MULTI-YEAR SECURITY CONSTRAINED & HYBRID GENERATION-TRANSMISSION EXPANSION PLANNING

A Project Report

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by

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CERTIFICATE

This is to certify that the thesis entitled **"Multi-year Security Constrained & hybrid Generation-Transmission Expansion Planning Studies"** submitted by **Ajinkya Mane, (EE14M032)** to the **Indian Institute of Technology Madras** in partial fulfillment of the requirements for the award of the degree in **Master of Technology** in **Power system and Power Electronics** a bona-fide record of project work by him under my supervision.

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ABSTRACT

KEYWORDS: *Generation Expansion Planning; Transmission Expansion Planning; Differential Evolution*

The electric power industry had evolved over many decades, from a low power generator, serving a limited area, to highly interconnected networks, serving a large number of countries, or even continents. Nowadays, an electric power system is one of the man-made largest scale systems; ever made, comprising of huge number of components; starting from low power electric appliances to very high power giant turbo-generators. Running this very large system will be a real difficult task.

The objective of my project is to make task of power system planning convenient, reliable and affordable in future. Mainly work is to present GEP (generation expansion planning), TEP, single year, multiyear studies on garver system. It shows advantages of hybrid GEP-TEP with differential evolution algorithm.

The work presents comparison study of different cases which includes TEP with redispatch, with security constraint. It shows complexity of various models with differential evolution algorithm. Multiyear GEP with consideration of LOLP, fuel transport, depreciation cost has been done and shows worthiness of Differential evolution over improved genetic algorithm referred from literature. Further differtial algorithm has been used for static and dynamic planning of hybrid GEP-TEP studies. It shows superiority of dynamic power system planning over static power system planning. TEP studies have been done with consideration of power flow constraints, security constraint. To match results with practical system studies have been done with maximum possible constraint depending on availibity of data from IEEE papers.

Study has been done to propose differential evolution for higher order networks like 47 buses, 76 bus systems. Although DE will be slower for higher order systems but still can provide optimal solution, It can be used for global optimal solution i.e. substation expansion planning, GEP,TEP,REP simultaneously.

Results of garver network have been compared with convergence graph and proper analysis has been done.

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ABBREVIATION/ACRONYMS

GEP	Generation expansion planning
TEP	Transmission expansion planning
DE	Differtial Evolution
WASP	Wein automatic system planning
IAEA	International atomic energy agency
SEP	Substation expansion planning
FOR	Forced outage rate
LOLP	Loss of load probability
IGA	Improved genetic algorithm
DCLF	Direct current load flow

CHAPTER 1

INTRODUCTION

Power system has evolved and grown complex over the last few decades. From simple DC Transmission System to highly meshed AC grids and High Voltage Transmission; Power system can well be termed as the most complex man-made system till date and it is expanding fast. Power system studies in general can be broadly classified into operation and planning from a time-horizon perspective, where planning being the study that seeks to answer the decisions to be made for the long future and operation being related to the immediate future. A rough border line demarcation between the immediate and long future is shown [1] as shown below.

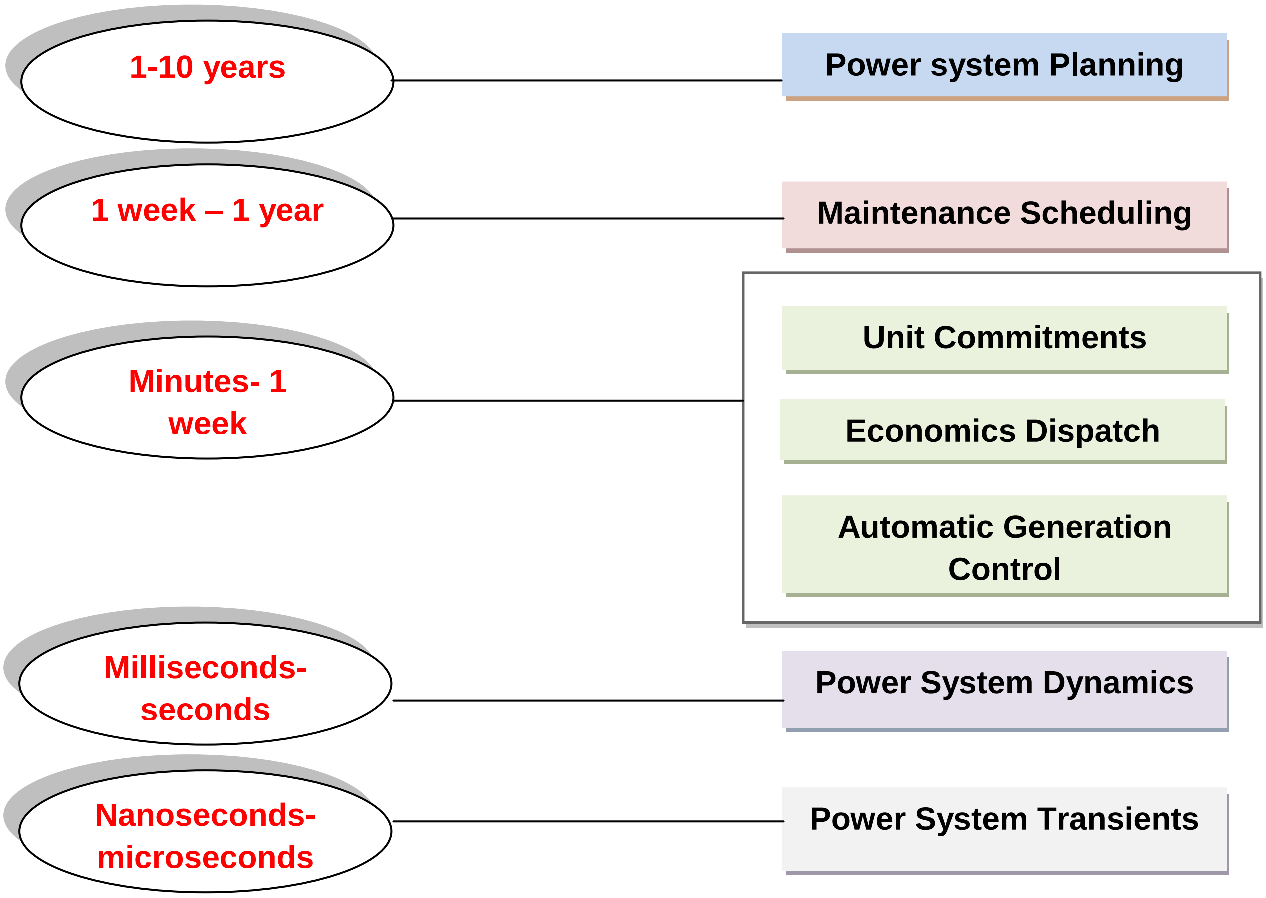


Fig. 1.1 A time-horizon perspective of power system studies

Our focus is on Power System Planning. Power System Planning is a process in which the aim is to decide on new as well as upgrading existing system elements, to adequately satisfy the loads for a foreseen future [1]. The various elements that are a part of study in planning could be:

- Generation stations and units
- Substations
- Transmission lines and cables
- Reactor units
- Distribution grid elements

Various decisions to be made in the planning process could be as follows:

- Where to place the element
- When to place the element
- Element Specification

1.1 CLASSIFICATION OF POWER SYSTEM PLANNING STUDIES

There are various classifications of planning studies possible. Some of these are as follows:

- Based on the planning stages considered - Static/Dynamic/Quasi-dynamic
- Based on the time horizon - Long term/Short term
- Based on the elements under focus GEP/TNEP/SEP/DNEP

1.1.1 Static and dynamic planning

To study each planning period individually and independently during the span of planning refers to as Static Planning. Whereas if the whole planning span is studied as a whole or all the planning periods planned simultaneously it is referred to as dynamic planning. Static planning could lead to impractical results as the planning periods are actually not independent from each other. However dynamic planning could be a more complex task.

1.1.2 Various Planning Studies

Power System Planning studies when classified based on elements under focus could lead to a sequential type of planning procedure where output of one stage becomes the input of another. The various stages in such a sequential Power System Planning study are as follows:

- Load Forecasting
- Generation Expansion Planning
- Transmission Network Expansion Planning
- Substation Expansion Planning
- Reactive Power Planning
- Distribution Network Expansion Planning

CHAPTER 2

HISTORICAL PERSPECTIVE

2.1 COMPUTERS IN POWER SYSTEMS

The first traceable reference to Power System Studies using Computer is Philip's Jennings and George. E Quinn of Puget Sound, Power and Light Company, Seattle, Wash, in 1946 [2] where the authors developed analyzer board equivalents using IBM (International Business Machines) usually available to members of light and power industry, for determining the Distribution of Load and Reactive components in power line networks. This had come as a relief to the power system engineers who were using analyzer boards as a welcome relief from tedious calculations, since analyzer boards were inconveniently located and were huge. The authors had developed a new method for solving complex determinants that the Business Machines could adapt to in form of a formula deck punched cards and coefficients in master card.

Till 1952 Digital Computers were being developed to replace the Analyzer boards. However the Analyzer boards did not get extinct all of a sudden as they survived by making themselves cheaper and smaller. The Northwestern University and Michigan State University were the some who were actively involved in improving the Analyzer boards. This led to the introduction of a compact and inexpensive Analyzer board by Kimbark, Starr and Van Ness [3] in 1952. However these direct type network analyzers were still no match for digital computers. In 1956 Van Ness and W.C. Peterson from Northwestern University developed an analog computer AC analyzer that used both direct and operational type of computations [4]. The initial AC analyzers were only direct type where the impedances, currents and voltages were represented by actual impedances, voltage and currents.

This time operational amplifiers were used as summing, integrators etc to recreate the system equations. By the end of 1950s the AC analyzers were an obsolete technology and digital computers had taken their place. One of the first works to show the use of digital computers in Power systems was in 1952 by J.Bennet et. al [5] where they used digital computers to solve power system problems for the first time, the first load flow program to be solved on digital computers was by Ward and Hale in 1956 [6]. By 1956 the power system studies like load flow, economic loading, load-curve analysis, three phase studies were done by digital computers [7] pioneered by Robinson, Tompsett, Nelson Research Laboratory, English electric Co. As mentioned earlier this was the year that saw the end of AC analyzers. In 1957 the concept of sparse matrices came into the picture to aid the computation as power systems problems were numerically challenging. The first work that exploited the sparse nature of power system matrices was done by Brown and Tinney in 1957 [8]. The By 1961 graph theory had come into the Power systems to aid the digital computers. Works by M.B Reed, G.B Reed, McKinley, Polk, Hugo, Martin [9] shows the use of graph theory for Power System studies in digital computers. The Transmission expansion planning was the first power system planning problem solved with logics and programs in 1960 by Baldwin, Hoffman, DeSalvo, and Ku [10]. A general overview of expansion in Electric supply was done by Edwards and Clark in 1962 [11]. The first Generation Expansion Planning programs were written by E.S.Bailey, C.D.Galloway, E.S.Hawkins and A.J.Wood in 1963 [12].

However these programs were crude as a formal and mature formulation for planning studies had not been developed by now. A lot of work had started in linearzing the power system problems as digital computers were already good at handling matrices, due to the methods developed by Jennings and Quinan as mentioned and Linear Programming was well mature technology by this time. In 1963-1969 many papers and works were dedicated to make proper mathematical models for power system planning studies. Two of the works that led to a boom in usage of digital computers for Power System studies was by Tinney and Walker [13] and Tinney and Hart [14] in 1967. These works by Tinney introduced Newton-Raphson method and ordered elimination techniques for the solution of non-linear simultaneous equations. In fact this era was one of the richest one in terms of Power System research. I. Lencz [15], V.I Nitu [16], R. Freiburger [17] in 1969 made significant contributions by making power system planning models suitable for digital computers for long range planning. 1970 saw the birth of first proper formal Transmission expansion planning work with linear programming by Len. L .Garver [18]. It would be an understatement to call Garver the father of Power System Planning as his works in true sense inspired and showed the way how planning should be done in Power Systems.

This work was highly debated for its oversimplifications but still remains one of the most influential works ever done in the field of Power System Planning. Generation Expansion Planning was a difficult and complex combinatorial problem that did not have a formal formulation by this time in 1970s. In 1972 the first approach to corporate model for system planning evaluations was shown by Sager and A.J. Woods [19]. However the final formulation widely accepted and used came out from the works of R.T Jenkins and D.S. Joy of Oak Ridge National Laboratory in 1974 [20], that was accepted by IAEA (International Atomic Energy Authority) for making the first commercially available Generation Expansion Planning Software WASP (Wien Automated System Planning). U.G Knight in 1974 did a survey of Computer in Power System Planning [21] and summarized the planning studies till then. The first book ever written on Power System planning was in 1976 by Robert Lee Sullivan of University of Florida who had created Interactive programs with D. Odom on Digital equipment corporation Gt44 and interactive power flow programs with H.B Putten of Federal Institute of Technology [22]. The first line of the preface in book says that a survey of all material regarding Power System Planning in 1976 showed the lack of a dedicated text to Power System Planning, and this shows how sparse the literature was on the topic despite being one of the most long term effecting and crucial decisions any utility makes even today.

The Power System Planning had become a mature study by now and was readily used in System Planning by many authorities and agencies.

2.2 SOLUTION METHODS- ALGORITHMS

As mentioned in the previous section in 1960s a lot of effort was put to linearize the power system planning studies. This comes with the acknowledgement that Len.L Garver in [18] had linearized the transmission expansion problem and was successful in solving and finding an optimum plan. This success in optimizing is attributed to efficient methods for solving linear programming problems that were available since 1930s. In

1939 Kantorovich found many solutions to some problems relating to production and transport planning.

In 1947, Dantzig developed a revolutionary method that is today called simplex method to solve the linear program. During World War II, Koopmans had contributed a lot to the solution of Transportation type problems. In 1960s John Holland had laid the stones of modern Heuristic Algorithms by presenting the world with Genetic Algorithm based on survival of the fittest but Simplex method was still a stronger force back then. In 1975 Kantorovich and Koopmans were bestowed upon with Nobel Prize for their contributions in economics. But simplex method still had a problem that it had an exponential worst case complexity and the world was moving towards high dimensional problems. This led to devising algorithms that had polynomial time complexity [23]. Khachiyan developed such an algorithm in 1979 but it got more theoretical popularity than practical. In 1984 Karmarkar proposed a new linear program solver with polynomial complexity that later gave rise to a whole class of non-simplex methods called interior point methods. However all Power System problems could not be linearize. Especially in Power System Planning, linearization led to over simplification and let to non practical plans by overlooking some details. For example in Transmission expansion planning by Len.L Garver [18] the power flow equations were completely overlooked to treat the system as a transport model equivalent before solving it. As the computational efficiency of computers increased a new class of algorithms called metaheuristic developed. This was the outcome of Genetic Algorithm by John Holland now being practical to implement on real world problems.

This gave a boom to introduction of a lot of other such meta-heuristic algorithms in 1980s and 1990s. A lot of these were nature inspired and could solve a high dimensional optimization problem to sufficient optimality in less time. Genetic Algorithm was first successfully tested and formulated by Goldberg in 1989 [24] on the lines proposed by John Holland in 1960s. To name a few important ones that have shaped the Power System area are Particle Swarm Optimization by Kenneth and Eberhart [25] in 1995, Differential Evolution by Storn and Price in 1997 [26], Gravitational Search Algorithm by Rashedi et al in 2009 [27], and many more. The list today is non ending with Ant colony Algorithm, Cuckoo Search, Bacteria Foraging Algorithm etc. The optimization problem in Power System Planning is a multidimensional problem and needs special algorithms to solve them. Many algorithms have been developed however no meta-heuristic algorithm can solve all planning problems satisfactorily.

2.3 GENERATION EXPANSION PLANNING - GEP

As mentioned earlier Oak Ridge Labs in 1974 developed a Generation expansion planning model, this study was supported by IAEA and had inputs from the survey it had done in 1972-1973. This led to the development of WASP. Based on past experience of IAEA members' changes and improvements were made to this program that led to the development of WASP II in 1976. When United Nations Economic Council for Latin America (ECLA) needed to study the interconnection of national grids with a huge hydro electric reservoir potential it led to joint ECLA/IAEA efforts between 1978 to 1980 to make WASP-III [28] Other programs were also made by IAEA to aid the planning procedure with WASP. The Model for Analysis of Energy Demand was made in 1981 for more accurate energy and demand forecasting to be considered in WASP program. To determine the optimal operating strategy for mixed hydro-thermal power systems was achieved by improving the determination of characteristics of hydroelectric stations to be fed into WASP by VALORAGUA model. As a part of integrated package for energy and electricity planning called ENPEP (Energy and Power Evaluation Program) PC versions of WASP-III and MAED were made as standalone software. [28] On the recommendations of Advisory committee on WASP experiences in member states which was convened in 1990 and 1991, additional components were added to WASP program allowing it to model additional generation system aspects, handle larger number of fuel types, and add flexibility to capital cost distribution over construction period and additional details. This version was called WASP-III plus and released to members. A PC version of VALORAGUA was made in 1992. With increasing complexity of system and increasing environmental concerns member states suggested changes in WASP.

