Invited Lecture

Power System Optimization

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Abstract—**Electric power systems have experienced continuous growth in all the three major sectors of the power system namely, generation, transmission and distribution. Electricity cannot be stored economically, but there has to be continuous balance between demand and supply. The increase in load sizes and operational complexity such as generation allocation, non-utility generation planning, and pricing brought about by the widespread interconnection of transmission systems and inter-utility power transaction contracts, has introduced major difficulties into the operation of power system. Allocation of customers' load demands among the available thermal power generating units in an economic, secure and reliable way has been a subject of interest since 1920 or even earlier. However practically, the generating units have non-convex input-output characteristics due to prohibited operating zones, valve-point loadings and multi-fuel effects considered as heavy equality and inequality constraints, which cannot be directly solved by mathematical programming methods. Dynamic programming can treat such types of problems, but it suffers from the curse of dimensionality. Over the past decade, many prominent methods have been developed to solve these problems, such as the hierarchical numerical methods, tabu search, neural network approaches, genetic algorithm, evolutionary programming, swarm optimisation, differential evolution and hybrid search methods. Review of evolutionary method has been presented.**

Index Terms—**Genetic Algorithm, Evolutionary Programming, Evolutionary Strategy, Tabu Search, Ant Colony Search, Simulated Annealing, Particle Swarm optimization, Gradient techniques**

I. INTRODUCTION

EVOLUTIONARY algorithms mimic natural evolutionary principles to constitute random search and optimization procedures. Evolutionary algorithms are different from direct search and optimization procedures in a variety of ways. Evolutionary optimization techniques find and maintain multiple solutions in one single simulation run. However, direct search and optimization algorithms use a single solution update during iterations and use a deterministic transition rule. The concept of a genetic algorithm was first conceived by John Holland of the University of Michigan, Ann Arbor. Genetic algorithms are search and optimization procedures that are motivated by the principle of natural genetics and natural selection. For higher precision, larger string length is required. The population size requirement is also large for large strings. Thereby the computational complexity of the algorithm increases. Since a fixed coding scheme is applied to code the decision variables. Variable bounds must be such that they bracket the optimum variable values. In many problems, this information is not usually known a priori then this may cause some difficulty in using binary-coded GAs in such problems. Furthermore, a careful thinking of the schema processing in binary strings reveals that not all Holland's schemata are equally important in most problems having a continuous search space. To a continuous search space, the meaningful schemata are those that represent the contiguous regions of the search space. Thus, the crossover operator used in the binary coding needs to be redesigned in order to increase the propagation of more meaningful schemata pertaining to a continuous search space.

