Chapter 1
Chapter 1

General Introduction

1.1 Power generation: a single and multi-objective problem

Electric power system is to be planned, operated, monitored and controlled in an optimal manner. The basic premise of optimal operation of power system is to distribute the demand imposed on it among the committed units in such a manner that the cost of producing the power is minimum. Though economy in the system operation is certainly one of the most important criteria of optimality but other factors, e.g., ecology, quality of power, etc. also deserve due considerations.

The choice of optimal criteria is always a subjective one, since, one has to first decide as what shall have to be minimized or maximized as the case may, in a particular problem so that objective function is defined. Once the optimality criterion is decided, it is then possible to proceed for mathematical formulations and solutions. The major challenges of an optimization problem are:

(i) When there is a single objective function of non-convex nature or

(ii) When there are more than one objective functions of conflicting nature and each one of them may be of non-convex type. These types of problems are usually called multi-objective optimization problems.
1.1. Power generation: a single and multi-objective problem

1.1.1 Economic Load Dispatch As Single Objective Optimization Problem

The economic load dispatch (ELD) problems in power system fall under the first categories of optimization problems. ELD in power system is used in real time energy management to allocate the total required generation among the committed units as well as in interchange evaluation, costing and billing, unit commitment and other operational functions. The accuracy of the models that describe the fuel cost-characteristics of the units plays vital role in the optimization of ELD problems significantly. Various techniques, like the Lambda-iteration method, the base point and participation factors method and the gradient search method have been reported in the literatures.

Today's quality requirements of power utilities are so demanding, especially in the context of deregulation of electric industry that the operators have to make every possible effort for minimizing the production cost to enable them to be the most demanding in a competitive environment. This has led to the adoption of system models and other operational constraints more akin to their realistic situations. Be it the model representation of thermal units or hydro units or the consideration of operational constraints, model accuracy as well as realistic constraints play a major role in deciding the optimum schedule. Thermal units with multi-valve steam turbines exhibit a greater variation in the fuel cost function. Besides, a power generation system usually employs a series of single-cycle gas turbines in conjunction with some heat-recovery combined cycle steam generators (HRSG). Since, the combustion unit is most economic when loaded with full capacity once it is placed on line, for economic operation the combustion engine should be either fully loaded or completely turned off in the EL dispatch. Also, thermal units may have other operational constraints like dynamic ramping rates, prohibited operating zones etc.

Consideration of more realistic unit cost-characteristics makes the power system ELD problems to be highly non-convex. Conventional classical dispatch algorithms employing the lambda-iteration method, the base point and participation factors method, and the gradient method require incremental cost curves to be of convex types. Unfortunately, the input-output characteristics of
modern units are inherently highly non-linear because of valve point loadings, rate limits, prohibiting operating zones etc resulting in multiple local minimum points in the cost functions. Traditional optimization techniques require to approximate modelling accuracy to some extent in order to make them amenable for solution by classical dispatch techniques. However, it is demonstrated [2] that approximation of models result into huge loss of revenues over the time. Consideration of highly nonlinear characteristics of the units demand for solution techniques having no restrictions on the shape of the units fuel cost-characteristics. Evolutionary Computational (EC) techniques under Soft computational (SC) techniques are the ideal choice for solving these highly non-convex optimization problems.

1.1.2 Combined Economic and Emission (CEED) Dispatch as Multi-Objective Optimization

In single objective optimization, one tries to find the best solution (called the optimal solution) for one objective only, which is either maximum or minimum depending upon the objective of the problem. But in multi-objective optimization, the objectives are more than one and may be of conflicting nature and there may not exist one solution, which is the best with respect to all the objectives.

Thermal power stations are major causes of atmospheric pollution; because of high concentration of pollutants they cause. Actual pollution output depends on emission rates under various loading conditions. Environment concerns and Kyoto Protocol objectives require taking into account emissions as objectives to be minimized.

Global environmental issues such as the greenhouse effect resulting from energy consumption are attracting considerable attention. The increasing public awareness of the environmental pollution and the passage of the Clean Air Act amendments in November 1990 have forced the utilities to modify their design or operational strategies to reduce pollution and atmospheric emissions such as $SO_2$, $CO_2$, and $NO_2$. Ideally, the utilities would like to supply power to its customers with minimum total emission as well as minimum total fuel cost. This gave rise to the emergence of a new method called CEED method to fight against air pollution. CEED is a multi-objective problem in power systems.
1.1. Power generation: a single and multi-objective problem

Electric Power Industry in US, had an actual CO₂ Emissions of 1,788 million metric tons for generation of 1,882 billion KWh in 1999 only from coal, other than emission of methane and nitrous oxide and the high Global Warming Potential gases such as HFCs, PFCs and sulfur hexafluoride. (ref:www.eia.doc.gov).