The Inter-Agency International Symposium on Electricity and the Environment, Helsinki, 1991 also suggested the need in improvements in WASP. In order to meet the needs of electricity planners and following the recommendations of Helsinki symposium, development of a new version of WASP was initiated in 1992 with cooperation of some Member States (Hungary and Greece). Advisory Group and Consultancy meetings on the subject convened during 1992 to 1996 focused on finding important changes to the model and suggested appropriate methods approaches to address new issues. The new version of the model with a lot of new features was completed and named WASP-IV. Like its predecessor, WASP-IV is designed to find the economically optimal generation expansion policy for an electric utility system within user specified constraints [28]. WASP used Dynamic Programming to solve the highly combinatorial Generation expansion planning problem.

Following this Electric Power Research Institute (EPRI) made its very own software Electric generation expansion analysis System (EGEAS) in 1982 that used Bender's Decomposition Algorithm for solving Hybrid Generation-Transmission expansion planning problem based on the works of J.A Bloom [29] at M.I.T. There are three main groups have worked on Generation Expansion Planning in recent times.

The Kwang Lee et. al, S.Kannan et al, and H.Seifi et al. Kwang Y Lee and group were the first to try and get an analytical approached solution to generation expansion planning in 1985 [30] using Pontryagin's maximum principle. David and Zhao used Integrating expert system with Dynamic Programming to solve the Generation expansion planning problem in 1989[31]. To remind this was the same year Goldberg had implemented Genetic algorithm as mentioned before. Their next work in 1996 was the first application of Genetic Algorithm for Generation Expansion Planning in 1996 [32]. A similar work was done independently in the same year by Fukuyama and Chiang [33] in the same year. The age for meta-heuristic algorithms had come and it had entered the planning problems. All the approaches mentioned above for solving the Generation expansion planning, that of Lee, David, or Bloom considered the decision variables in the continuous domain which is not the actual case and was leading to sub-optimal solutions. A remarkable improvement was made when Lee et. al made a formulation that could treat the decision variables to be discrete by applying an Improved Genetic Algorithm in 2000 [34]. This work in 2000 has become a standard for almost any Generation expansion planning work to follow ahead in the new millennium. After the work in 2000 Meta-heuristic boomed in Power System Planning studies, with S.Kannan and group contributing their most important findings in 2005 by comparing nine different algorithms for solving Generation Expansion planning problem which showed that Differential evolution was the most appropriate choice to solve the problem [35]. The group can be attributed to a significant contribution of Virtual Mapping Procedure that helps in reducing a high dimensioned problem to a low dimensioned one allowing more computational efficiency. In 2004 Kannan et. al. used six variants of Particle Swarm Optimization to solve the Generation Expansion Planning [36]. In the same year Chung, Li and Wang implemented Genetic Algorithm again to find optimal generation expansion plan [37].

In the year 2009 NSGA-II was used to solve the problem by Kannan et. al [38] By this time almost all meta-heuristic algorithms had been tested for the GEP and works had started to look for a GEP in deregulated environment. Kannan et. al used nine algorithms to solve a GEP problem in partially deregulated environment to maximize utility profit which showed a two phase Differential Evolution-Simulated Annealing Hybrid Algorithm to give the best results in 2007 [39]. The Seifi et. al has worked on multi-bus Generation expansion planning rather than the single bus approach to its predecessors [1] and has recently shown that a Hybrid Generation-Transmission Expansion Planning gives a better optimum plan as compared to the traditional sequential approach. We shall discuss about this later after the Transmission Expansion Planning has been discusses ahead.

2.4 TRANSMISSION EXPANSION PLANNING -TEP

In the Historical Perspective section we had discussed the formulation of Transmission Expansion Planning problem by Len. L. Garver in 1970 [18], and Robert Lee Sullivan creating interactive planning tools [22] in 1976. There are three groups that have contributed to the recent development of Transmission Expansion Planning. The Romero et. al, The Ashu Verma et. al, and H. Seifi et. al. Romero et. al can be attributed to single handedly dominate the area of transmission expansion planning for over a decade. Being pioneers they have given some of the most complex test cases that are used even today for studying the transmission planning process. Their first paper came in 1993 [40] in which they used bender's decomposition method to solve the Transmission Expansion Planning. The model used was Transport Model, Hybrid Model and full DC model. The Algorithm was tested on Garver system and 46 bus South

Brazilian System. Their next work came in 2000 in which they used Branch and Bound Algorithm to solve transmission expansion planning problem [41]. This paper used the Transport model to solve the Transmission expansion planning and used two test systems (Garver and 46 bus South Brazilian System). In the year 2002 the group compiled all the test cases available during the time and analyzed their complexity [42]. This included Garver system, 46 bus South Brazilian system, 78 bus south eastern Bus network and 87 bus North-North Eastern network. It showed that as the number of buses in the system increases the complexity increases. In 2003 the group static and multistage transmission expansion problems using transport model [43]. Till this point of time no algorithm was able to solve the full DC model TNEP satisfactorily. In 2005 the group proposed a constructive heuristic algorithm to solve a full DC TNEP problem [44]. A new test system IEEE 24 bus system was used to test the algorithm in this case. This is the point where heuristic algorithms enter the domain of transmission expansion planning. In the same year following this work the group presented the security constrained transmission expansion planning problem and solved it using Genetic Algorithm[45].

The group's next work came on Transmission Network Expansion planning considering uncertainties in Demand in 2006 [46]. The group is still active and is one of the most respected groups in Transmission Expansion Planning. Following the works of Romero et. al , Ashu Verma et. al implemented various test cases in TNEP using various Meta heuristic algorithms. In 2009 the group implemented Transmission Expansion Planning problem with Adaptive Particle Swarm Optimization [47]. In the same year the group used Heuristic methods for Transmission expansion planning with security constraints and uncertainty in load [48]. The major difference between the works of two mentioned groups is the way they take care for the islanding in system while planning. While the Romero et. al uses artifical generations and adds it as a penalty to cost, which increases the dimensionality of the problem, the Ashu Verma et. al uses graph theory based heuristic to make any violating plan to comply with the islanding constraint. This does not increase the dimensionality, accelerates the convergence of meta- heuristic algorithms but often leads to convergence to local minima in a lot of cases. The Hossein Seifi et. al is attributed to be the pioneers in finding the method to handle the islanding constraint very easily by their novel idea of voltage angle difference across lines. This did not increase the dimensionality of problem neither did give a premature convergence at a local minima point. This contribution came along with a novel idea of multi-voltage approach to long term network expansion planning in the works done by group in 2007 [49].In the year 2010 Ashu Verma et. al. implemented and compared three meta-heuristic algorithms on security constrained Transmission Expansion Planning on three different test systems- to mention an addition was 93 bus Colombian systems. In this work they found and established the superiority of Harmony Search Algorithm [50]. This happened to be the last active contribution in the area of Power System Planning by this group.

Following this Hossein Seifi et. al has gone on a spree of works that show that generation and transmission expansion planning if dealt simultaneously. The group has also made the idea of multiyear transmission expansion planning started by Romero et. al. The only commercially available software that can do Transmission Expansion Planning is NEPLAN by Asean Brown Boveri (ABB). Unlike WASP this software is not open to the academic community and the constraints or the formulation is classified. However they claim that the planning software can take into constraints like short circuit studies in addition to load flow for the planning purposes.

2.5 HYBRID GENERATION-TRANSMISSION EXPANSION PLANNING

The Hossein Seifi et. al has actively worked on the Hybrid Generation-Transmission Expansion Planning and believes that it is the most optimal way to plan a grid. Hossein Seifi being an important advisor to TANVIR, Iran's Power grid it can be safely said that all planning processes in Iran happen after solving the Hybrid Planning problem. The main contribution by the group is the idea that the planning problem while being hybrid should also include the fuel supply costs as that can influence the final plan drastically. This came out in 2009 through their work- A multiyear Security constrained Hybrid Generation-Transmission Expansion planning algorithm including Fuel Supply Costs [51]. The paper also had included the concept of multiyear planning that is quasi-static planning, and is solved using the traditional algorithms of Forward Search, Backward Search and Hybrid Search. Following this in 2013 the group implemented the Generation and Transmission Expansion planning with a natural gas grid, it was considered that all the generating units are gas powered and there is a gas pipeline work to supply fuel [52]. In 2015 the group presented its most noteworthy contribution to planning area, Multi-Period Integrated Framework of Generation-Transmission, and Natural-Gas Expansion Planning for large scale systems. The paper simultaneously solved three planning problems to get the global minimum, GEP, TEP and Natural Gas NEP [53]. It can be said that the works of Seifi et. al is recent and has a lot of scope for improvement.

2.6 RECENT TRENDS IN POWER SYSTEM PLANNING

Recent trend in Power System Planning involve planning in the deregulated environment and modeling uncertainties. However some work has been done on this area but no definitive framework has come up that is widely or unanimously considered as a mature framework. [54], [55], [56] are some of the widely cited works in the area of Transmission Expansion planning in deregulated environment. These works use probabilistic approaches to plan for the future.

CHAPTER 3

GEP-TEP FORMULATIONS AND CONSTRAINTS

3.1 GEP (GENERATION EXPANSION PLANNING)

Generation Expansion Planning (GEP) is the important step in long-term planning issues, after the load is properly forecasted for known future period. GEP is the problem of determining when, what and where the generation plants are required so that the loads are adequately supplied for a foreseen future. This problem is solved with in this section. We will see how complex the problem is, so that, we first ignore the transmission system to make the problem easy to handle [1].

3.1.1 Single Bus Generation Expansion Planning

This single-bus GEP is different to a multi-bus GEP problem which will be dealt in next sections. The total costs should be minimized while considering various constraints, such as Generation-load balance, should be satisfied. If the decision variable is denoted by $\boldsymbol{X_{it}}$, representing the number of unit type $\boldsymbol{i}$ for year $\boldsymbol{t}$, the objective function terms and the constraints are described in the following subsections [1].

Objective function and Costs:

Generally speaking, GEP is a convex optimization problem in which the aim is to determine the new generation plants in terms of when to be available, what type and capacity they should be and where to allocate so that an objective function is optimized and all different kind of constraints are met. It may be of static approach in which the solution is found only for a specified stage (typically, year) or a dynamic approach, in which, the solution can be found for several stages in a specified period. The objective function consists of,

$$objective\ function = Capital\ Cost + Operation\ Cost \tag{3.1}$$

Before going further towards complexity, we define some of the terms in as follows;

- **Investment cost [1]**:
  This term gives the cost of a power plant, in terms of R/kW. The total investment cost is the product of this given value with the power capacity in kW.
- **Plant life [1]**:
  Two plants with the same total investment costs, but with different lives, have different values. If the plant life is say, 20 years, and the study period is say, 5 years, at the end of this period, still some values are left, defined as salvation value. This value will be deducted from the capital cost so that the actual investment cost can be determined.
- **Fuel cost [1]:**
  The fuel cost of a plant is, in fact, dependent on its production level (i.e. f (PGt)). In some words, the cost is variable with the production level. For simplicity, however, the cost (R/MWh) is considered to be fixed here. Total cost is calculated from the product of this value and the energy production of the unit.
- **O & M cost parameters [1]**:
  Operation and Maintenance (O & M) is the cost required for the proper operation of power plants, defined in of the number of days/year.
  Two cost parameters are also normally defined for maintenance.
  – **A fixed term**, independent of energy generation (in terms of R/kW month); the total value is calculated from the product of this given value times the plant capacity times 12 (12 months).
  – **A variable term**, defined in terms of R/MWh. Note that the total variable cost is affected by the period of maintenance, as during these days, the plant is not generating any power.

Total cost, $\boldsymbol{C_{total}}$, to be minimized may be described as,

$$C_{total} = C_{inv} + C_{fuel} + C_{O\&M} + C_{ENS} \tag{3.2}$$

Where,

$\boldsymbol{C_{inv}}$ - *The investment cost*

$\boldsymbol{C_{fuel}}$ - *The fuel cost*

$C_{O\&M}$ - *The operation and maintenance cost*

C_{ENS} - *The cost of energy not served*

a. The Investment Cost [1]:

If ***X_{it}*** represents the number of unit type ***i*** required in year ***t***, ***C_{inv}*** is given by,

$$C_{inv} = \sum_{t=1}^{T}\sum_{i=1}^{Ng} Cost\_Inv_{it} PG_i X_{it} \tag{3.3}$$

Where,

$Cost\_Inv_{it}$- *The cost in Rs. /MW for unit type i in year t*

PG_i- *The capacity of unit **i** (MW)*

T *-The study period (in years)*

N_g- *The number of units types*

X_{it} *- represents the number of unit type **i** required in year **t***

b. The Operation and Maintenance Cost [1]:

Similar to ***C_{inv}*,** the operation and maintenance cost is given as a linear function of ***PG_i*** given by [1],

$$C_{O\&M} = \sum_{t=1}^{T}\sum_{i=1}^{Ng} Cost\_O\&M_{it} PG_i X_{it} \tag{3.4}$$

Where,

$Cost\_O\&M_{it}$ *The operation and maintenance cost (in Rs. /MW) for unit type **i** in year **t**,*

X_{it} *Cumulative number of units in year **t** vector*

c. The Cost of Energy not served:

A generation unit could be tripped out in a rate given by its Forced Outage Rate *(FOR)*. It represents probability percentage of a time; the unit may be unavailable due to unexpected outages. Due to the Forced Outage Rate of the units based on the demand and the available reserve, some portion of the load demand can't be catered. Thus so called Energy Not Served *(ENS)* can't be made zero, but should be minimized as a cost term. It is given by [1],

$$C_{ENS} = \sum_{t=1}^{T} Cost\_ENS_t ENS_t \tag{3.5}$$

Where,

Cost_ENS$_t$ *- The cost of the energy not served in year t (Rs. /MWh)*

ENS$_t$ *- The energy not served in year t (MWh), (probabilistic value)*

Constraints:

Some constraints have to be observed during the optimization process. The ones considered here are described in the following subsections.

a. Technical Constraints:

The generation capacity should be sufficient in catering the load while some uncertainties are involved and the generation units can be tripped out at any time. The following two constraints may, be considered

$$(1 + Res_t/100) * PL_t \leq \sum_{i=1}^{Ng} PG_i X_{it} + PG_t \quad \forall t = 1, \dots \dots, T \tag{3.6}$$

$$LOLP_t \leq \overline{LOLP} \quad \forall t = 1, \dots \dots, T \tag{3.7}$$

Where,

Res$_t$- *The required reserve in year t*

PL$_t$- *The load in year t*

PG$_t$- *The capacity available due to existing units in year t*

LOLP$_t$- *The Loss of Load Probability in year t*

$\overline{\boldsymbol{LOLP}}$- *The maximum acceptable LOLP*

The first constraint shows that the generation capacity should meet the load plus a reserve. ***LOLP*** is a reliability index used to represent the system robustness in response to elements contingencies.

b. Fuel Constraint:

Fuel type $\boldsymbol{j}$ in year $\boldsymbol{t}$ may be limited to $\boldsymbol{Fuel_{jt}}$ based on its availability for the system. As a result,

$$Fuel_{jt} \leq \overline{Fuel_{jt}} \quad \forall\, j \in N_f \;\&\; \forall\, t = 1, .., T \tag{3.8}$$

Where,

$\boldsymbol{Fuel_{ij}}$- *The fuel consumption type* $\boldsymbol{j}$ *for unit type* $\boldsymbol{i}$ *(m^3/MWh)*

$\boldsymbol{N_f}$ - *The number of the available fuels*

$\overline{\boldsymbol{Fuel_{jt}}}$ - *The fuel consumption type* $\boldsymbol{j}$ *for existing units in year* $\boldsymbol{t}$ *(m^3)*

3.1.2 Multi-Bus Generation Expansion Planning

GEP is, in fact, the process of determining the generation requirements for a system so that the loads will be satisfied in an efficient (typically the most economical) manner while various technical and non-technical constraints are met. The approach presented in single bus GEP is based on single bus representation of the system. In other words, we basically ignored the transmission system and find out the total generation requirements based on an optimization t. In a techniques practical life, we will be confronted with determining the total load generation requirements. In other words, we need to, somehow, allocate the total generation requirements among buses. The solution may be simple if the transmission system strength was infinite, the fuel costs are the same for all buses, the cost of land is also similar and there are no other practical limitations. In that case, we could have arbitrarily allocated the total generation requirements among the buses according to our wish. The assumptions above are not valid in practical life. We should, somehow, find a way, while easy to solve**,** should have a sound engineering basis. If we are going to consider all details, the problem ends up with a model which might be impossible or very difficult to solve. Instead, we can develop a model with the following observations [1].