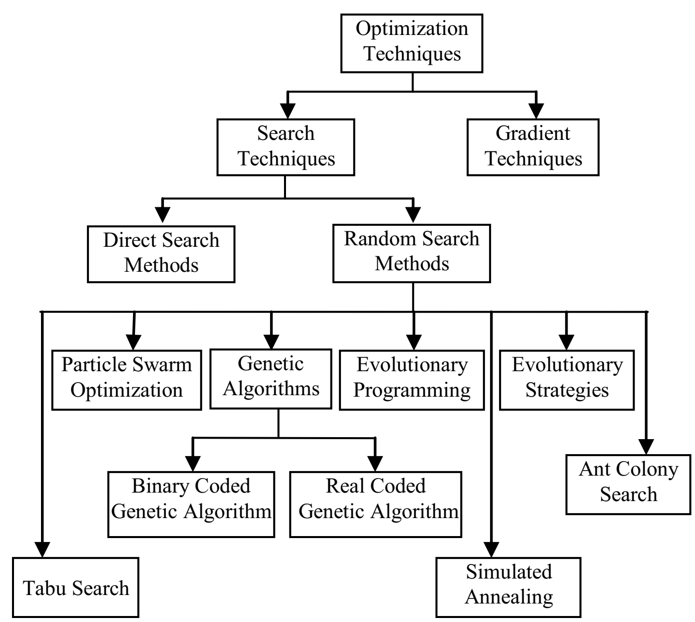

Figure 1 Classification of optimization techniques

Real-parameter GA applies crossover and mutation operators directly to real parameter values. Since real parameters are used directly, without any string coding, solving real-parameter optimization problems is a step easier when compared to the binary-coded GAs. Unlike in the binary-coded GAs, decision variables can be directly used to compute the fitness values. Since the selection operator works with the fitness value, any selection operator used with binary-coded GAs can be used in real-parameter GAs. However, the difficulty arises with the search operators. In the binary-coded GAs, decision variables are coded in. finite-length strings and exchanging portions of two parent strings is easier to implement and visualize. Simply flipping a bit to perform mutation is also convenient and resembles a natural mutation event. In real-parameter GAs, the main challenge is how to use a pair of real-parameter decision variable vectors to create a new pair of offspring vectors or how to perturb a decision variable vector to a mutated vector in a meaningful manner. The term 'crossover' is not that meaningful and can be best described as blending operators. However, most blending operators in real-parameter GAs are known as crossover operators.

Evolution strategy (ES) is suggested during the early Sixties by P. Bienert, I. Rechenberg and H.-P. Schwefel of Technical University of Berlin. Since the evaluation of a solution in each of these problems was difficult and time-consuming, a simple two-membered ES was used in all of the early studies. However, Schwefel was the first to simulate a different version of the ES on a computer in 1965. Thereafter, rnulti-membered ESs, recombinative ESs, and-self-adaptive ESs were all suggested. However, the early ES procedure is fundamentally different from binary GAs in mainly two ways:

(i) ESs use real parameter values and

(ii)early ESs do not use any crossover-like operator.

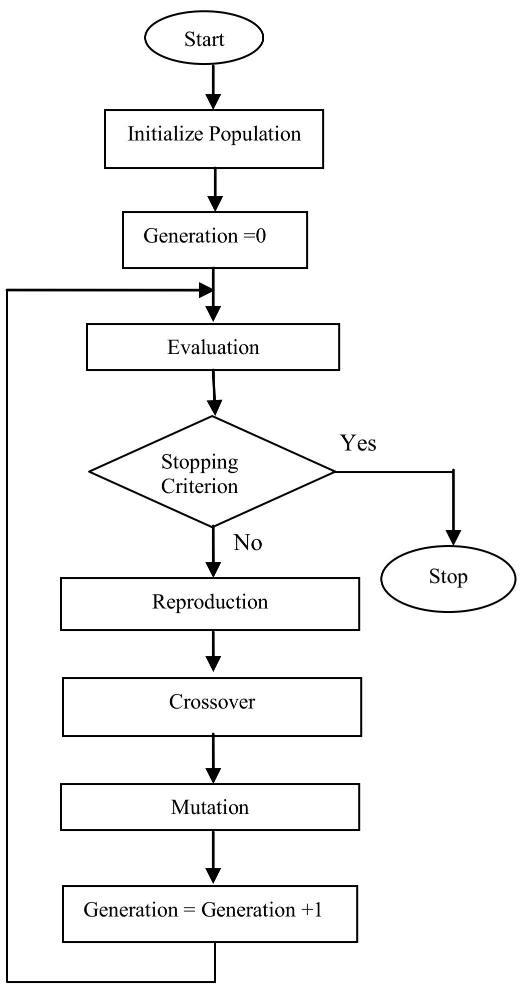

Figure 2: Genetic Algorithm

However, an ES's working principle is similar to that of a real-parameter GA used with selection and mutation operators only. ES studies have introduced crossover-like operators.

Evolutionary programming (EP) is a mutation-based evolutionary algorithm applied to discrete search spaces. David Fogel extended the initial work of his father Larry Fogel for real-parameter optimization problems. Real-parameter EP is similar in principle to evolution strategy (ES). Normally distributed mutations are performed in both algorithms. Both algorithms encode mutation strength or variance of the normal distribution for each decision variable. Self-adapting rule is used to update the mutation strengths. EP begins its search with a set of solutions initialized randomly in a given bounded space. Thereafter, EP is allowed to search anywhere in the real space, similar to the real-parameter GAs. Each solution is evaluated to calculate its objective function value.

Although evolutionary programming (EP) was first proposed as an approach to artificial intelligence, it has been recently applied with success to many numerical and combinatorial optimization problems. Optimization by EP can be summarized into two major steps

1) mutate the solutions in the current population;

2) select the next generation from the mutated and the current solutions.

