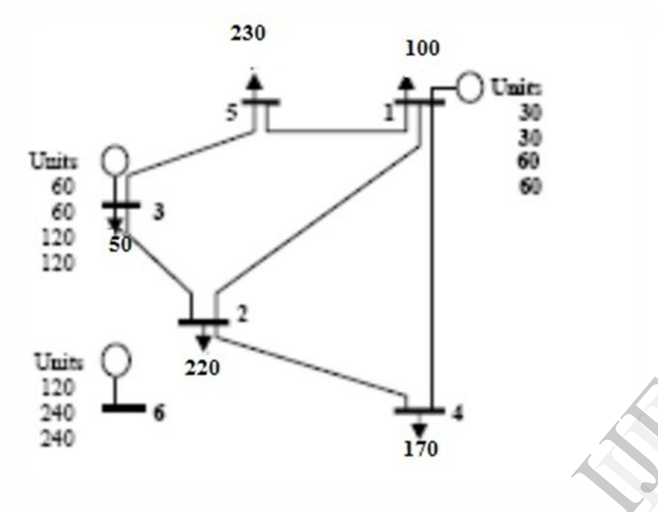

Figure 3 Existing Network with Future Load and Generation

TABLE I PLANS OF ADDER NETWORK

Plan No.	Bus 1-5 Adder Circuit	Bus 2-6 Adder Circuit	Bus 3-5 Adder Circuit	Bus 4-6 Adder Circuit
A1	0	4	1	2
A2	0	3	1	3
A3	0	5	1	1
A4	1	4	0	2
A5	1	3	0	3

TABLE II CONSTRUCTION OF THE NETWORK

From Bus	To Bus	Length(km)	Resistance(Ω)	Reactance(Ω)
1	2	90	0.012	0.04
1	3	100	0.0114	0.038
1	4	120	0.018	0.06
1	5	70	0.0072	0.024
1	6	180	0.0204	0.068
2	3	70	0.0066	0.022
2	4	140	0.0132	0.044
2	5	60	0.0078	0.026
2	6	90	0.009	0.03
3	4	125	0.0186	0.062
3	5	40	0.006	0.02
3	6	130	0.0144	0.048
4	5	170	0.01884	0.0628
4	6	85	0.0102	0.034
5	6	140	0.0192	0.64

Resistance and leakage reactance per kilometer of each line are 0.00012Ω and 0.0004 Ω, respectively.

The methodology has been applied on Graver Six-bus Network with considering uncertainties (including losses in transmission line expansion) for optimization transmission Expansion planning total cost of alternatives plans and compare the result of each simulation to each other.

$$C_{loss}=loss*C_{mwh}*k_{loss}*8760 \quad (4)$$

$$Loss = \sum R_{ij}\, i_{ij}^{2} \quad (5)$$

$$\text{Objective function} = \sum C_{loss} \quad (6)$$

TABLE III ARRANGEMENT OF LOAD

Bus	Load(MW)	Bus	Load(MW)
1	100	4	170
2	220	5	230
3	50	6	0

TABLE IV CONSTRAINT CONDITION OF PLAN A1

Plan	A1
Current in 5-1 bus	16.33 Amp
Current in 3-5 bus	0.24 Amp
Current in 6-2 bus	22.69 Amp
Current in 6-4 bus	22.69 Amp

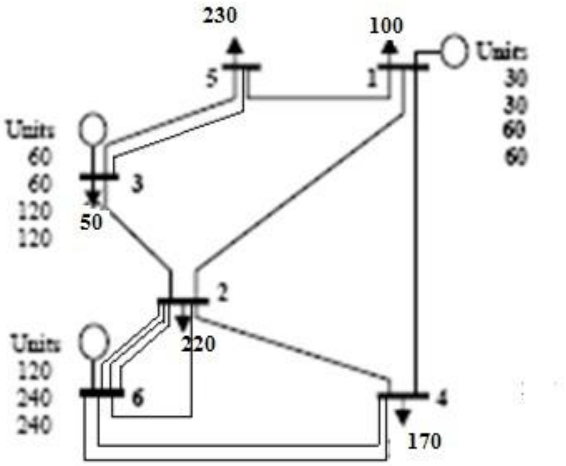

Figure 4 Construction View of Plan A1

TABLE V CONSTRAINT CONDITION OF PLAN A2

Plan	A2
Current in 5-1 bus	7.19 Amp
Current in 3-5 bus	13.23 Amp
Current in 6-2 bus	0.29 Amp
Current in 6-4 bus	0.29 Amp