We assumed that the total generation requirements as well as the types and the capacities of the generation units are known from single bus GEP. We assumed that some practical limitations and data are available for system buses. For instance, some types of generations (for example, steam generations) might be allocated in some specific buses or the maximum generation which can be installed in a specific bus is known. The aim is to allocate the generations among the buses in a way that transmission enhancement requirements can be minimized [1].

In a practical situation, the investment cost of a generation unit, besides the actual cost of equipment, depends also on some technical and non-technical factors such as the cost of land, the fuel supply piping cost, the interconnection cost to the main grid, etc. It can be assumed that the effect of all terms can be reflected into $\boldsymbol{\beta^k}$ (Rs. / MW) showing the generation cost in area $\boldsymbol{k}$. A mathematical optimization problem is then will be developed with the details given below [1].

Objective Function:

As we discussed earlier, the investment cost of a generation unit is area dependent, reflected as $\boldsymbol{\beta^k}$. Moreover, once a generation unit is installed at a bus, any of the existing lines might be needed to be enhanced to a higher capacity. As a result, the objective function considered in this chapter is [1],

$$F = \sum_{k=1}^{Na} \beta^{k} PG_{k} + \sum_{i=1}^{M} \gamma L_{i}(B_{i} - 1) \tag{3.9}$$

Where, the first term is the generation investment cost and the second term is the transmission enhancement cost ($\boldsymbol{L_i}$ *is the length of the line* ***i****). Note that* $\boldsymbol{\gamma}$ *is the investment cost (Rs. /km) of a line and* ***bi*** *is loading of line* ***i****, if the line is overloaded.*

Note that if line was not overloaded, $\boldsymbol{b}_i$ is set to **1.0**. The decision variables are $\boldsymbol{PG^k s}$ and $\boldsymbol{b}_i s$. It is worth mentioning that in an extreme case, an area may consist of a single bus so that, instead of area-based, the problem may be solved bus-based.

Next we will discuss different technical and nontechnical constraints.

Constraints:

The constraints to be observed during the optimization process are as follows,

$$-b_i P_{Li}' \leq \sum_{k=1}^{Na} (A^k{}_{Gi} PG^k + c_i) \leq b_i P_{Li}' \qquad i = 1, \ldots\ldots, M \tag{3.10}$$

$$1 \leq b_i \leq b' \quad i = 1, \ldots\ldots, M \tag{3.11}$$

$$\underline{PG^{kmin}} \leq PG^k \leq \overline{PG^{kmax}} \quad k = 1, \ldots, Na \tag{3.12}$$

$$\sum_{k=1}^{Na} PG^k = PG^0 \tag{3.13}$$

*Where, **M** is the sum of the number of the lines between the areas, **b'** is the maximum capacity that a line may be expanded (to be specified by the user), **PG⁰** is the total generation capacity as determined from the approach presented in single bus GEP*

3.2 NETWORK EXPANSION PLANNING (TRANSMISSION EXPANSION PLANNING)

In previous section, we looked at the generation expansion planning. Although in GEP, the network conditions are, somehow, accounted for, the modeling was very approximate and needs much further investigations. The so called Network Expansion Planning (NEP) process tries to find the optimum routes between the generation buses (determined in GEP phase) and the load centers (determined from load forecasting)

In such a way that Loads can be completely supplied during both

- Normal conditions
- Once some types of contingencies occur on some system elements
- Least costs are incurred

In fact; NEP is an optimization process in which the allocation (the sending and the receiving ends) and class (voltage level, number of conductors, conductor type) of new transmission elements, together with their required availability times are specified.

NEP, the problem is to determine the transmission paths between substations (both existing and new) as well as their characteristics (voltage level, number of circuits, conductor type, and so on).

In doing so,

- The investment cost shall be minimized
- The operational cost shall be minimized
- Various constraints shall be met during
    - Normal conditions
    - Contingency conditions

We can see shortly that in its easiest form, the investment cost involves the cost of adding new transmission elements. Moreover, the operational cost should be the cost of power losses during the element life. In terms of the constraints, an obvious case is the limiting transfer capability of an element, which shall not be violated. The contingency is, in fact, an outage occurring on a single element (such as a line, a transformer, power generation unit) or some elements. The single element case is commonly called as N – 1 condition. Simultaneous contingencies on two elements (for instance one line and one transformer, two lines, etc.) are referred to N - 2 conditions and so on. By contingency conditions (say N - 1), we mean that the network shall be so planned that with every single element, out, the load is completely satisfied and no violation happens.

As already described, in NEP, the problem is to determine the transmission paths between substations (buses); both existing, new; as well as their characteristics. In its simplest form, the objective function consists of the investment cost for new transmission lines, while the constraint terms consist of load-generation balance and transmission limits. The terms are described below. The aim is to minimize the total cost (C_{total}), consisting of the investment cost for new transmission lines ($C_{new\text{-}line}$), i.e.

(3.14)

$$C_{total} = C_{new\text{-}line}$$

Where,

$$C_{new\text{-}line} = \sum_{i \in Lc} C_L(x_i) L_i \tag{3.15}$$

Where, $\boldsymbol{L_i}$ is the transmission length (km) of the candidate, $\boldsymbol{L_c}$ is the set of candidates, xi is the transmission type of the candidate (set of various types such as number of bundles, conductor types and number of circuits) and $\boldsymbol{C_L}$ (x_i) is the investment cost per km for type $\boldsymbol{x_i}$.

Constraints for different Models:

DC Model:

As mentioned before, the load-generation balance should be observed during the optimization process. Moreover, the capacities of transmission lines should not be violated, too. These constraints are described below.

a. Load flow Equations:

For most basic planning studies, it is of normal practice to use DCLF equations, as the planner avoids any anxiety about voltage problems and possible convergence difficulties. Moreover, especially for large-scale power systems, the solution time may be exceptionally high, if ACLF is employed. It is obvious that in the final stage, ACLF should be performed to have an acceptable voltage profile during normal as well as contingency conditions. [Appendix A]

DCLF Equations:

$$\sum_{J=1}^{N} B_{ij}(\theta_i - \theta_j) = P_{Gi} - P_{Di} \tag{3.16}$$

$$\sum_{j=1}^{N} B_{ij}^{m}\left(\theta_i^{m} - \theta_j^{m}\right) = P_{Gi}^{m} - P_{Di} \tag{3.17}$$

*Where, $\boldsymbol{\theta}_i$ and $\boldsymbol{\theta}_j$ are the voltage phase angles of buses **i** and **j**, respectively; $\boldsymbol{B}_{ij}$ is the imaginary part of the element ij of the admittance matrix, $\boldsymbol{P}_{Gi}$ is the power generation at bus **i,** $\boldsymbol{P}_{Di}$ is the power demand at bus i, and n is the set of system buses. The index **m** shows the contingency parameters and variables. **N** is the system number of buses.*

b. Transmission Limits:

For all transmission lines, the power transfer shall not be violated its rating during both normal and contingency conditions [1]

$$b_k(\theta_i - \theta_j) \leq \overline{P}_k^{No} \tag{3.18}$$

$$b_k^m(\theta_i^m - \theta_j^m) \leq \overline{P}_k^{Co} \quad \forall\, k\, \in \tag{3.19}$$

Where, $\overline{\boldsymbol{P}}_{\boldsymbol{k}}^{\boldsymbol{No}}$ and $\overline{\boldsymbol{P}}_{\boldsymbol{k}}^{\boldsymbol{Co}}$ are the line k ratings during normal and contingency conditions, respectively; $\boldsymbol{\theta_i}$and $\boldsymbol{\theta_j}$ are the voltage phase angles of line k during normal conditions; θ_i^m and θ_j^m are the voltage phase angles of line k following contingency m; and L_e is the set of existing lines. $\boldsymbol{L_c}$ Is defined earlier, $\boldsymbol{b_k}$ & $\boldsymbol{b_k^m}$ represent the line k admittances in normal and contingency conditions, respectively.

Transportation Model:

This model can be obtained by relaxing the nonlinear constraint DC load flow of the DC model described above. In this case the network is represented by a transportation model, and the resulting expansion problem becomes an integer linear problem (ILP). This problem is normally easier to solve than the DC model although it maintains the combinatorial characteristic of the original problem. An optimal plan obtained with the transportation model might not be feasible for the DC model, since part of the constraints were ignored; depending on the case, additional circuits are needed in order to satisfy the constraint in DC load flow eqn. which implies higher investment cost [42].

3.3 MULTI-YEAR GEP AND TEP

Multi-year GEP:

The multi-period GEP problem can be formulated as follows;

Objective Function:

$$Cost_{GEP} = \sum_{t=1}^{T} I(U_t) + M(X_t) + O(X_t) - S(X_t) \tag{3.20}$$

$$s.t \quad X_t = X_{t-1} + U_t \tag{3.21}$$

Where, $\boldsymbol{I}(\boldsymbol{U_t})$ *the investment cost of new units is constructed at time t,* $\boldsymbol{M}(\boldsymbol{X_t})$ *and* $\boldsymbol{O}(\boldsymbol{X_t})$ *are maintenance and outage costs of all new and existing units, respectively, and* $\boldsymbol{S}(\boldsymbol{X_t})$ *is salvage value of new units constructed at time.*

Constraints:

Following constraints can be considered [34],

$$LOLP(X_t) < \in \qquad (t = 1, \dots, T) \tag{3.22}$$

$$R \le R(X_t) \le \bar{R} \quad (t = 1, \dots, T) \tag{3.23}$$

$$\underline{M_t^j} \le \sum_{i \in \Omega_j} x_t^i \le \overline{M_t^j} \qquad (t = 1, \dots, T) \& (j = 1, \dots, J) \tag{3.24}$$

$$0 \le U_t \le \overline{U_t} \; (t = 1, \dots, T) \tag{3.25}$$

Where, $\boldsymbol{T}$ *number of years in planning horizon,* $\boldsymbol{J}$ *number of fuel types,* Ω_j *index set for* $\boldsymbol{j}^{th}$ *fuel type plant,* $\boldsymbol{X_t}$*, cumulative capacity vector of plants in year t,* $\boldsymbol{x_t^i}$ *cumulative capacity of* i^{th} *type plant in year t,* $\boldsymbol{U_t}$ *capacity addition vector in year t,* $\overline{\boldsymbol{U_t}}$ *maximum capcity vector,* $\boldsymbol{LOLP}(\boldsymbol{X_t})$ *loss of load probability in year t,* $\boldsymbol{R}(\boldsymbol{X_t})$ *reserve* *margin in year t,* $\overline{\boldsymbol{R}}, \boldsymbol{R}$ *upper and lower bound of reserve margin,* , $\overline{\boldsymbol{M}_t^j}$, $\underline{\boldsymbol{M}_t^j}$ *lower and upper bounds of fuel type in year.*

Multi-year TEP:

The multi-period TEP problem can be formulated as single year TEP no need to differ from constraints also. Though we need to consider depreciation of cost every year, so TEP cost function is as following [53];

$$Cost_{TEP} = \sum_{t=1}^{T} [(1-d)^{(t-1)} \sum_{i,j} c_{i,j} n_{i,j,t}] \tag{3.26}$$

Where,

$\boldsymbol{c_{i,j}}$- *Capital cost of constructing new line between i & j*

,$\boldsymbol{n_{i,j,t}}$ *total lines new and existing between i and j in year t*, $\boldsymbol{d}$ *is annual discount rate*

Economical terms definitions for multiyear GEP/TEP

- **Investment cost**: Investment cost is the cost caused in investing on machinery equipment and buildings used in providing the services.
- **Operational cost:** Operational cost is the cost incurred in running a system to provide the services. Wages, resources (fuel, water, etc.), taxes are such typical costs.
- **Depreciation:** Depreciation is the loss in value results from the use of machinery and equipment during the period. During a specific period, the cost of using a capital good is the depreciation or loss of the value of that good, not its purchase price. Depreciation rate is the rate of such a loss in value.
- **Nominal interest rate:** Nominal interest rate is the annual percentage increase in the nominal value of a financial asset. If a lender makes a loan to a borrower, at the outset, the borrower agrees to pay the initial sum (the principal) with interest (at the rate determined by interest rate) at some future date.
- **Inflation rate:** Inflation rate is the percentage increase per a specific period (typically a year) in the average price of goods and services.

- **Real interest rate:** Real interest rate is the nominal interest rate minus the inflation rate.
- **Present value:** Present value of some money at some future date is the sums that if it is lent out today, will be accumulate to ***x*** by that future date. If this present value is represented by ***P*** and the annual interest rate is termed ***i***, after ***N*** years we would have ***F*** [57]

$$F = P(1 + i)^N \tag{3.27}$$

- **Discount factor:** Discount factor is the factor used in calculating present values.
- **Salvation cost:** Salvation value is the real value of an asset/equipment, remaining, at a specific time and after considering the depreciation rate.

3.4 HYBRID GEP-TEP

Combining both GEP and TEP such that,

$$Total_{Cost} = GEP_{cost} + TEP_{cost} \tag{3.28}$$

Constraints:

The constraints to observe during the optimization process are as follows:

- DC load flow equations;
- Transmission lines and transformers power transfers;
- Islanding conditions;
- Limits on generation capacities;
- Fuel constraint;
- Load balance.

a. DC Load Flow Equations:

DC load flow equations are normally used in planning studies, as it can provide good approximations for the nonlinear equations of transmission flows, as well as it can make the convergence of the problem possible which is of vital importance, especially for large-scale system [52].

b. Transmission lines and power transfers:

The security constraints can be meet after the the power transfer through any transmission elements (either lines or transformers) should not violate its respective capability both in normal and N-1 conditions (single contingency on any line or any transformer) [52].

c. Islanding Conditions:

The grid shall be so designed that no islanding happens in normal or contingency conditions. As a line contingency (outage) is modeled in the algorithm by choosing a very high value for the line reactance, an islanding is detected by checking the phase angle difference across the line to be a large number. This happens due to the fact that the far end of the line terminates at a load bus [52].

d. Limits on Generation Capacities:

Due to the different policies of the decision makers, the generations on each node might be limited to some specific values in normal as well as contingency conditions [52].

e. Fuel Constraint:

Each fuel supply is capable of supplying a maximum amount of generation capacity [52].

f. Load Balance:

The total generation shall balance the total consumption involving the actual demand of buses and the losses of transmission network. Since, the transmission network losses can not be considered in dc load flow equations in this paper, the losses are assumed to be supplied from the slack bus.

We consider many other constraints like load outage probability etc. availability of data, as we increase the constraints complexity and cost will be increasing [52].