These two steps can be regarded as a population-based version of the classical generate-and-test method, where mutation is used to generate new solutions (offspring) and selection is used to test which of the newly generated solutions should survive to the next generation. Formulating EP as a special case of the generate-and-test method establishes a bridge between EP and other search algorithms, such as evolution strategies, genetic algorithms, simulated annealing (SA), tabu search (TS), and others, and thus facilitates cross-fertilization among different research areas.

One disadvantage of EP in solving some of the multimodal optimization problems is its slow convergence to a good near-optimum. The generate-and-test formulation of EP indicates that mutation is a key search operator which generates new solutions from the current ones. A new mutation operator based on Cauchy random numbers is proposed and tested on a suite of 23 functions in this paper. The new EP with Cauchy mutation significantly outperforms the classical EP (CEP), which uses Gaussian mutation, on a number of multimodal functions with many local minima while being comparable to CEP for unimodal and multimodal functions with only a few local minima. The new EP is denoted as “fast EP” (FEP).

The process to heat up a metal and to cool it down slowly is referred to as annealing. On the other hand, the process to heat up a metal and cool it down fast is referred to as quenching or hardening. Since According to the molecule’s behavior, internal energy is large when its temperature is satisfactorily high and state or internal energy of metal is determined stochastically. From high temperature state, if temperature is cooled down slowly, its internal thermal energy decreases slowly. Since a cooling process of metal is ruled by stochastic thermal dynamics, the final state of molecules is determined randomly according to the behavior of the molecules or its cooling speed. By simulating a nature of an annealing process in which the smallest internal energy can be reached to find the minimum of an objective function.

Tabu search is a restricted neighbourhood search technique, and is an iteration algorithm. The fundamental idea of TS is the use of flexible memory of search history which thus guides the search process to surmount local optimal solutions. The basic components of the Tabu search are the moves, Tabu list and aspiration level.

Ant colony search algorithms, to some extent, mimic the behavior of real ants. As is well known, real ants are capable of finding the shortest path from food sources to the nest without using visual cues. They are also capable of adapting to changes in the environment, for example, finding a new shortest path once the old one is no longer feasible due to a new obstacle. The studies by ethnologists reveal that such capabilities ants have are essentially due to what is called "pheromone trails" which ants use to communicate information among individuals regarding path and to decide where to go/ Ants deposit a certain amount of pheromone while walking, and each ant probabilistically prefers to follow a direction rich in pheromone rather than a poorer one.

In 1995, Kennedy and Eberhart first introduced the Particle Swarm Optimization (PSO) method, motivated by social behavior of organisms such as fish schooling and bird flocking. PSO, as an optimization tool, provides a population-based search procedure in which individuals called particles change their positions (states) with time. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience.

II. CONCLUSION

The search technique is simple and takes small time to arrive at final solution. With the advent of the fast computation facilities, the sophisticated methods for higher accuracy can be the criterion for adjudging the 'best' solution. Evolutionary optimization algorithm is very sensitive to the initial feasible values may be termed as initial population selected to start the search procedure. A heuristic search method can be proposed for the selection of initial values to start the search which should not be a cumbersome procedure. The methods are also sensitive to the parameter tuning. The search techniques easily work even if the objective function is non-convex, discontinuous and non-differential at some points. Other population based optimization techniques such as Genetic Algorithm, Particle Swarm Optimization, and Evolutionary Programming sometimes struck to local minimum solution. It has been observed that memetic algorithm that combines both local and global population based algorithms may be the future to solve optimization problems.

REFERENCES

[1] Abido, M.A.: Multiobjective evolutionary algorithms for Electric power dispatch problem, *IEEE Transactions on Evolutionary Computation*, Vol. **10(3)**, pp. 315-329, 2006.

[2] Abido, M.A., Optimal design of power system stabilizers using particle swarm optimization, *IEEE Transactions on Energy Conversion*, Vol. **17(3)**, pp. 406–413, 2002.