Several strategies to reduce the atmospheric emissions have been proposed and discussed. These include installation of pollutant cleaning equipment such as gas scrubbers and electrostatic precipitators, switching to low emission fuels, replacement of the aged fuel burners and generator units with cleaner and more efficient ones, and emission dispatching. The first three options require installation of new equipments and/ or modification of the existing ones that involve considerable capital investment and, hence, can be considered as long term options.

The emission dispatching option is an attractive short term alternative in which the emissions in addition to the fuel cost objective are to be minimized. Thus, an Economic Emission Dispatch (EED) problem is a multi-objective optimization problem, which is to determine the allocation of power demand among the committed generating units, to minimize a number of objectives viz. operating cost, minimal impacts on environment etc., subject to physical and technological constraints.

Classical methods for EED scalarize the vector of objectives into a single objective by summing up the objectives scaled by a weight vector and hence a single solution is available at every simulation run. In a typical multi-objective problem, a set of optimal solutions is possible. These solutions are termed as Pareto-optimal or non-dominated solutions [47] [48]. These solutions are classified as superior to the rest of solutions in the search space when all objectives are considered but are inferior to other solutions in one or more objectives. The rest of the solutions are called dominated solutions. Since none of the solutions in the non-dominated set is absolutely better than any other, any of them is an acceptable solution. Thus the designer in a multiobjective environment should have knowledge of other Pareto-optimal solutions.
1.2 Soft Computing (SC)

Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. Hard computing means computation with precise (strict) rules while SC means computing with approximate reasoning (strict rules are relaxed). In effect, the role model for SC is the human mind. The guiding principle of SC is: exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost. SC techniques can find better solutions based on certain fitness criterion, which evaluates the performance of the algorithm in optimizing certain objectives.

SC techniques allow consideration of precise modelling of generating units for ELD problems, as they are capable of tackling objective functions with any degree of non-linearity. Besides, there is no need for having an explicit objective function. Even when the objective function is available, it need not be differentiable.

Therefore, the power system utility engineers are inspired to apply different SC techniques to a variety of optimization problems in power system in recent times. The main (principal) constituents of SC techniques are:

1. Fuzzy systems
2. Neural Networks
3. Evolutionary Computing (EC)

Again EC can be implemented by:

(i) Genetic Algorithm
(ii) Evolutionary Programming (EP) (Probabilistic selection)
(iii) Evolutionary Strategy (ES) (Deterministic selection)
(iv) Simulated Annealing (SA)
(v) Particle Swarm Optimization (PSO)
(vi) Differential Evolution (DE)
A lot of development has taken place over more than last four decades in EC techniques, which are based on simulated evolutionary process of natural selection and genetics. They are more flexible than the classical methods. These algorithms start with a trial population of control variables, which is then improved using some rules, by generating new population with better fitness values. In Genetic Algorithm (GA), the operators for producing new population (offspring) are mutation and crossover, while in EP, mutation is the only operator to create new population. In binary GA, control parameters are coded into binary form and decoded into real values, but in EP, such coding and decoding are not needed. Hence, considerable computation time may thus be saved in EP. The SA [4] [5] also has the capability of seeking global optimum solution but appropriate setting of the relevant control parameters in SA is a difficult task and the speed of the algorithm often becomes slow when applied to practical sized power system. Moreover, tremendous achievements have been made in enhancing the speed of EP algorithms and are demonstrated on the benchmark mathematical functions. These have resulted in the development of fast EP (FEP) and improved fast EP (IFEP) [2][6-9].

Very recent addition to these types of search techniques are PSO [10-12] and DE [82][89-90]. In comparison to population based evolutionary algorithms, PSO is computationally inexpensive in terms of memory and speed. Constructive cooperation rather than survival of the fittest is the fundamental principle of PSO technique. Therefore, the optimal solution is reached by cooperation of all of the individuals within the population.

While in DE, the key feature in generating more promising trial solutions is by adding the weighted difference vector between two population members to a third member. The values of the weights play vital role in the success of the algorithm. The weights are dependent on the nature and size of the objective functions. They are reported to have performed very efficiently on many benchmark mathematical problems and on some problems of power system.

Hence, the most recent trends for research have been directed towards development of more efficient techniques by hybridization of evolutionary computational techniques i.e. GA, EP, PSO and DE.
Even when finding the solution of multi-objective problems with more than two convex objective functions is difficult, if the objective functions are non-convex types, the problem becomes more challenging. For solution of these types of multi-objective optimization problems, EC techniques based algorithms are the most promising ones and the right choice to apply. The potential of evolutionary algorithms (EAs) for solving multi-objective optimization problems was hinted as early as in late 1960's by Rosenberg [51].