3.5 FLOWCHARTS OF GEP, TEP AND HYBRID GEP-TEP

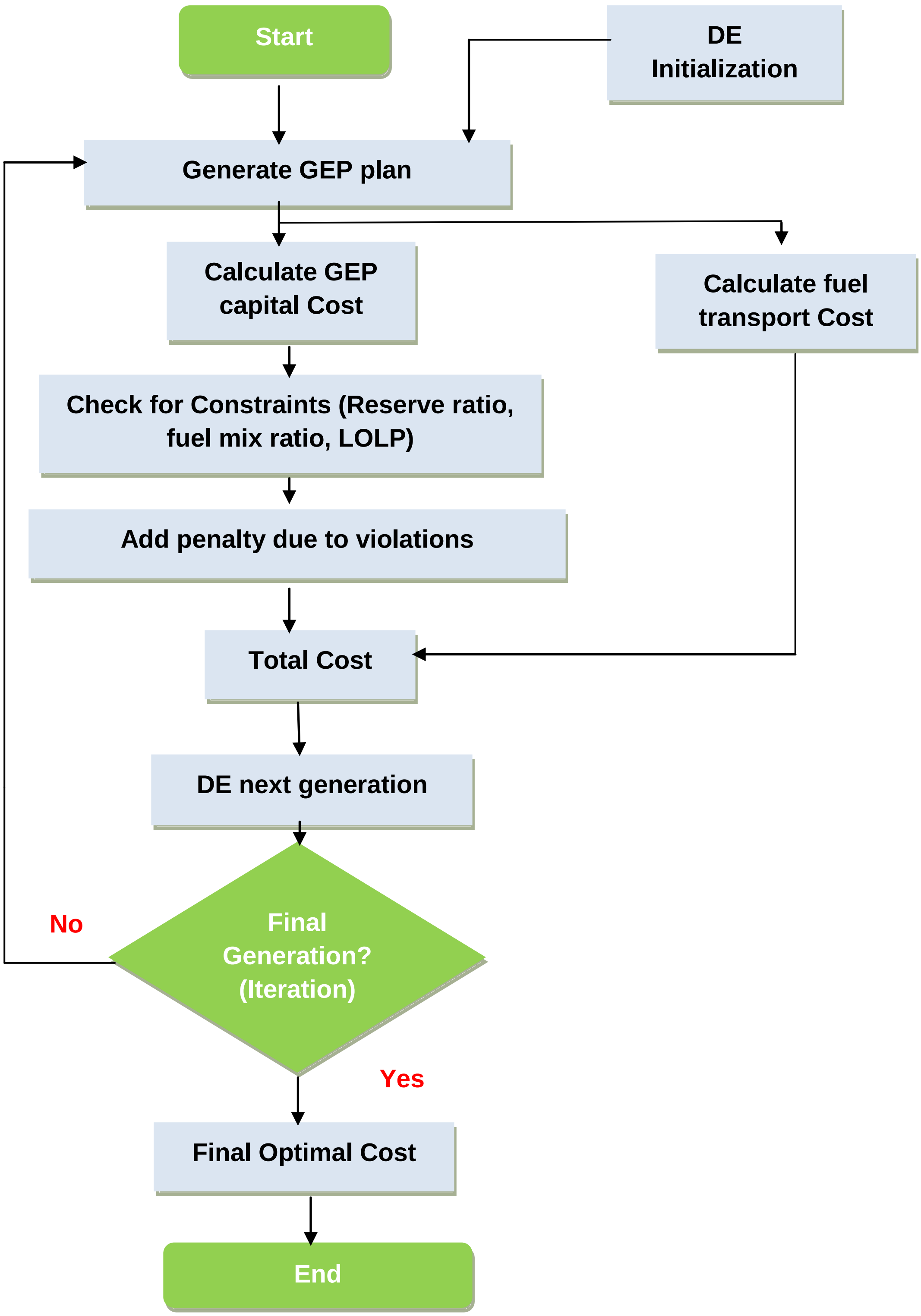


Fig. 3.1 GEP flowchart

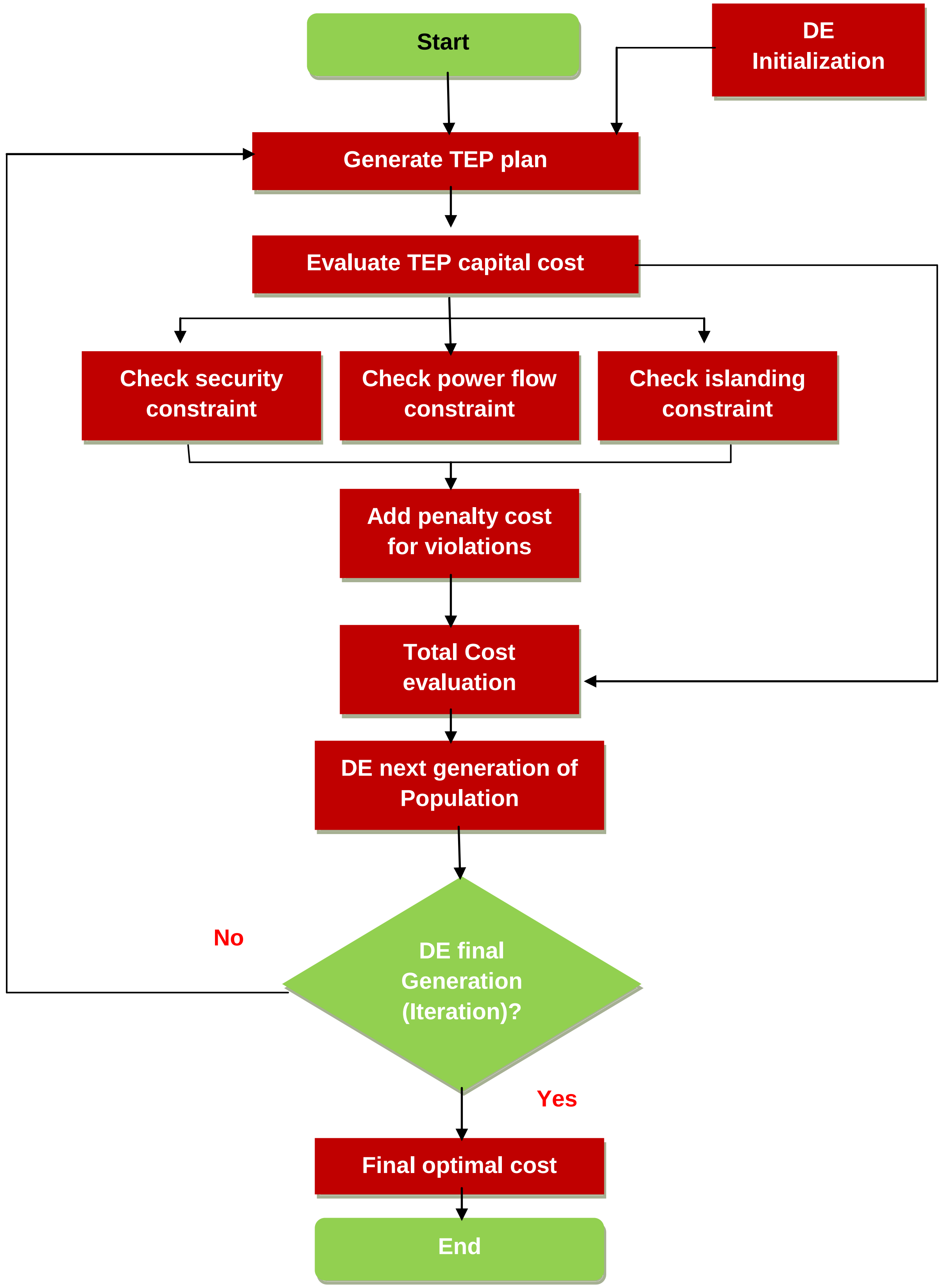


Fig. 3.2 TEP flowchart

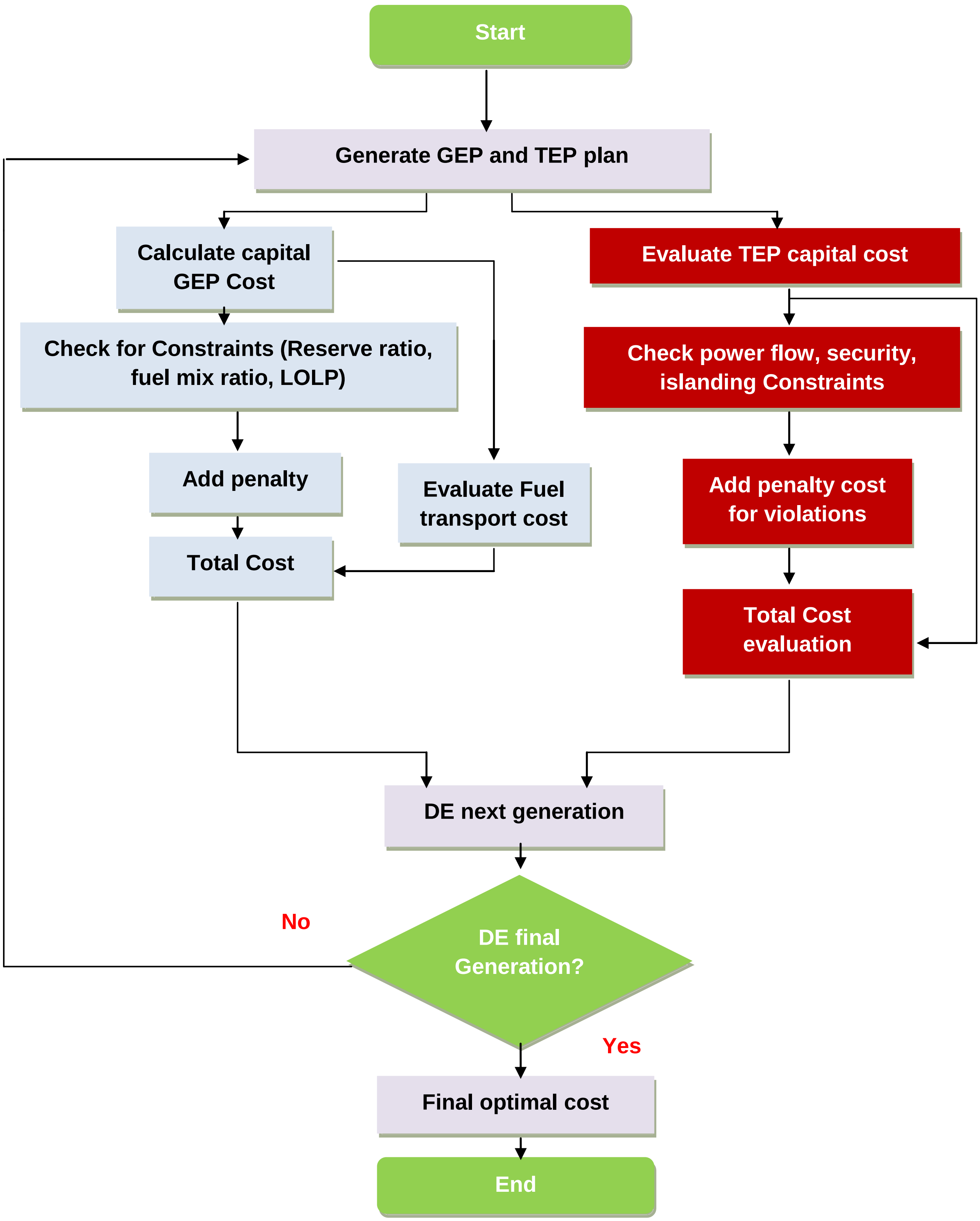


Fig. 3.3 Hybrid GEP-TEP Dynamic planning flowchart

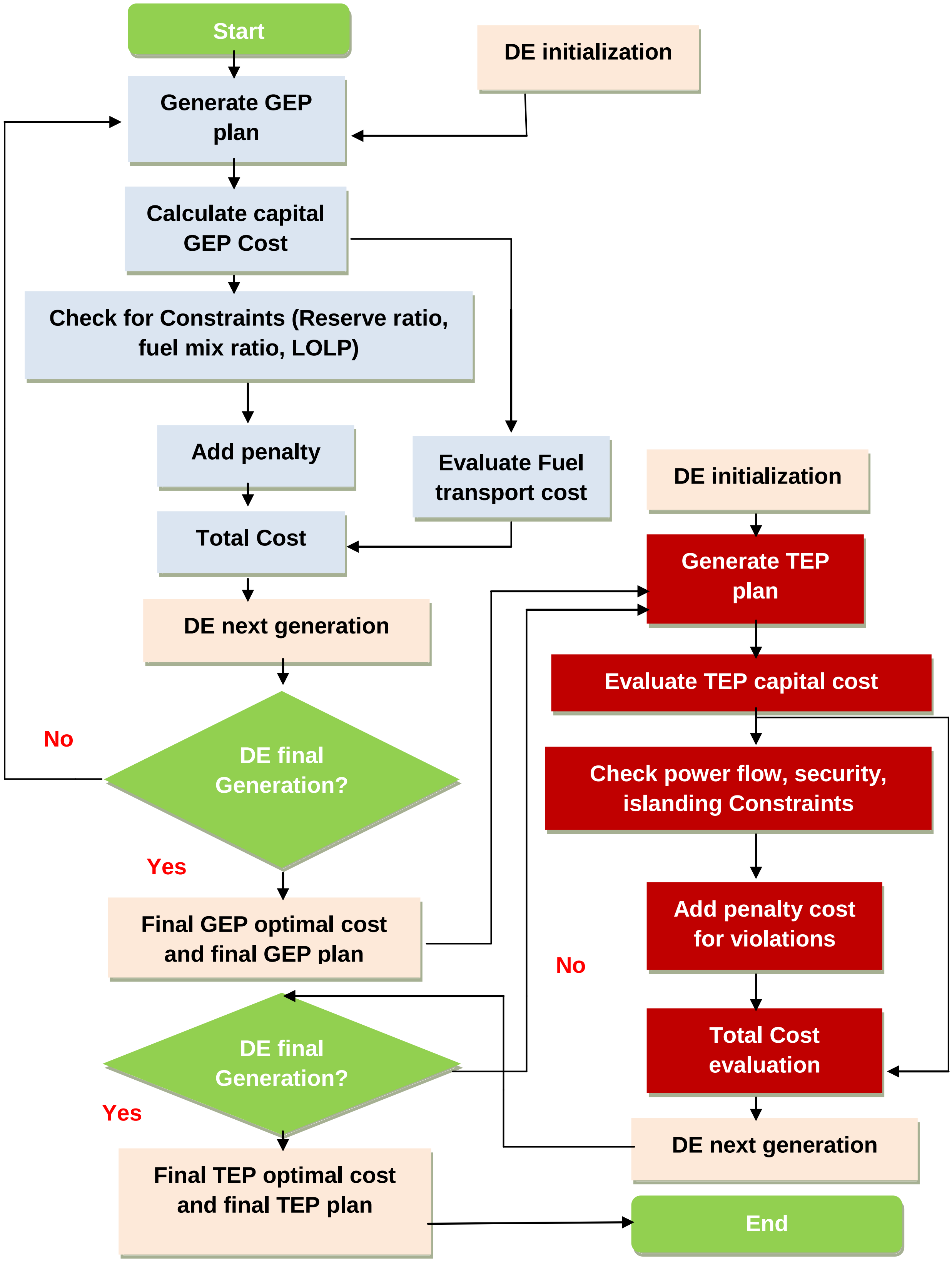


Fig. 3.4 Static hybrid GEP-TEP planning

CHAPTER 4

OPTIMISATION TECHINQUES AND METHODOLOGY

In everyday life, all of us are confronted with some decision makings. Generally, we try to decide for the best. If someone buys a commodity, he or she tries to buy the best quality, with the least cost. These types of decision makings can be categorized as optimization problems in which the aim is to find the optimum solutions; where the optimum might be either the least or the most. The aim of this section is to review briefly the basics of optimization problems [1].

The problem formulated might be solved by available optimization techniques. Both mathematical based options and heuristic types might be tried, each with its own capabilities and drawbacks. For a practical purpose mainly large scale system, the approach employed shall be robust and flexible enough to be applied. Two main methods and their classification are defined below [1].