[3] Amjady, N. and H. Nasiri-Rad, Economic dispatch using an efficient real-coded genetic algorithm, *IET Generation, Transmission, Distribution*, Vol. **3(3)**, pp. 266–278, 2009

[4] Bergh, F. van den and A.P. Engelbrecht, A cooperative approach to particle swarm optimization, *IEEE Transactions on Evolutionary Computation*, Vol. **8(3)**, pp. 225–239, 2004.

[5] Brar, Y.S., J.S. Dhillon, and D.P. Kothari, Multiobjective load dispatch by fuzzy logic searching weightage pattern, *Electric Power Systems Research*, Vol. **63(2)**, pp.149-160, 2002.

[6] Chang, C.S. and W. FU, Stochastic multiobjective generation dispatch of combined heat and power system, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **145(5)**, pp.583-591, 1998.

[7] Chang, H.C. and P. H. Chen, Hydrothermal generation scheduling package: a genetic based approach, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **145(4)**, pp.451-457, 1998.

[8] Chen, Po-Hung and Hong-Chan Chang, Large -scale economic dispatch by genetic algorithm, *IEEE Transactions on Power Systems*, Vol. **10(4)**, pp. 1919-1926, 1995.

[9] Chiang, C.L., Improved genetic algorithm for power economic dispatch of units with valve-point effects and multiple fuels, *IEEE Transactions on Power Systems*, Vol. **20(4)**, pp. 1690–1699, 2005.

[10] Chiou, Ji-Pyng: Variable scaling hybrid differential evolution for large-scale economic dispatch problems, *Electric Power Systems Research*, Vol. **77(3-4)**, pp.212-218, 2007.

[11] Coelho, L.S. and V.C. Mariani, Combining of chaotic differential evolution and quadratic programming for economic dispatch optimization with valve-point effect, *IEEE Transactions on Power Systems*, Vol. **21(2)**, pp. 989-996, 2006 (Erratum: Vol. **21(3)**, pp. 1465, 2006).

[12] Coelho, L.S. and V.C. Mariani, Improved differential evolution algorithms for handling economic dispatch optimization with generator constraints, *Energy Conversion and Management*, Vol. **48(6)**, pp. 1831-1639, 2007.

[13] Esmin, A.A.A., G. Lambert-Torres and A.C. Zambroni de Souza, A hybrid particle swarm optimization applied to loss power minimization, *IEEE Transactions on Power Systems*, Vol. **20(2)**, pp. 859–866, 2005.

[14] Farag, A., S. Al-Baiyat, and T.C. Cheng, Economic load dispatch multi-objective optimization procedure using linear programming techniques, *IEEE Transactions on Power Systems*, Vol. **10(2)**, pp. 731-738, 1995.

[15] Gaing, Zwe-Lee: Particle Swarm Optimization to Solve the Economic Dispatch Considering the Generator Constraints, *IEEE Transactions on Power Systems*, Vol. **18(3)**, pp. 1187-1195, 2003.

[16] He, Dakuo, Fuli Wang and Zhizhong Mao, A hybrid genetic algorithm approach based on differential evolution for economic dispatch with valve-point effect, *International Journal of Electric Power and Energy Systems*, Vol. **30**, pp. 31-38, 2008

[17] Hota, P.K., R. Chakrabarti, and P.K. Chattopadhyay, A simulated annealing-based goal attainment method for economic emission load dispatch with non-smooth fuel cost and emission level functions, *Electric Machines and Power Systems*, Vol. **28(11)**, pp.1037-1051, 2000.

[18] Jayabarathi, T., G. Sadasivam and V. Ramachandran, Evolutionary programming based multiarea economic dispatch with tie line constraints, *Electric Machines and Power System*, Vol. **28(12)**, pp. 1165-1176, 2000.

[19] Jayabarathi, T., K. Jayaprakash, D.N. Jeyakumar, and T. Raghunathan, Evolutionary Programming Techniques for Different Kinds of Economic Dispatch Problems, *Electric Power Systems Research*, Vol. **73(2)**, pp.169-176, August 2005,.

[20] Kennedy, J. and R. Eberhart, Particle swarm optimization, Proceedings of the *IEEE International Conference on Neural Networks*, pp. 1942–1948, 1995.