But the implementation of Multiobjective Evolutionary Algorithm (MOEA) was delayed until mid-1980s. Since, EAs work with a population of solutions, hence it is possible for EA to provide a diverse set of solutions for a multi-criterion environment. Moreover, EAs are less susceptible to the shape or continuity of the Pareto front (i.e. they can easily deal with discontinuous and concave Pareto fronts), on the other hand, mathematical programming techniques have these as known problems. Very recent addition is the nondominated sorting GA (NSGA) proposed by Deb et al. [56].

Rosenberg [51] in 1967 suggested a method of search resembling the human evolution. Genes of a chromosome carry properties or objectives of an individual. Practical implementation was done by Schaffer [58] in his VEGA (Vector Evaluated GA). However, VEGA faced a problem called speciation (i.e., biological species were evolved with the population which excel on different aspects of performance). This problem had arisen because VEGA selects individuals taking into consideration a particular objective function and not all. These middling solutions were good for compromise results and not very good when all objectives are taken into consideration. One of the problems of VEGA was its biasness toward some Pareto-optimal solutions. Later Goldberg suggested a nondominated sorting procedure to overcome the situation. Thereafter Srinivas and K. Deb [56] developed the idea of NSGA in which Pareto-optimal solutions were classified into different fronts.

Among the others, elitist multiobjective EAs like Fonseca and Fleming’s MOGA [54], Horn et al.’s NPGA [55] and Kalyanmoy et al.’s NSGA-II [59] were important. These algorithms demonstrated the necessary additional operators for converting a simple EA to a MOEA.
Developing algorithms for modified NSDE for solving multiobjective power system problems like CEED was inspired by the reported impressive performance of DE algorithm [82] [89] [90] in solving non-convex optimization problems on benchmark mathematical functions.

1.3 Comparison between SC techniques and conventional methods

SC techniques like EC, fuzzy systems and neural networks differ from conventional search and optimization paradigms mainly in the following ways:

1. SC paradigms can use the previous knowledge for the solution of a problem and its behavior under various circumstances while finding new solutions;

2. SC paradigms utilize a population of points (potential solutions) in their search leading to parallel processing;

3. SC paradigms use direct fitness information instead of function derivatives or other related knowledge;

4. SC paradigms use probabilistic rather than deterministic transition rules;

5. Conventional paradigms move from one point in the decision hyperspace to another without any parallelism;

6. Conventional paradigms use some deterministic rules;

7. Conventional paradigms use gradient or higher order statistics of the cost function.

Most of the classical conventional methods of optimization generate a deterministic sequence of trial solutions based on the gradient or higher order statistics of the cost function. These techniques usually asymptotically converge to locally optimal solutions. They move from one point in the decision hyperspace to another using some deterministic rule. These methods often fail to perform adequately when random perturbations are imposed on the cost function. The other drawback of this approach is the likelihood of getting stuck at a local optimum.
1.4 Motivation behind the present work

SC techniques, on the other hand, start with a population point (hyperspace vectors). They usually generate a new population with the same number of members in each generation. Thus, many maxima or minima can be explored simultaneously reducing the probability of getting stuck at a local minimum.

1.4 Motivation behind the present work

With deregulation in practice, which results in growing competition, there has been a tremendous impetus towards incorporation of more and more realistic features in model representation for more rigorous optimization, essentially due to the fact that any sort of approximation in model representation leads to suboptimal solution with consequent huge loss of revenue. Consideration of more realistic features in characteristic cost functions of generating units makes them non-convex. Optimization problems with non-convex cost functions demand for global stochastic search methods designed out of EC techniques.

Earlier, with conventional gradient based optimization methods, the trend was to use approximate generator cost-characteristics for the purpose of optimization as because the techniques were not capable enough to tackle highly non-linear features of realistic models and of constraints as well. With more competition imminent, every effort is made towards saving revenue, as "Revenue saved is revenue earned". This has urged us to search for more robust and efficient optimization techniques that are competent enough to give near global optimum result within a reasonable time. In that sense, all stochastic global search techniques like GA, ES, and EP are all competent enough in solving highly non-linear optimization problems as they do not impose any restrictions on the nature of the cost function and of objective function. Recent additions to these techniques are PSO and DE. All these have contributed towards improvement of SC techniques in terms of speed, quality, efficiency and hence, they are being increasingly applied in solving highly non-linear optimization problems. These techniques have been reported to have performed excellently on benchmark mathematical functions. This has urged us in developing still more efficient methods by hybridization of EP and PSO algorithms. Also, the reported better performance of NSGA-II on benchmark multi-objective problems has inspired us to develop solution techniques for
1.5 Scope and objectives of the present work

The present work mainly aims in developing intelligent algorithms based on SC techniques for solving power system optimization (minimization) problems, both single objective and multi-objective types, using intelligent optimization techniques.