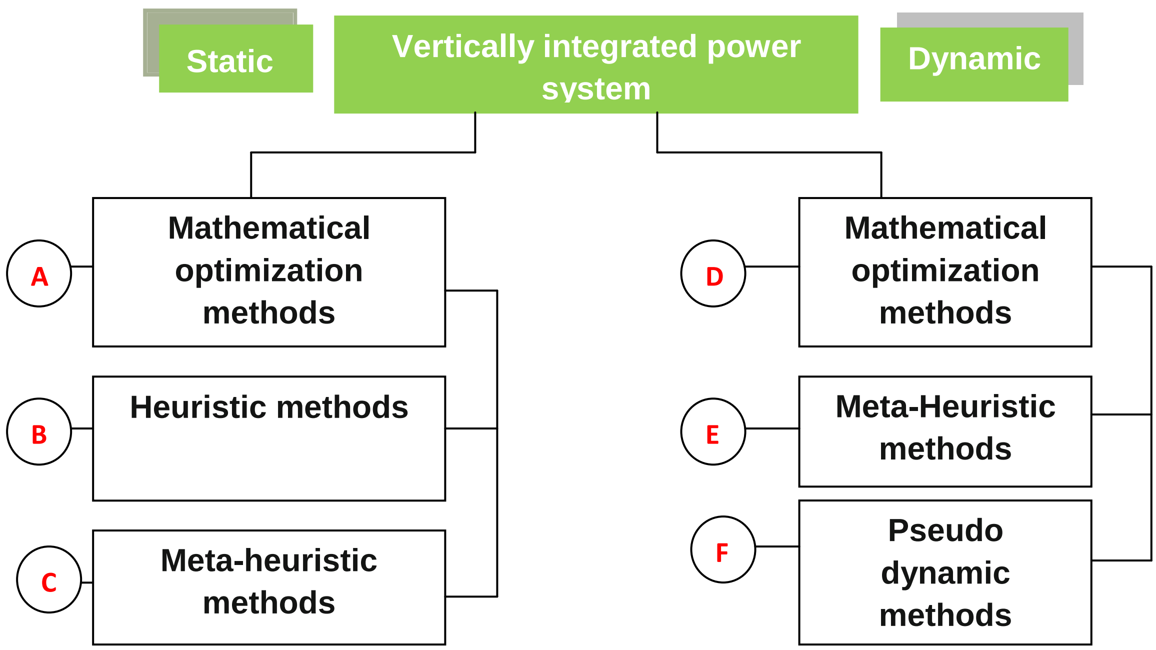
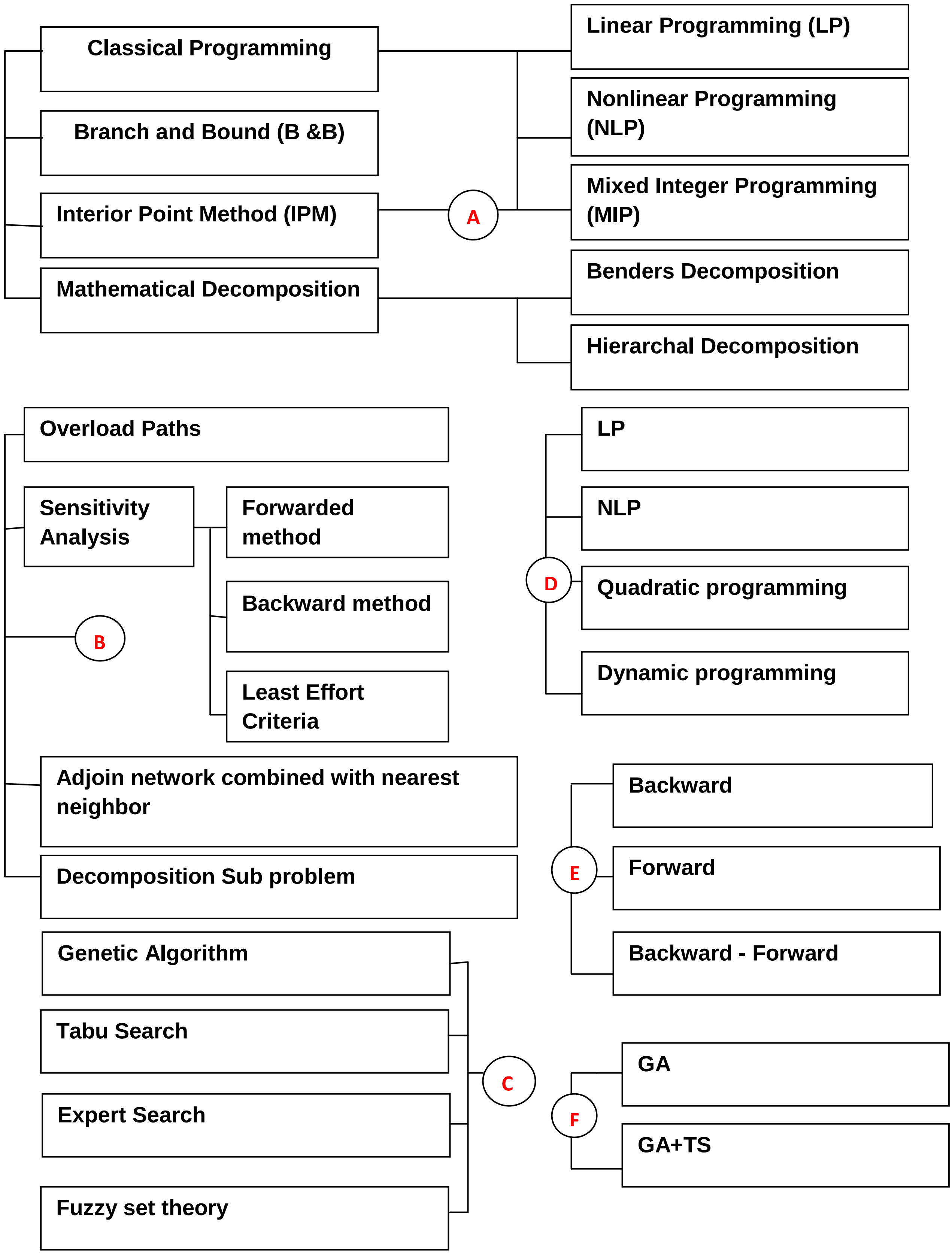


Fig. 4.1 Classification block diagram of solution methodologies



Classical Programming
Branch and Bound (B &B)
Interior Point Method (IPM)
Mathematical Decomposition
A
Linear Programming (LP)
Nonlinear Programming (NLP)
Mixed Integer Programming (MIP)
Benders Decomposition
Hierarchal Decomposition
Overload Paths
Sensitivity Analysis
B
Forwarded method
Backward method
Least Effort Criteria
Adjoin network combined with nearest neighbor
Decomposition Sub problem
D
LP
NLP
Quadratic programming
Dynamic programming
E
Backward
Forward
Backward - Forward
Genetic Algorithm
Tabu Search
Expert Search
Fuzzy set theory
C
F
GA
GA+TS

4.1 SOLUTION ALGORITHMS, MATHEMATICAL AND HEURISTIC TECHNIQUES

The constrained optimization problem might be solved by some available optimization techniques. These techniques can be generally classified as mathematical and heuristic methods. They have received attention in power system literature. These are reviewed in the following subsections [1].

4.1.1 Mathematical Algorithms

A mathematical optimization technique formulates the problem in a mathematical representation; given the objective function and the constraints are nonlinear, the resulting problem is named as Non Linear optimization Problem (NLP). A special case of NLP is quadratic programming in which the objective function is a quadratic function of x. If both the objective functions and the constraints are linear functions of x, the problem is named as a Linear Programming (LP) problem. Other categories may also be identified based on the nature of the variables. If x is of integer type, the problem is named by Integer Programming (IP). Mixed types such as MILP (Mixed Integer Linear Programming) can also exist in which while the variables might be both real and integer, the problem is also of LP type [1].

For mathematical based formulations, some algorithms have, so far, been developed; based on them some commercial software was generated. In the following subsections, we will briefly review these algorithms. We shall, however, note that generally speaking, a mathematical algorithm might suffer from numerical problems and might be quite complex in implementation. However, its convergence might be guaranteed but finding the global optimum solution can only be guaranteed for some types such as LP. There is no definite and fixed classification of mathematical algorithms. Here, we are not discussing them in details. Instead, we will discuss topics related to heuristic and meta-heuristic algorithms applicable to power system planning issues [1].

4.2 HEURISTIC METHODS

One way to solve such a problem can be to choose the methods based, somehow, on engineering judgments. For instance in the so called forward method, the candidates are added one-by-one. We can proceed so far as the system conditions are acceptable for both normal and N – 1 contingency condition. The backward approach works exactly opposite in such a way that, all candidates will be initially added to the network and the candidates will be removed, one-by-one till now as a violation happens in either normal or N - 1 condition. As a matter of fact, the backward approach can start from a point within the feasible region while the forward approach could start from outside such a region. As the number of candidates might be much higher than the real number justified and required, the execution time of the backward approach is normally higher than that of the forward approach. However, as it starts within the feasible region, the solutions can remain feasible through the solution process [1].

As a result, the solutions might be more favorable in comparison with the forward approach especially when some feasible solutions are to be compared. In fact, as in the backward approach, we remain in the feasible region throughout the solution process; the most costly candidates will be, normally, removed first. However, in the forward approach, as we start from a point outside the feasible region, the most effective candidates will be initially selected. As a result, typically, the backward process ends up with more justified candidates in comparison with the forward process; however with less costly paths. There is no guarantee that either of the approaches ends up at the same results or one makes sure that the solution of one is better than the other. Most mathematical based algorithms could guarantee reaching an optimal solution; while do not necessarily guarantee reaching a global optimum. Global optimality might be only reached, checked or guaranteed for simple cases. On the other hand, many practical optimization problems do not fall in strict forms and assumptions of mathematical based algorithms.

Moreover, if the problem is highly complex, we might not readily be able to solve them, at all, through mathematical algorithms. Besides, finding global optimum is of interest, as finding a local one would be a major drawback. Heuristic algorithms are devised to tackle the above mentioned points. They will solve the combinatorial problems, sometimes very complex, yet in a reasonable time. However, they could seek good solutions, without being able to guarantee the optimality, or even how close the solutions are to the optimal point.

Moreover, some modified heuristic algorithms had been developed in literature by which improved behaviors were attained, claiming that the optimal solutions are guaranteed. A simple heuristic algorithm might be devised based on some types of sensitivity analysis. For instance, in a capacitor allocation problem, the sensitivities of the objective function might be determined by the application of a capacitor bank in a bus. Once done, the capacitor is added to the most sensitive bus and the procedure will be repeated until no further improvement is achieved in terms of the objective function. However, most heuristic algorithms are based on some biological behaviors. Basically, all start from either a point or a set of points, moving towards a better solution; through a guided search. Few have been developed so far, some of them are worth mentioning here;

- Differential Evolution
- Genetic Algorithm (GA), based on genetics and evolution,
- Simulated Annealing (SA), based on some thermodynamics principles,
- Particle Swarm (PS), based on bird and fish movements,
- Tabu Search (TS), based on memory response,
- , based on how ants behave.

  Ant Colony (AC)

One of efficient methods we are can use is Differtienal Evolution, which has been explained in following subsection [1].

4.2.1 Differential Evolution: Meta- heuristic Methods

Problems which involve global optimization over continuous spaces were ubiquitous throughout the scientific community. In general, the task optimizing certain properties of a system by pertinently chooses the system parameters. For convenience, a system's parameters were usually represented as a vector. The standard approach to an optimization problem begins by designing an objective function that can model the problem's objectives while including any constraints. Although these methods could make formulating a problem simpler, they were usually inferior to techniques which make use of an objective function. Consequently, we can only regard optimization methods that use the objective function. In most cases, the objective function defines the optimization problem as a minimization task. To this end, the following investigation can be restricted to minimization problems [57].

Users generally demand that a practical optimization technique shall fulfill three requirements. First, the method should find the true global minimum, regardless of the initial system parameter values. Second, convergence shall be fast. Third, the program could have a minimum of control parameters so that it will be easy to use. In our search for a fast and easy to use "sure fire" technique, we developed a method which is not only simple, but also performs well on a wide variety of test problems. It will be inherently parallel and hence lends itself to computation via a network of computers or processors. The basic strategy employs the difference of two randomly selected parameter vectors as the source of random variations for a third parameter vector. In the following, we present a more rigorous description of the new optimization method which we call Differential Evolution. [57]

4.2.2 The Method of Differential Evolution (DE)

Differential Evolution (DE) is a parallel direct search method which utilizes *NP* parameter vectors $X_{i,\,G}$, $i = 0, 1, 2, NP\text{-}1$ as a population for each generation *G*. *NP* cannot change during the minimization process. The initial population will be chosen randomly if nothing is known about the system. As a rule, we can assume a uniform probability distribution for all random decisions unless otherwise stated. In case a preliminary solution will be available, the initial population will often generated by adding normally distributed random deviations to the nominal solution $X_{num},\ 0$. The crucial idea behind DE will be a scheme for generating trial parameter vectors. DE generates new parameter vectors by adding a weighted difference vector between two population members to a third member. If the resulting vector yields a lower objective function value than a predetermined population member, the newly generated vector replaces the vector with which it compares in the following generation. The comparison vector could but need not be part of the generation process mentioned above [57].

In addition the best parameter vector $X_{best,\,G}$ is evaluated for every generation in order to keep track of the progress that is made during the minimization process. Extracting distance and direction information from the population to generate random deviations results in an adaptive scheme with excellent convergence properties, several variants of DE had been tried,

The two most promising of which are subsequently presented in greater detail. [57]

Differential Evolution Scheme no. 1:

The first variant of DE will work as follows: for each vector $X_{i,\,G}$, $i = 0, 1, 2\ldots NP\text{-}1$, a trial vector v is generated according to,

$$\underline{v} = \underline{x}_{r1,G} + F.(\underline{x}_{r2,G} - \underline{x}_{r3,G}) \tag{4.1}$$

$$r_1\,, r_2\,, r_3 \in [0, NP-1], integer\ and\ mutually\ different, F > 0$$

*The integers **r1, r2** and **r3** are chosen randomly from the interval [**0, NP-1**] and are different from the running index i. **F** is a real and constant factor which controls the amplification of the differential variation ($\underline{x}_{r2,G} - \underline{x}_{r3,G}$).*

In order to increase the diversity of the parameter vectors, the vector [57],

$$\underline{u} = (u_0\,, u_1, \ldots, u_{D-1})^T$$
$$u_j = \begin{cases} v_j & for\ j = < n >_D, < n+1 >_D, \ldots \\ (x_{i,G})_j & for\ \ all\ other\ j \in [0, D-1] \end{cases} \tag{4.2}$$

*Is formed where the acute brackets **<>$_D$** denote the modulo function with modulus D. Equations yield a certain sequence of the vector elements of u to be identical to the elements of v, the other elements of u acquire the original values of $\boldsymbol{x_{i,G}}$, Choosing a subgroup of parameters for mutation is similar to a process known as crossover in GAs or ESs.*

Differential Evolution Scheme no. 2:

Basically, scheme DE2 will work the same way as DE1 but generates the vector $\underline{V}$ according to

$$\underline{V} = \underline{x_{i,G}} + \lambda.\left(\underline{x_{best,G}} - \underline{x_{i,G}}\right) + F.\left(\underline{x}_{r2,G} - \underline{x}_{r3,G}\right) \tag{4.3}$$

Introducing an additional control variable λ, the idea behind λ provides a means to enhance the greediness of the scheme by incorporating the current best vector $\underline{x_{best,G}}$ this feature will be useful for objective functions where the global minimum is relatively easy to find [57].

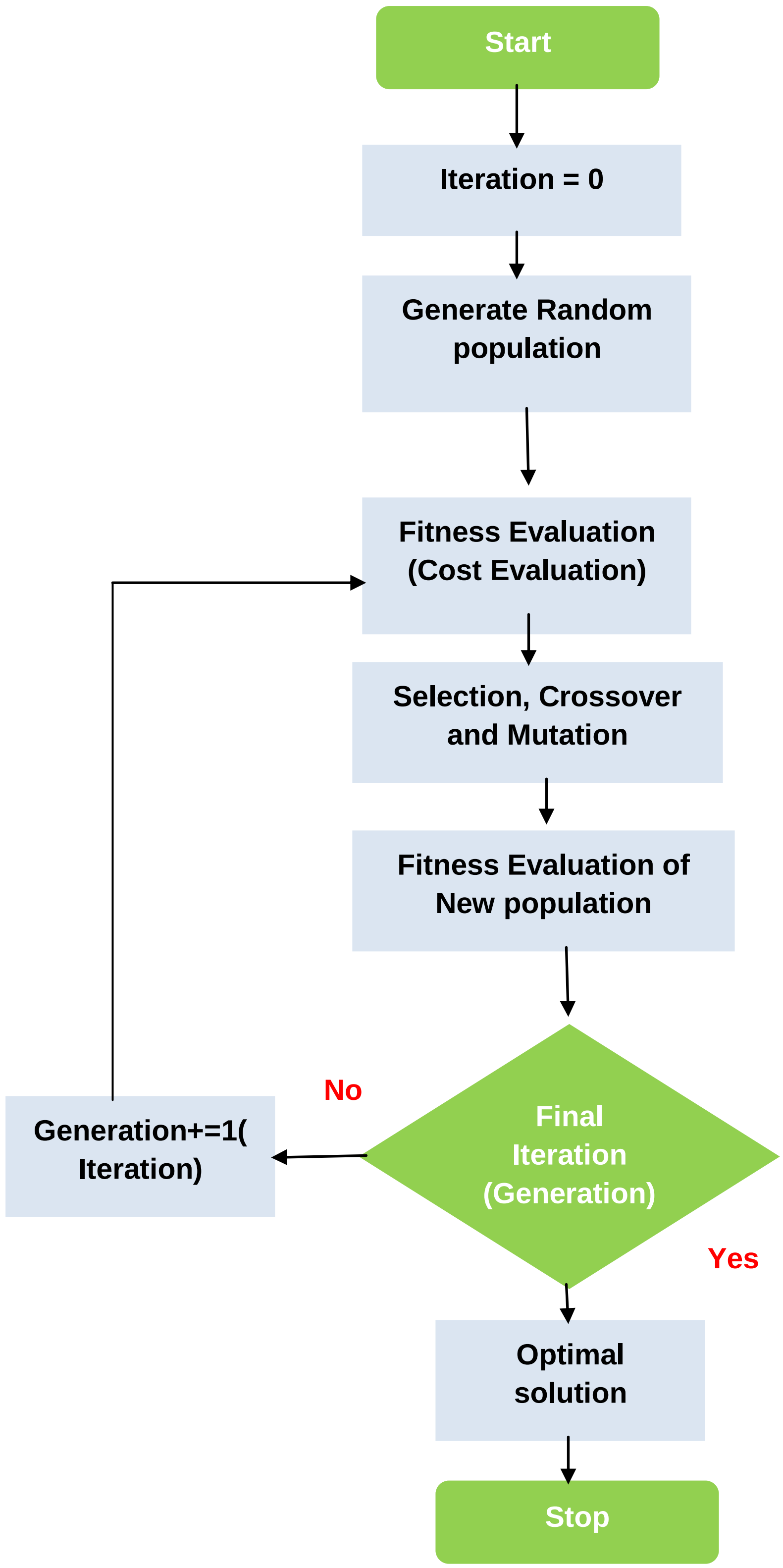


Fig. 4.2 Differential Evolution Meta-Heuristic Algorithm Flowchart

As we can see in above flowchart Figure 4.2 that how Differential evolution work.