[21] Lee, F. N., and A.M. Breipohl, Reserve Constrained Economic Dispatch with Prohibited Operating Zones, *IEEE Transactions on Power Systems*, Vol. **8(1)**, pp. 246-254, 1993.

[22] Lee, K.Y., A. Sode-Yome, and J.H.Park, Adaptive Hopfield neural networks for economic load dispatch, *IEEE Transactions on Power Systems*, Vol. **13(2)**, pp. 519-526, 1998.
[23] Liang, Z.X. and J.D. Glover, A zoom feature for a dynamic programming solution to economic dispatch including transmission losses, *IEEE Transactions on Power Systems*, Vol. **7(2)**, pp. 544–550, 1992.
[24] Lin, W.M., F.S. Cheng and M.T. Tsay, An improved tabu search for economic dispatch with multiple minima, *IEEE Transactions on Power Systems*, Vol. **17(1)**, pp. 108–112, 2002.
[25] Lin, C.E. and G.L. Viviani, Hierarchical economic dispatch for piecewise quadratic cost functions, *IEEE Transactions on Power Apparatus and Systems*, Vol. **103(6)**, pp. 1170–1175, 1984.
[26] Ma, J.T. and L.L. Lai, Evolutionary programming approach to reactive power planning, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. 143(4), pp.365-370, 1996.
[27] Mendes, R., J. Kennedy and J. Neves, The fully informed particle swarm: simpler, maybe better, *IEEE Transactions on Evolutionary Computation*, Vol. **8(3)**, pp.204–210, 2004.
[28] Naka, S., T. Genji, T. Yura and Y. Fukuyama, A hybrid particle swarm optimization for distribution state estimation, *IEEE Transactions on Power Systems*, Vol. **18(1)**, pp.60–68, 2003.
[29] Nara, K., A. Shiose, M, Kitagawa and T. Shihara, Implementation of genetic algorithms for distribution systems loss minimum reconfiguration, *IEEE Transactions on Power systems*, Vol. **7(3)**, pp. 1044-1050, 1992.
[30] Naresh, R., J. Dubey, and J. Sharma, Two-phase neural networks based modeling framework of constrained economic load dispatch, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **151(3)**, pp. 373-378, 2004.
[31] Orero, S.O. and M.R. Irving, Economic dispatch of generators with prohibited operating zones: a genetic algorithm approach, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **143(6)**, pp.529-534, 1996.
[32] Park, J.B., K.S. Lee, J.R. Shin, and K.Y. Lee, A particle swarm optimization for economic dispatch with nonsmooth cost functions, *IEEE Transactions on Power Systems*, Vol. **20(1)**, pp. 34–42, 2005.
[33] Pereira-Neto, A., C. Unsihuay, and O.R. Saavedra, Efficient evolutionary strategy optimization procedure to solve the nonconvex economic dispatch problem with generator constraints, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **153(5)**, pp. 653-660, 2005.
[34] Po-Hung, Chen and Chang Hong-Chan, Large-Scale Economic Dispatch by Genetic Algorithm, *IEEE Transactions on Power Systems*, Vol. **10(4)**, pp. 1919-1926, 1995.
[35] Ratnaweera, A., S.K. Halgamuge and H.C. Watson, Self-organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients, *IEEE Transactions on Evolutionary Computation*, Vol. **8(3)**, pp. 240–255, 2004.
[36] Roa-Sepulveda, C.A., M. Herrera, B. Pavez-Lazo, U.G. Knight and A.H. Coonick, Economic Dispatch Using Fuzzy Decision Trees, *Electric Power Systems Research*, Vol. **66(2)**, pp. 115-122, 2003.
[37] Salomon, Ralf, Evolutionary algorithms and gradient search: Similarities and differences, *IEEE Transactions on Evolutionary Computation*, Vol. **2(2)**, pp. 45-55, 1998
[38] Selvakumar, A.I. and K. Thanushkodi, A new particle swarm optimization solution to nonconvex economic dispatch problems, *IEEE Transactions on Power Systems*, Vol. **22(1)**, pp.42-51, 2007.
[39] Selvakumar, A.I. and K. Thanushkodi, Anti-predatory particle swarm optimization: Solution to nonconvex economic dispatch problems, *Electric Power Systems Research*, Vol. **78(1)**, pp. 2-10, 2008.