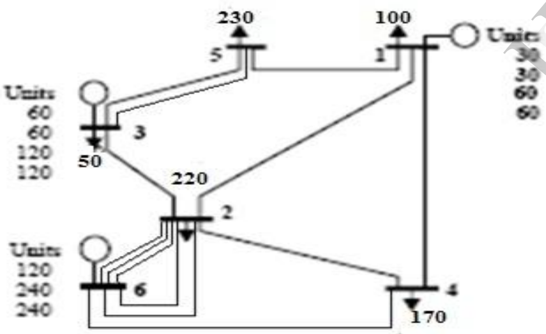

Figure 5 Construction View of Plan A2

TABLE VI CONSTRAINT CONDITION OF PLAN A3

Plan	A3
Current in 5-1 bus	15.21 Amp
Current in 3-5 bus	10.43 Amp
Current in 6-2 bus	0.27 Amp
Current in 6-4 bus	63.45 Amp

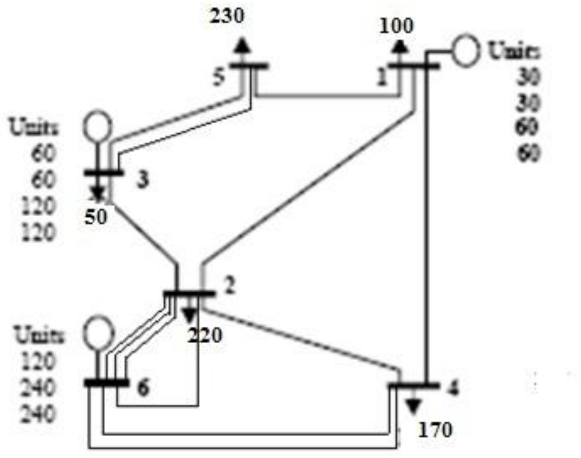

Figure 6 Construction View of Plan A3

TABLE VII CONSTRAINT CONDITION OF PLAN A4

Plan	A4
Current in 5-1 bus	12.07 Amp
Current in 3-5 bus	6.78 Amp
Current in 6-2 bus	61.68 Amp
Current in 6-4 bus	63.68 Amp

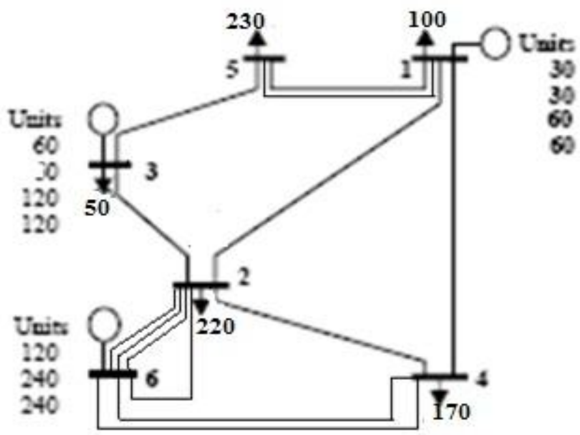

Figure 7 Construction View of Plan A4

TABLE VIII CONSTRAINT CONDITION OF PLAN A5

Plan	A5
Current in 5-1 bus	35.49 Amp
Current in 3-5 bus	62.39 Amp
Current in 6-2 bus	9.27 Amp
Current in 6-4 bus	8.19 Amp

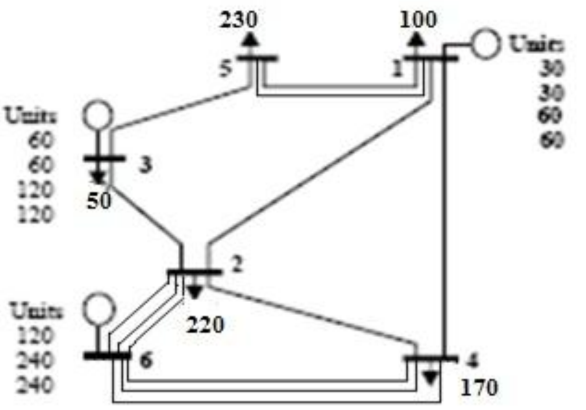

FIGURE 8 CONSTRUCTION VIEW OF PLAN A5

VI. RESULTS

Plan	Generation	f-count	f(x)	Best Mean
A1	41	6300	40.92	40.92
A2	39	6000	2.949	2.949
A3	51	7800	7.663	7.663
A4	51	7800	31.98	31.98
A5	51	7800	13.65	13.65

In the case study,

Graver Six-bus Network problem has been undertaken taking Uncertainties on account of transmission losses. The result has been obtained by using Methodology developed and compared with those available Table. These were found to be in good agreement. In both the case A2 plan has been found be most effective plan.

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