Following are the steps for the algorithm:

STEP 1: Algorithm generates random population as its first generation (Iteration)

STEP 2: Randomly generated vectors will be evaluated.

STEP 3: Selection of vectors on random basis and crossover to generate new population and mutation will result in new vector population

STEP 4: Evaluation for new population

STEP 5: Generations will happen depending on generation factor decided by us.

STEP 6: It will compare evaluation of old population and new population and will order population in ascending order and again starts new iteration and evaluates cost till final generation.

STEP 7: After final generation (Iteration) will provide optimal solution.

Some important factors/parameters in Differential Evolution:

- **Scaling Factors:** As discussed earlier there are two schemes for DE and it depends on whether you are taking two or five vectors at a time for crossover. During the same crossover some factors get multiplied known as scaling factors.
- **Crossover probability:** It is a probability of any vector to get selected for crossover to generate new population.

These factors are basically used for tuning of DE to solve specific problem and to reach global optimum solution faster.

CHAPTER 5

CASE STUDY RESULTS AND INTERFERENCE

5.1 SIX BUS GARVER TEST SYSTEM DESCRIPTION

Is this Section the data sets for transmission expansions planning of garver systems were presented, the reactance data are in p.u. considering a 100 MW base.

This system has six buses and 15 right-of-ways for the addition of new circuits. The demand is of 760MW and the relevant data are given in Tables 5.1 and 5.2. The initial topology have been shown in Fig. 5.1 [42]

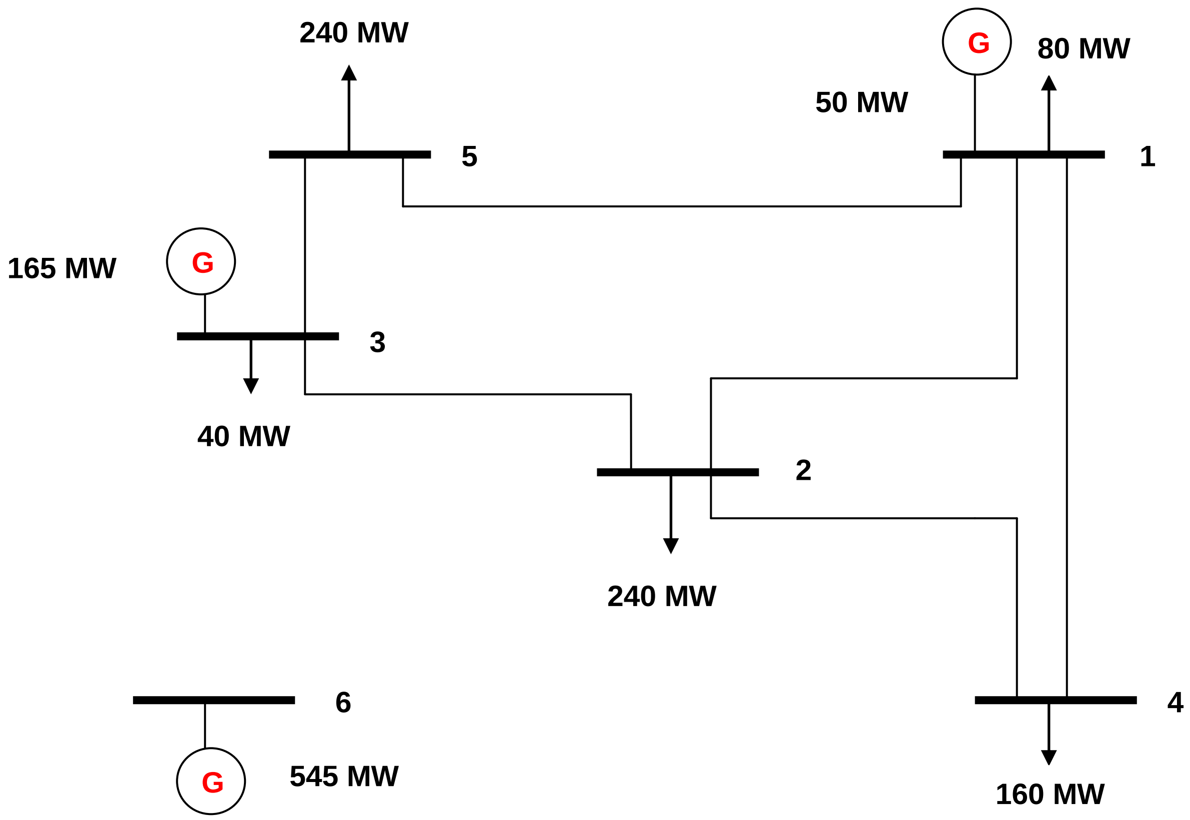


Fig 5.1 Garver Network (Initial Network)

Table 5.1 Load-Generator Data: Garver Network

Bus No.	Generation (MW) Maximum	Level (MW)	Load (MW)
1	150	50	80
2	0	0	240
3	360	165	40
4	0	0	180
5	0	0	240
6	600	545	0

Table 5.2 Line Data: Garver Network

From-To	$n_{ij}{}^{0}$(Initial No. of Lines)	Reactance p.u.	$\overline{f}_{ij}$(Maximum Power flow limit) (MW)	Cost $ (10^3)
1-2	1	0.40	100	40
1-3	0	0.38	100	38
1-4	1	0.60	80	60
1-5	1	0.20	100	20
1-6	0	0.68	70	68
2-3	1	0.20	100	20
2-4	1	0.40	100	40
2-5	0	0.31	100	31
2-6	0	0.30	100	30
3-4	0	0.59	82	59
3-5	1	0.20	100	20
3-6	0	0.48	100	48
4-5	0	0.63	75	63
4-6	0	0.30	100	30
5-6	0	0.61	78	61

5.2 RESULTS: GARVER SYSTEMS TEP (TRANSMISSION EXPANSION PLANNING)

In these section results of six bus garver system transmission expansion planning for different conditions has been mentioned.

Case 1- Six bus Garver systems with no redispatch TEP (Transmission Expansion Planning) without security constraint:

Following are the parameters used in DE algorithm,

Population Size=200,

No of Generations=1000,

F1=0.5(Scaling_factor_1)

F2=0.3(Scaling_factor_2),

CR=0.8 (Crossover Probability)

Convergence Graph without security constraint:

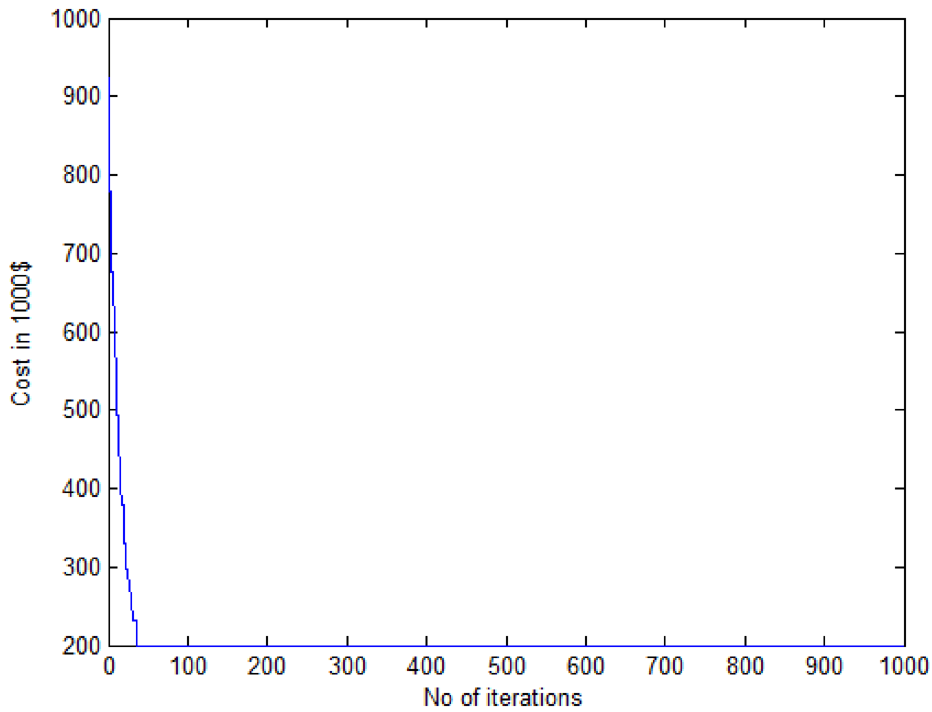


Fig. 5.2 Case1: Convergence Graph *(Scale: X-axis: 100000 $/div, Y-axis: 100 Iterations/div)*

Table 5.3 Final Optimal Results after TEP case1

From-To	n_{ij} (New final No. of Lines)	Cost $ (10^3)	Total Cost $ (10^3)
1-2	0	40	0
1-3	0	38	0
1-4	0	60	0
1-5	0	20	0
1-6	0	68	0
2-3	0	20	0
2-4	0	40	0
2-5	0	31	0
2-6	4	30	120
3-4	0	59	0
3-5	1	20	20
3-6	0	48	0
4-5	0	63	0
4-6	2	30	60
5-6	0	61	0
Total Optimal Cost TEP			**200**

Observation: As we can see in above convergence graph for TEP without redispatch and without security constraint DE is taking 36 iterations and optimal cost is 200000 $ with new addition of lines in between bus 2-6, 3-5 and 4-6.

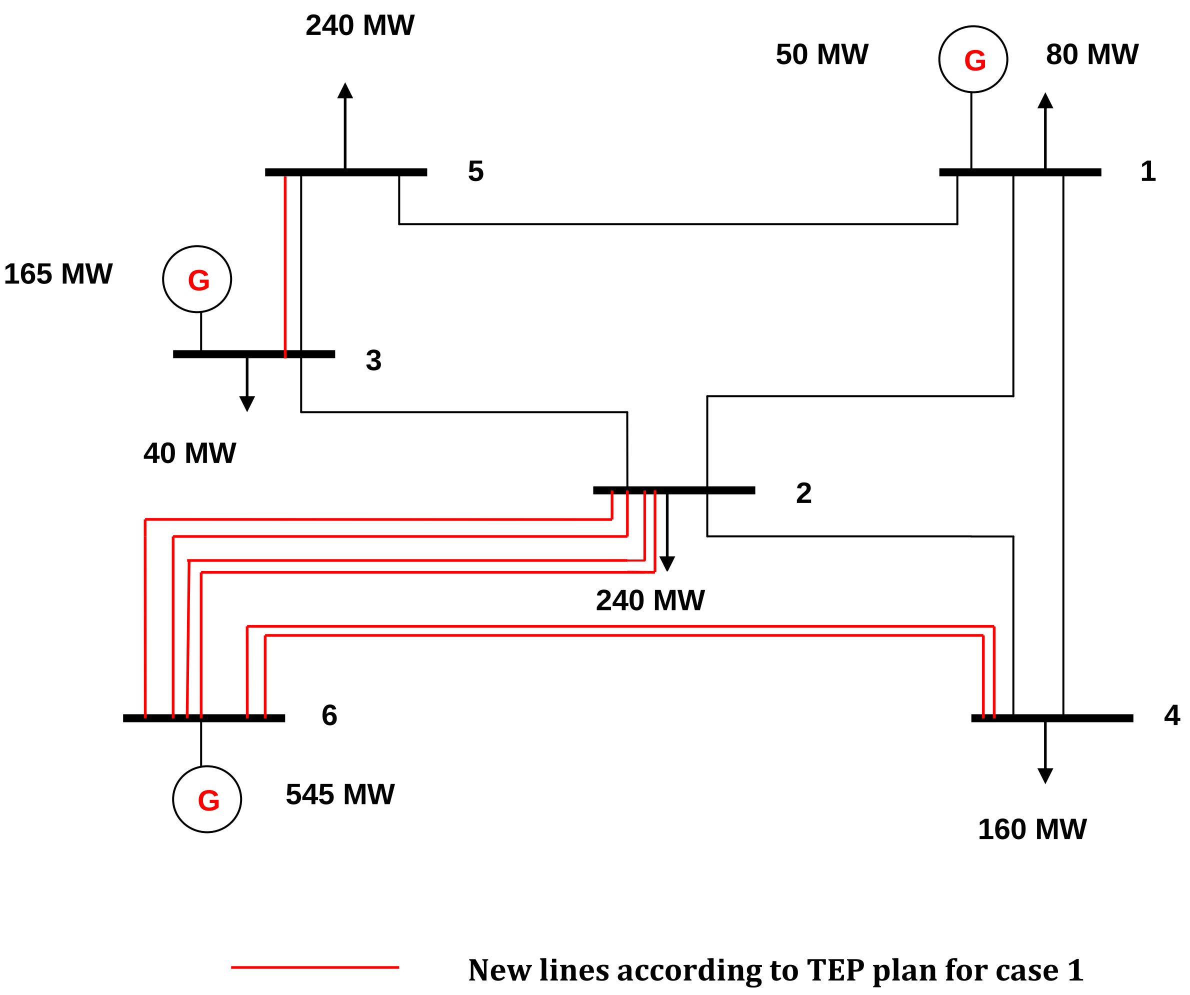


Fig. 5.3 Garver system after case 1 TEP

Case 2: Six bus Garver systems with No redispatch TEP (Transmission Expansion Planning) with security constraint Results:

Following are the parameters used in DE algorithm,

Population Size=200,

No of Generations=1000,

F1=0.5 (Scaling factor_1),

F2=0.3 (Scaling factor_2),

CR=0.8 (Crossover Probability)

Convergence Graph with security constraint:

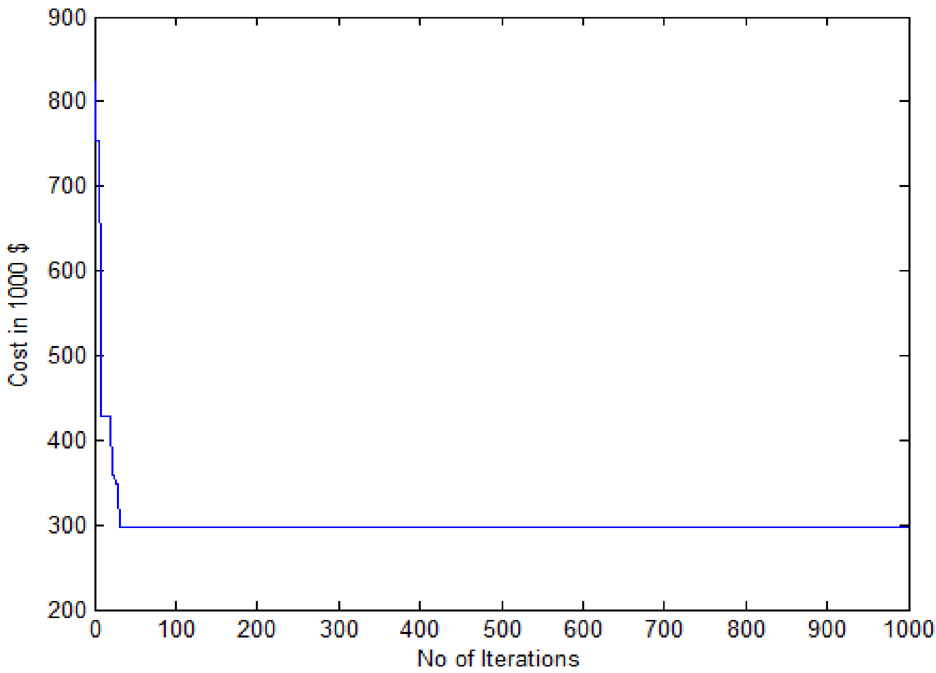


Fig. 5.4 Convergence Graph after case 1 TEP *(Scale: X-axis: 100000 $/div, Y-axis: 100 Iterations/div)*

Table 5.4 Final Optimal Results after TEP case 2

From-To	n_{ij} (New final No. of Lines)	Cost $ (10^3)	Total Cost $ (10^3)
1-2	0	40	0
1-3	0	38	0
1-4	0	60	0
1-5	0	20	0
1-6	0	68	0
2-3	0	20	0
2-4	0	40	0
2-5	0	31	0
2-6	4	30	120
3-4	0	59	0
3-5	2	20	40
3-6	1	48	48
4-5	0	63	0
4-6	3	30	90
5-6	0	61	0
Total Optimal Cost TEP			**298**

Observation: As we can see in figure 5.3 convergence graph for TEP without redispatch and with security constraint DE is taking 47 iterations and optimal cost is 298000 $ with new addition of lines in between bus 2-6, 3-5 and 4-6 and 3-6.