[40] Sheble, G.B., T.T. Maifeld, K. Brittig, G. Fahd and S. Fukurozaki-Coppinger, Unit commitment by genetic algorithm with penalty methods and a comparison of Lagrangian search and genetic algorithm- economic dispatch, *International Journal of Electric Power and Energy Systems*, Vol. **18(6)**, pp. 339-346, 1996.
[41] Sinha, N., R. Chakrabarti, and P.K. Chattopadhyay, Evolutionary Programming Techniques for Economic Load Dispatch, *IEEE Transactions on Evolutionary Computation*, Vol. **7(1)**, pp. 83-94, 2003.
[42] Song, Y.H. and C.S.V. Chou, Advanced engineered conditioning genetic approach to power economic dispatch, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **144(3)**, pp. 285-292, 1997.
[43] Song, Y.H., G.S. Wang, P.Y. Wang, and A.T. Johns, Environmental/economic dispatch using fuzzy logic controlled genetic algorithms, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **144(4)**, pp. 377-382, 1997.
[44] Storn R., Differntial evolution- a simple and efficient heuristic for global optimization over continuous space, *Journal of Global Optimization*, Vol. **11(4)**, pp. 341-359, 1997
[45] Sum-Im, T., G.A. Taylor, M.R. Irving and Y.H. Song, Differential evolution algorithm for static multistage transmission expansion planning, *IET Generation, Transmission, Distribution,* Vol. **3(4)**, pp. 365-384, 2009
[46] Tapia, C.G. and B.A. Murtagh, Interactive fuzzy programming with preference criterion in multi-objective decision making, *Computers and Operations Research*, Vol. **18(3)**, pp.307-316, 1991.
[47] Varadarajan, M. and K.S. Swarup, Solving multi-objective optimal power flow using differential evolution, *IET Generation, Transmission, Distribution*, Vol. **2(5)**, pp. 720–730, 2008
[48] Venkatesh, P., P.S. Kannan and M. Sudhakaran, Application of computational intelligence to economic load dispatch, *Journal of Institution of Engineers, India,* Vol. **81**, pp. 39-43, 2000.
[49] Venkatesh, P., P.S. Kannan and S. Anudevi, Application of micro Genetic algorithm to economic load dispatch, *Journal of Institution of Engineers, India*, Vol. **82**, pp. 161-167, 2001.
[50] Victorie, T.A.A. and A.E. Jeyakumar, Hybrid PSO-SQP for economic dispatch with valve-point effect, *Electric Power Systems Research*, Vol. **71(1)**, pp. 51–59, 2004.
[51] Walter, D. C., and G. B. Sheble, Genetic algorithm solution of economic dispatch with valve point loading, *IEEE Transactions on Power Systems*, Vol. **8(3)**, pp.1325-1332, 1993,
[52] Wong, K.P. and Y.W. Wong, Genetic and genetic/simulated-annealing approaches to economic dispatch, *IEE Proceedings- Generation, Transmission and Distribution,* Vol. **141(5)**, pp. 507–513, 1994.
[53] Wong, K.P. and Y.W. Wong, Thermal Generator Scheduling Using Hybrid Genetic / Simulated Annealing Approach, *IEE Proceedings- Generation, Transmission and Distribution*, Vol.**142(4)**, pp. 372-380, 1995.
[54] Wu, Q.H. and J.T. Ma, Power system optimal reactive power dispatch using evolutionary programming, *IEEE Transactions on Power Systems*, Vol. **10(3)**, pp. 1243-1249, 1995.
[55] Yang, H.T. and P.C. Yang, C.L. Huang, Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions, *IEEE Transactions on Power Systems*, Vol. **11(1)**, pp. 112–118, 1996.
[56] Yang, P.C., H.T. Yang, C.L. Huang, Scheduling short-term hydrothermal generation using evolutionary programming techniques, *IEE Proceedings- Generation, Transmission and Distribution*, Vol. **143(4)**, pp. 371-376, 1996.
[57] D.P. Kothari and J.S. Dhillon, Power System Optimization, 2nd ed. Prentice-Hall India, New Delhi, 2011, pp. 15–64.