The targeted problems are:

(i) To develop intelligent algorithms through hybridization of EP and PSO in different variations, e.g. embedding swarm direction of PSO into mutation (strategy parameter) of self-adaptive CEP (called as PSO-CEP), or embedding strategy parameter into swarm directions (called as CEP-PSO) or two stage hybridization wherein first new solutions are created with CEP and better individuals are chosen for finding new swarm directions of PSO in the second stage (called as CEP-PSO'), and study their comparative performances on medium and moderately larger systems of ELD problems including the effects of valve point loading to decide as which proposition is the best. Then to develop an improved version of the algorithm CEP-PSO', viz. IFEP-PSO' to solve the similar problems.

(ii) To develop an algorithm based on modified NSGA-II and to study its performance in solving CEED problems on medium and moderately larger systems including valve point loading and other non-convex features.

(iii) To develop an algorithm using modified NSDE and to study its performance in solving CEED problems on medium and moderately larger systems including valve point loading and other non-convex features.

The targeted problem (i) has been treated in Chapter-2 in this thesis. This chapter introduces the basic idea of self-adaptive evolutionary programming, the difference between Gaussian mutation and Cauchy mutation, their relative advantages and disadvantages, classical EP (CEP) and improved fast EP (IFEP).
It also describes the idea of PSO technique, different variations of hybridizations like PSO-CEP, CEP-PSO, CEP-PSO' and IFEP-PSO'. The ELD problems considered here have quadratic unit cost functions together with the effects of valve point loading. Two test problems, one small system with 15 units and the other moderately larger system with 40 generating units were considered to test the performances of the algorithms.

Chapter-3 of this thesis is a review work, which provides basic concepts of multi-objective optimization problems and introduces the different techniques together with their strong and weak points in solving multi-objective optimization problems. The idea of NSGA is introduced and its different features are addressed to.

The targeted problem (ii) has been treated in Chapter-4 of this thesis. The features of NSGA-II, proposed by Deb et al. [59] are investigated and some modifications are proposed to the original NSGA-II. The developed algorithms are tested on two test cases, one small with 15 units and the other moderately larger with 40 units with non-convex objective functions.

In Chapter-5, an algorithm for target (iii) has been developed using modified NSDE and its performance is investigated on the same two test systems as in chapter-4.

1.6 Achievements

In a modest way, the following contributions was tried to make in this thesis work:

1. Intelligent algorithms through hybridization of SC techniques like self-adaptive EP and PSO are developed for solving ELD problems with cost functions including valve point loading effects. While hybridizing, different propositions like, should the swarm direction of PSO be embedded into mutation (strategy parameter) of self-adaptive EP, or strategy parameter be embedded into swarm directions; or two stage hybridization wherein new solutions are first created with CEP and better individuals are chosen for applying on them new swarm directions of PSO in the second stage, are considered and algorithms using each of the propositions are developed and their performances
1.6. Achievements

on two test cases, one small size of 15 units and other moderately larger size of 40 units, are investigated. Comparison is drawn to decide which proposition is the best. Out of the three propositions, CEP-PSO' is found to be the best. In order to pursue for enhancing convergence rate and efficiency, an improved algorithm in similar proposition like IFEP-PSO' is developed and compared with CEP-PSO' to show its improved performance.

(2) Intelligent algorithms using modified NSGA-II wherein some of the features as proposed by Deb et al. [59] are modified to improve its capability in finding more non-dominated solutions and also to improve explorability of the algorithm. The performance of the algorithm is demonstrated on two test cases of multi-objective problems in power systems like CEED. One of the two test cases is of small size of 15 units and the other is of moderately larger sized system of 40 units with valve point loading effects. Results demonstrate that the algorithm is well competent and efficient in solving multiobjective optimization problems like CEED specifically when more than two conflicting and highly nonlinear objective functions are to be optimized.

(3) Intelligent algorithms using Non-dominated Sorting Differential Evolution (NSDE) are developed for solving multi-objective optimization problems of power systems. The performance of the algorithm is demonstrated on two test cases of optimization in power systems like CEED. One of the two test cases is of small size of 15 units and the other is of moderately larger sized system of 40 units with valve point loading. Results demonstrate that this algorithm too is well competent and efficient in solving multi-objective optimization problems like CEED problem specifically when more than two conflicting and highly nonlinear non-convex objective functions are to be optimized.