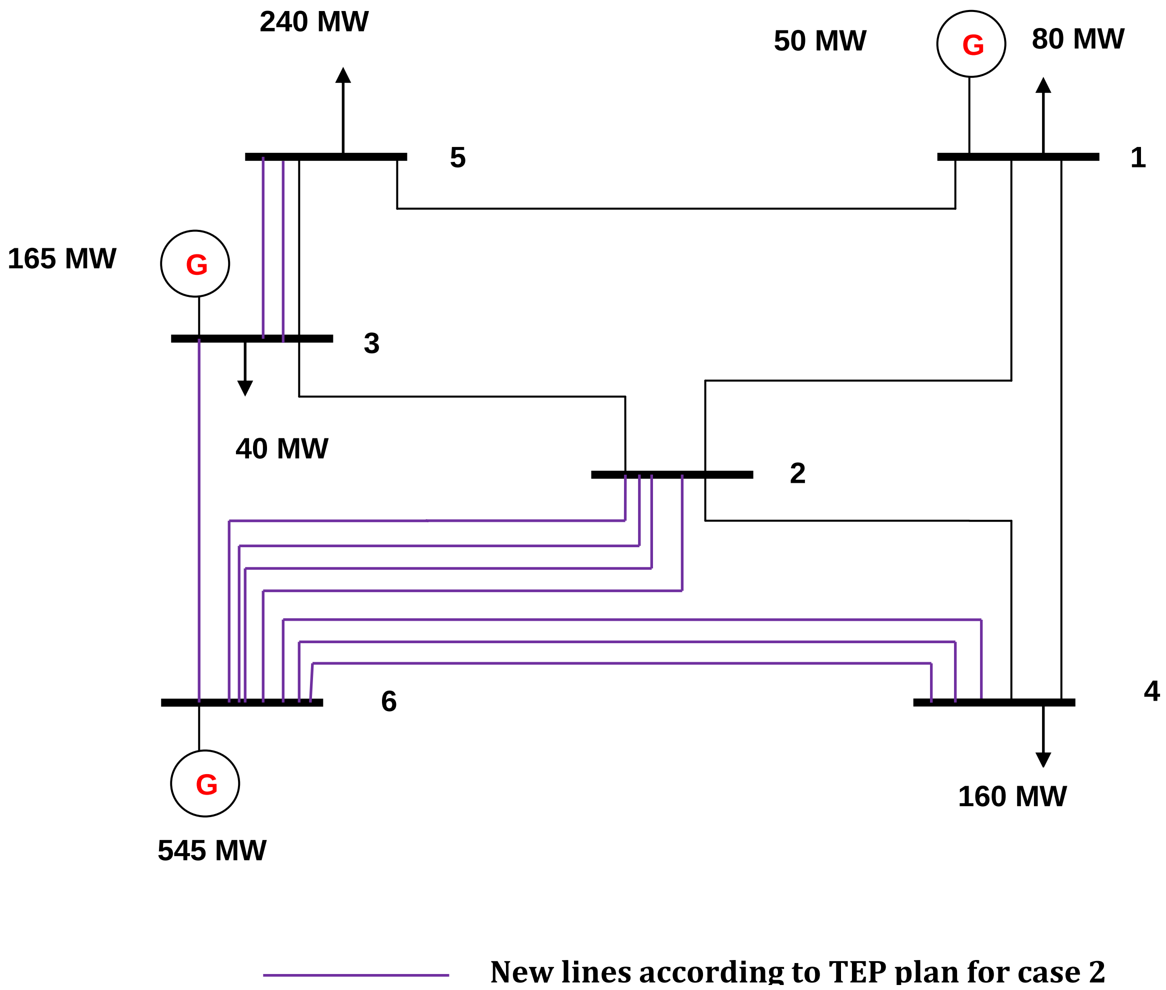


Fig. 5.5 Garver system after case 2 TEP

Case 3: Six bus Garver systems with Redispatch TEP (Transmission Expansion Planning) without security constraint Results:

Following are the parameters used in DE algorithm,

Population Size=200

No of Generations=1000,

F1=0.5 (Scaling factor_1),

F2=0.3 (Scaling factor_2),

CR=0.8 (Crossover probability)

<u>Convergence Graph with redispatch and security constrained TEP:</u>

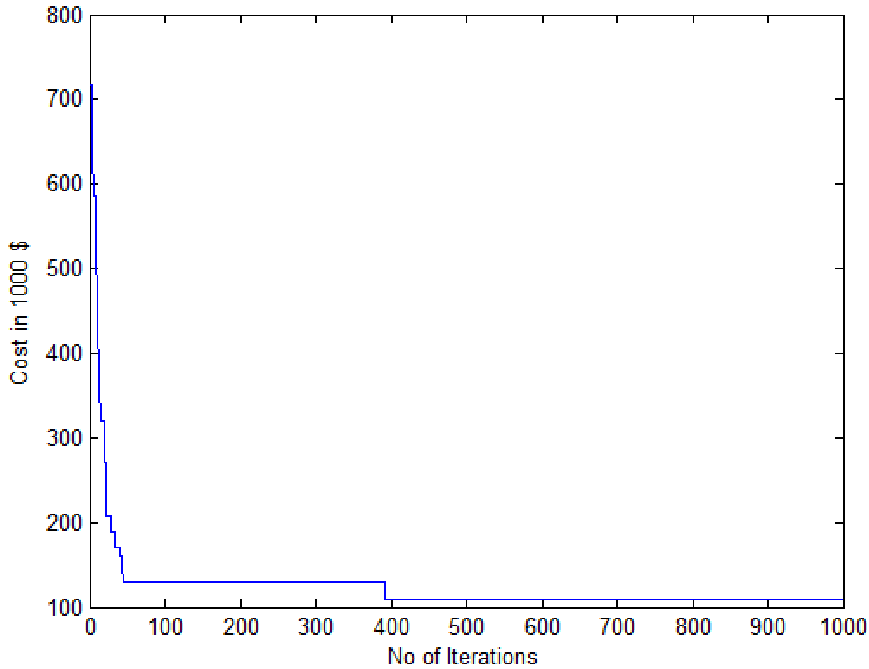


Fig. 5.6 Convergence graph after case 3 *(Scale: X-axis: 50000 $/div, Y-axis: 10 Iterations/div)*

Table 5.5 Final Optimal Results after TEP case 3

From-To	n_{ij} (New final No. of Lines)	Cost $ (10^3)	Total Cost $ (10^3)
1-2	0	40	0
1-3	0	38	0
1-4	0	60	0
1-5	0	20	0
1-6	0	68	0
2-3	0	20	0
2-4	0	40	0
2-5	0	31	0
2-6	0	30	0
3-4	0	59	0
3-5	1	20	20
3-6	0	48	0
4-5	0	63	0
4-6	3	30	90
5-6	0	61	0
Total Optimal Cost TEP			**110**

Table 5.6 Load-Generator Data after TEP with redispatch

Bus No.	Generation (MW) Maximum	Level after redispatch(MW)	Load (MW)
1	150	**147**	80
2	0	0	240
3	360	**313**	40
4	0	0	180
5	0	0	240
6	600	**140**	0

Observation: As we can see in fig. 5.6 convergence graph for TEP with redispatch and without security constraint DE is taking 144 iterations and optimal cost is 110000 $ with new addition of lines in between bus 3-5 and 4-6. New generation levels after redispatch is 147,313 and 140 MW

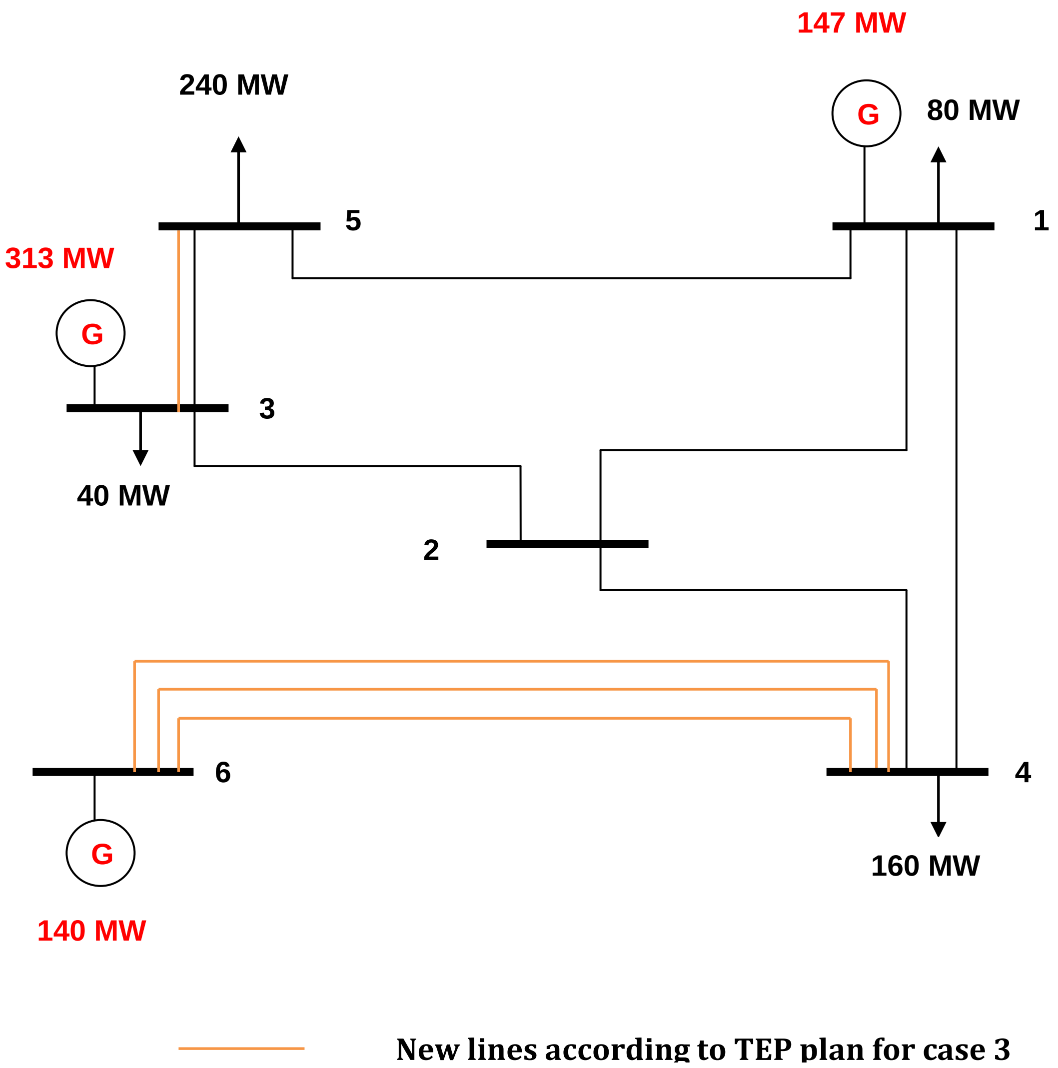


Fig. 5.7 Garver system after case 3 TEP

5.3 COMPARISON BETWEEN TEP IN DIFFERENT CASES FOR GARVER SYSTEM

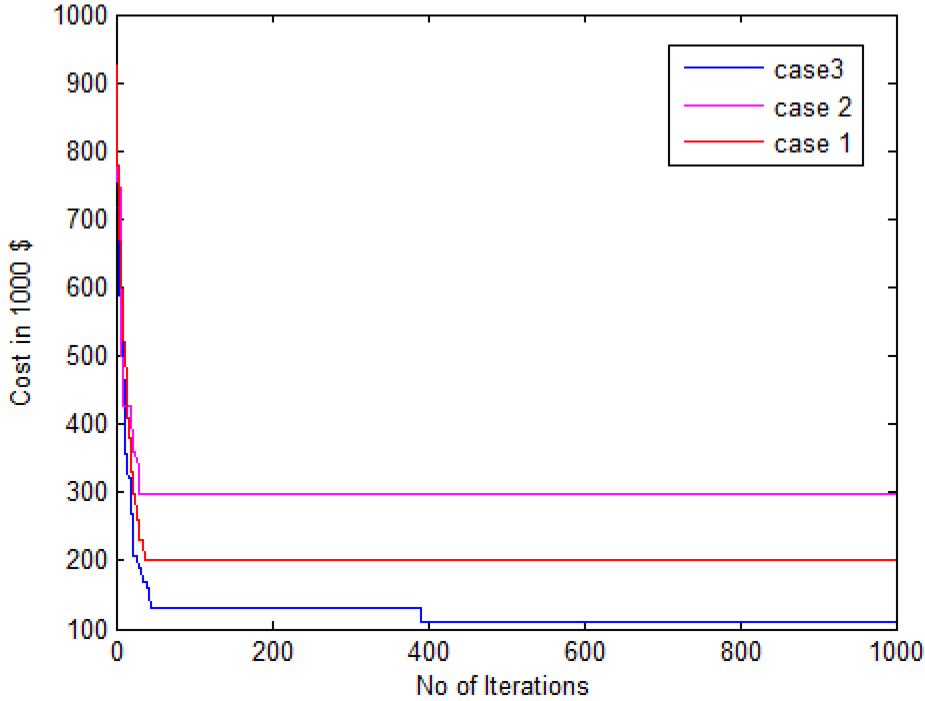


Fig. 5.8 Comparison of convergence graph after case 1, 2, and 3 *(Scale: X-axis: 50000 $/div, Y-axis: 10 Iterations/div)*

Table 5.7 Comparison for TEP in different cases DC model

Case No.	No. of Iterations for Convergence	Cost $ (10^3)	Complexity
1. Garver Network TEP without Security Constraint with no redispatch	38	**200**	Low
2. Garver Network TEP with Security Constraint with no redispatch	43	**298**	High
3. Garver Network TEP without Security Constraint with redispatch	380	**110**	High

The analysis of the Table 5.7 given above is as follows:

Observations: Table 5.7 shows how no of iteration changes for each case. Iterations are 38, 43,380 and costs are 200000 $, 298000 $, 110000 $ for case 1, case 2, case3 respectively.

Conclusion: Table 5.7 implies that as we increase the constrained no. of iterations for differential algorithm to solve transmission expansion planning increases which infers to higher complexity. As we can see in same table that final cost for TEP is least in case of security constraint with redispatch as differential algorithm gets to alter generation levels to optimize cost further in comparison to other cases.

When we consider redispatch option then we have to use generation levels given in data itself which gives less flexibility to optimize cost.

5.4 COST COMPARISON BETWEEN TEP FOR DC MODEL AND TRANSPORTATION MODEL ON GARVER SYSTEM

Table 5.8 Comparison for TEP in different models and algorithms

Case	Transportation Model (Branch and Bound Algorithm) cost (10^3\$)[42]	DC Model (DE algorithm) cost (10^3\$)
No redispatch	**200**	**200**
With redispatch	**110**	**110**

The analysis of the Table 5.8 given above is as follows:

Observations: Table 5.8 shows how costs are 200000 $, 110000 $ for both models. Transportation model results are taken from literature review to compare with DC model and DE algorithm.

Conclusion: Table 5.8 implies that DE algorithm better than Branch and bound algorithm. Where transportation model is approximation of DC model and classical programs take more time to converge, known from literatures available with more complex model DE is giving same optimal global minima in short time makes it better algorithm for power system planning especially for small systems like garver network.

5.5 CASE 4: MULTI-YEAR GENERATION EXPANSION PLANNING

Test system description:

Case 4 for a real-scale system with a 24-year study period, the planning horizons of 24 years are divided into 12 stages (two-year intervals).

The forecasted peak demand over the study period is given in Table 5.9, tables 5.10 and 5.11 show the technical and economic data of the existing plants and candidate plant types for future additions, respectively [34].

Table 5.9 Forecasted peak demand

Stage (Year)	0 (1996)	1 (1998)	2 (2000)	3 (2002)	4 (2004)	5 (2006)	6 (2008)
Peak (MW)	5000	7000	9000	10000	12000	13000	14000
Stage (Year)	-	7 (2010)	8 (2012)	9 (2014)	10 (2016)	11 (2018)	12 (2020)
Peak (MW)	-	15000	17000	18000	20000	22000	24000

Table 5.10 Technical and Economic Data of existing plants

Name(fuel type)	**No of units**	**Unit capacity (MW)**	**FOR (%)**	**Operating cost ($/kwh)**	**Fixed O & M Cost ($/KW-Month)**
Oil# 1 (Heavy oil)	1	200	7.0	0.024	2.25
Oil# 2 (Heavy oil)	1	200	6.8	0.027	2.25
Oil# 3 (Heavy oil)	1	150	6.0	0.030	2.13
LNG G/T #1 (LNG)	3	50	3.0	0.043	4.52
LNG C/C #1 (LNG)	1	400	10.0	0.038	1.63
LNG C/C #2 (LNG)	1	400	10.0	0.040	1.63
LNG C/C #3 (LNG)	1	450	11.0	0.035	2.00

Coal #1 (anthracite)	2	250	15.0	0.023	6.65
Coal #2 (Bituminous)	1	500	9.0	0.019	2.81
Coal #3 (Bituminous)	1	500	8.5	0.015	2.81
Nuclear #1 (PWR)	1	1000	9.0	0.005	4.94
Nuclear #2 (PWR)	1	1000	8.8	0.005	4.63

Table 5.11 Technical data and Economical data of candidate plants

Candidate Type	Construction upper limit	Capacity (MW)	FOR (%)	Operating cost ($/kWh)	Fixed O & M cost	Capital cost ($/kW)	Life time (yrs)
Oil	5	200	7.0	0.021	2.20	812.5	25
LNG C/C	4	450	10.0	0.035	0.90	500.0	20
Coal (Bitumin.)	3	500	9.5	0.014	2.75	1062.5	25
Nuclear (PWR)	3	1000	9.0	0.004	4.60	1625.0	25
Nuclear (PHWR)	3	700	7.0	0.003	5.50	1750.0	25

Parameters for GEP:

There are several parameters to be pre-determined, which are related to the GEP problem and GA-based programs. In this paper, we use **8.5%** as a discount rate, **0.01** as LOLP criteria, and **15%** and **60%** as the lower and upper bounds for reserve margin, respectively. The considered lower and upper bounds of capacity mix are **0%** and **30%** for oil-fired power plants, **0%** and **40%** for LNG-fired, **20%** and **60%** for coal-fired, and **30%** and **60%** for nuclear, respectively [34].

Table 5.12 Comparison of IGA (Improved genetic algorithm) and DE for case 4

Algorithm	GEP Cost (10^{12} $)
IGA (Improved genetic algorithm)	2.92
DE (Differential Algorithm)	2.42

Table 5.13 Cumulative number of newly introduced plans in case 4 in DE

Type Year	Oil (200 MW)	LNG C/C (450 MW)	Coal (500 MW)	PWR (1000 mw)	PHWR (700 MW)
1998	3	1	3	1	1
2000	6	3	5	2	3
2002	8	4	5	2	3
2004	8	4	5	2	3
2006	8	4	5	2	3
2008	9	6	8	5	5
2010	12	8	9	7	5
2012	12	8	9	7	5
2014	12	8	9	7	5
2016	14	10	9	7	6
2018	14	10	9	9	6
2020	15	11	9	10	7

Analysis of Table 5.12 as following:

Observation: Table 5.12 shows cost difference for given 12 year GEP with improved genetic algorithm and with Differential evolution.

Conclusion: As we can see from table we are able to get $0.5*10^{12}$ $ profit with DE solution over IGA solution given in literature. Although formulation used by us was different than used in IGA but getting better result for equally closed formulation shows DE is better in multiyear complex GEP also.

5.6 CASE 5: HYBRID GEP-TEP

Test system description:

Table 5.14 Generation-Load Data

Bus No.	Generation Maximum (MW)	Generation Minimum (MW)	Load (MW)
1	150	50	80
2	0	0	240
3	360	50	40
4	0	0	160
5	0	0	240
6	600	0	0

Table 5.15 Candidate line data

From-to bus	X p.u.(reactance)	Flow limit (MW)	Cost ($10^3$$)
1-2	0.4	100	40
1-3	0.38	100	38
1-4	0.6	80	60
1-5	0.2	100	20
1-6	0.68	70	68
2-3	0.2	100	20
2-4	0.4	100	40
2-5	0.31	100	31
2-6	0.3	100	30
3-4	0.59	82	59
3-5	0.2	100	20
3-6	0.48	100	48
4-5	0.63	75	63
4-6	0.3	100	30
5-6	0.61	78	61

Case 5: Dynamic planning-

Following are the parameters used in dynamic planning DE algorithm,

Population Size=100

No of Generations=100,

F1=0.5 (Scaling factor_1),

F2=0.3 (Scaling factor_2),

CR=0.8 (Crossover probability)

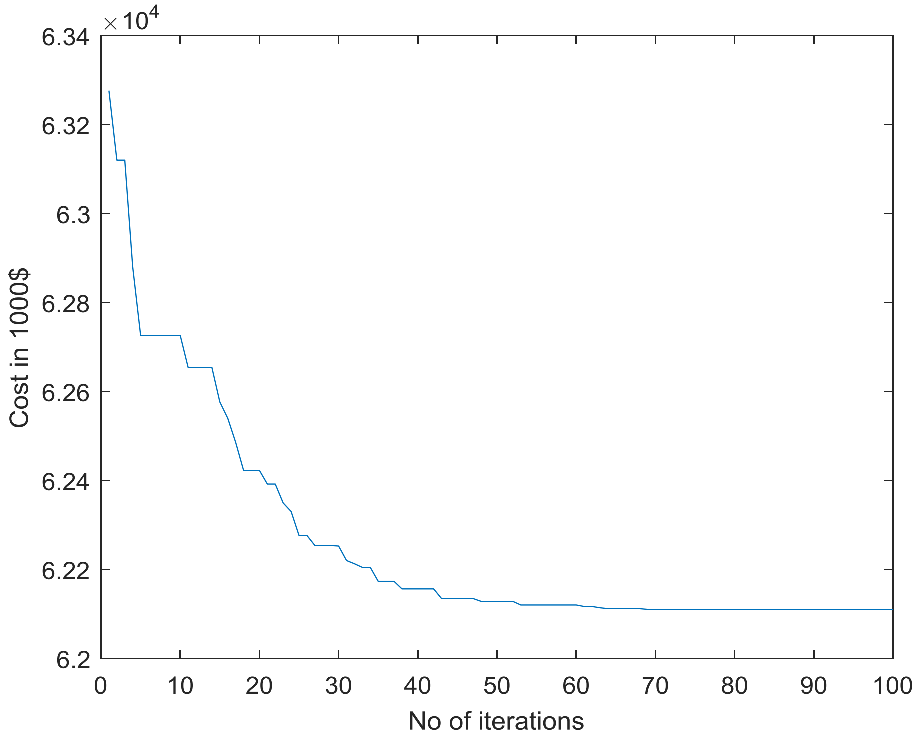


Fig. 5.9 Convergence graph after case 5 dynamic planning *(Scale: X-axis: 200000 $/div, Y-axis: 10 Iterations/div)*

Case 5: Static planning-

Following are the parameters used in dynamic planning DE algorithm,

Population Size=5,

No of Generations=100,

F1=0.5 (Scaling factor_1),

F2=0.3 (Scaling factor_2),

CR=0.8 (Crossover probability)

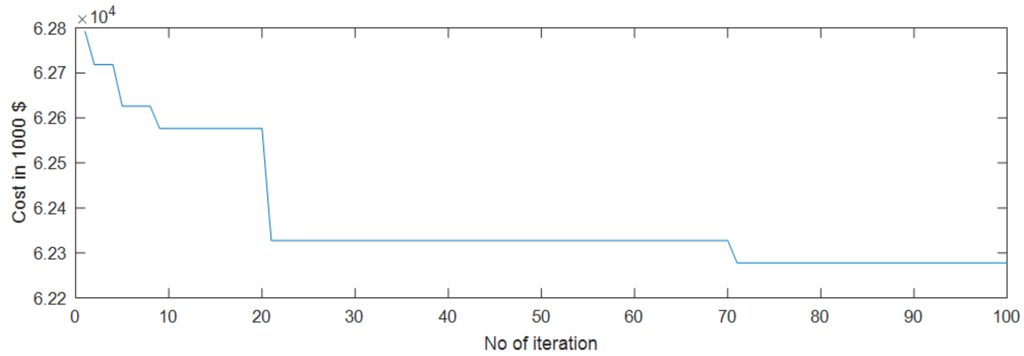


Fig. 5.10 Convergence graph after case 5 static planning *(Scale: X-axis: 100000 $/div, Y-axis: 10 Iterations/div)*

Case 5: Comparison hybrid GEP-TEP static and dynamic approach with DE-

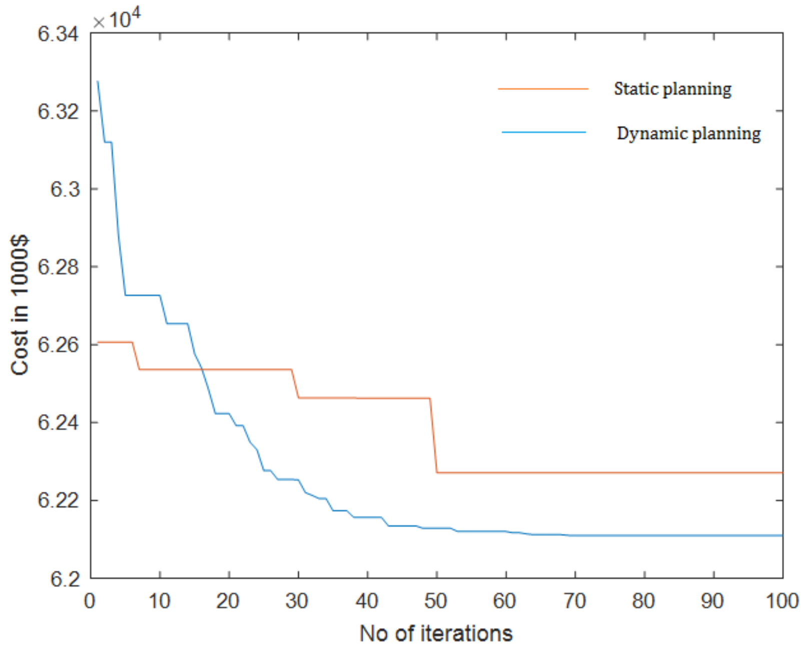


Fig. 5.11 Convergence graph: comparison of static and dynamic planning after case 5 *(Scale: X-axis:200000 $/div, Y-axis: 10 Iterations/div)*

Table 5.16 Comparison hybrid GEP-TEP static and dynamic approach with DE

Approach		Cost (10^3\$)	Iterations
Dynamic		**62110**	71
Static	**GEP**	**61764**	55
	TEP	**526**	
	Total Cost	**62290**	

Cost assumptions:

Transport Cost: ***0.3x1000$/km***

Construction Cost at Gen1: ***80000$/MW***

Gen2: 100000$/MW, Gen3: ***90000$/MW***

Analysis of Table 5.16 as follows:

Observation: As we can see in table 5.16 that Dynamic approach for given case 5 has given 62110000 $ cost and Static cost for GEP is 61764000 $ and for TEP is 446000 $.

Conclusion: It implies that dynamic approach is better than static approach with DE as it gives better optimal solution although it takes more time. Another conclusion comes is that GEP cost is always greater and takes more time than TEP because of greater complexity. It also tells us that DE gives optimal solution with increase in complexity.

CHAPTER 6

FUTURE SCOPE

It would be a good opportunity to study the problem formulations on various test cases. The test case considered in all of my report is the Garver system which is quite small system. We could modify the 46, 78, 84, 93 bus standard systems to our needs in order to see the performance of meta-heuristic algorithms. We can do the addition of Smart Grid features like Electric Vehicles in the grid to see its effects on the planning process. We speculate that the cost of plan would be reduced if DSM is able to reduce the peak load. Future work can be done in following area.

- Add smart grid components to the system.
- Formulate a global Optimization problem considering GEP, TEP, SEP, REP all at once to show that the global minima are achieved by simultaneous optimization rather than sequential.
- Test the sub-routine with various meta-heuristic algorithms.

APPENDIX A

A.1 LOAD FLOW PROBLEM

Formulation of classic load flow problem will require considering four variables at each bus i of power system. These variables are

1. ***Pi*** *(Net active power injection)*

2. ***Qi*** *(Net reactive power injection)*

3. ***Vi*** *(Voltage magnitude)*

4. ***θi*** *(Voltage angle)*

the active and reactive power injections calculated as follows-

$$P_i = P_{Gi} - P_{Di} \tag{A.1}$$

$$Q_i = Q_{Gi} - Q_{Di} \tag{A.2}$$

In which $\boldsymbol{P_{Gi}}$and $\boldsymbol{Q_{Gi}}$are active and reactive power generations at bus i, respectively, whereas $\boldsymbol{P_{Di}}$ and $\boldsymbol{Q_{Di}}$ are active and reactive power demands at this bus, respectively. Based on the application of Kirchhoff's laws to each bus

$$I = VY \tag{A.3}$$

$$I_i = \frac{(P_i - jQ_i)}{|V_i|} e^{j\theta_i} \tag{A.4}$$

Where,

I_i-Net injected current at bus i

V- Vector of bus voltages

I- Vector of injected currents at the buses

Y- Bus admittance matrix of the system

To solve full load flow equations, two of four variables must be known in advance at each bus. This formulation results in a non-linear system of equations which requires iterative solution methods. In this formulation, convergence is not guaranteed [1].

A.2 DC LOAD FLOW SOLUTION

Direct Current Load Flow (DCLF) will give estimations of lines power flows on AC power systems. DCLF looks only at active power flows and neglects reactive power flows. This method is non-iterative and absolutely convergent but less accurate than AC Load Flow (ACLF) solutions. DCLF can be utilized wherever repetitive and fast load flow estimations are required.

In DCLF, nonlinear model of the AC system is simplified to a linear form through these assumptions [1],

1. Line resistances (active power losses) are negligible i.e. $R \ll X$
2. Voltage angle differences are assumed to be small i.e. $\sin(\theta) = \theta$ and $\cos(\theta) = 1$.
3. Magnitudes of bus voltages are set to 1.0 per unit (flat voltage profile).
4. Tap settings are ignored.

Based on the above assumptions, voltage angles and active power injections are the variables of DCLF. Active power injections are known in advance.

$$P_i = \sum_{j=1}^{N} B_{ij}(\theta_i - \theta_j) \tag{A.4}$$

In which B_{ij} is the reciprocal of the reactance between bus i and bus j. As mentioned earlier, B_{ij} is the imaginary part of Y_{ij}. As a result, active power flow through transmission line i, between buses s and r, can be calculated as below-

$$P_{Li} = \frac{1}{X_{Li}}(\theta_s - \theta_r) \tag{A.5}$$

Where X_{Li} is the reactance of line i. DC power flow equations in the matrix form and the corresponding matrix relation for flows through branches are represented below-

$$\theta = [B]^{-1}P \tag{A.6}$$

$$P_L = (b \times A)\theta \tag{A.7}$$

Where,

P *N ×1 vector of bus active power injections for buses 1, …, N*

B *N × N admittance matrix with R = 0*

θ *N ×1 vector of bus voltage angles for buses 1, …, N*

$\boldsymbol{P_L}$ *M× 1 vector of branch flows (**M** is the number of branches)*

b *M×M matrix (*$\boldsymbol{b_{kk}}$ *is equal to the susceptance of line k and non-diagonal elements are zero)*

A *M× N bus-branch incidence matrix*

*Each diagonal element of **B** (i.e.* $\boldsymbol{B_{ii}}$*) is the sum of the reciprocal of the line.*

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