Economic dispatch in isolated networks with renewables using evolutionary programming

L. M. Proença (2,3)
lproenca@inescn.pt

J. Luís Pinto (2)
jpinto@duque.inescn.pt

Manuel A. Matos (1,2)
mmatos@inescn.pt

(1) FEUP - Faculdade de Engenharia da Universidade do Porto, Porto - Portugal
(3) ISLA – Instituto Superior de Línguas e Administração - Vila Nova de Gaia - Portugal
(2) INESC, Instituto de Engenharia de Sistemas e Computadores, Porto, Portugal

Abstract - The paper presents a new technique for the Economic Dispatch of isolated power systems with a high penetration of renewable forms of energy. It also describes a software module based on this technique integrated on a real-time control system.

Keywords: Economic Dispatch, Evolutionary Programming, Renewable Energy, Isolated Systems.

I. INTRODUCTION

The paper addresses the problem of dispatching a medium-size isolated power system where the penetration of renewable sources, especially wind power, is considerable. It is the case of many islands that have favorable conditions to use wind power combined to a conventional generating system with Diesel units and gas turbines, and sometimes steam turbines. This problem is similar to the conventional economic dispatch problem, but most cost functions of typical generating units are not well-behaved (non-convex functions), and there may also exist the need to satisfy additional constraints on security and spinning reserve that are generally difficult to include in analytical formulations.

In these circumstances, the use of Evolutionary Programming [1,5-7], a variety of Evolutionary Algorithms [2,3], that relies on mutation rather than crossover [4], is an attractive hypothesis, due to the inherent flexibility of using a fitness function (to evaluate each candidate solution) that is not constrained regarding convexity, etc. The ease of codification and implementation of the method and its implicit parallelism lead to fast prototyping and good performances regarding execution times.

The paper reports the development of an Economic Dispatch module in the framework of the project CARE - "Advanced control advice for power systems with large scale integration of renewable energy sources" (ENN-JOULE program). Partners are NTUA (Greece), INESC (Portugal), ARMINES (France) and DEI (Greece), the Public Power Corporation of Greece, and tests are made with the Power System of Crete.

The module follows the usual steps in an Evolutionary Programming algorithm, where the solutions are not coded in chromosomes (as in Genetic Algorithms). The algorithm operates directly over the solutions by small mutations, but also uses a selection process based on elitism.

Paper BPT99-361-25 accepted for presentation at the IEEE Power Tech'99 Conference, Budapest, Hungary, Aug 29-Sept 2, 1999.

Solutions are defined as generation values for all the units in the system and initially are identical to the pre-dispatch values proposed by an unit commitment algorithm run previously.

The fitness function assesses the quality of the proposed solution setting the basis for the selection process. It proposes a penalty for constraint violations (voltage levels in PQ buses and line load limits) that increases with the number of generations, in order to allow initially the digression of the algorithm through unfeasible parts of the universe of possible solutions. It also contains processes of auto-correction of power losses and voltage levels.

Furthermore, a process to evaluate the dynamic security of a proposed solution can easily be added to the global cost calculation, provided that a fast tool for security assessment is available (neural networks and decision trees are successfully used for that in CARE). This possibility is especially important when wind penetration is strong and weather conditions are bad, due to the isolated nature of the networks.

II. EVOLUTIONARY PROGRAMMING

Evolutionary Algorithms (EA) are computer-based problem-solving systems based on principles of evolution theory. A variety of EA have been developed and they all share a common conceptual base of simulating the evolution of individual structures via processes of Selection, Mutation and Recombination. The processes depend on the perceived performance of the individual structures as defined by an environment. The interest in these algorithms has been rising fast for they provide robust and powerful adaptive search mechanisms. The interesting biological concepts on which EA are based also contribute to their attractiveness.

There has been a great interest in the use of EA in Power Systems [8] because these approaches are very well suited to deal with all those kinds of problems that usually represent nightmares for researchers and developers: integer variables, non convex functions, non differentiable functions, domains not connected, badly-behaved functions, multiple local optima, multiple objectives, etc. Furthermore, they are not necessarily restricted to deal with numerical models, allowing the natural building of hybrid models including knowledge, under the forms of rules or other. This complexity is what is required, in order to build larger Power System models with more adherence to reality. In very complex situations, they seem to be the only practical tool available. There are several references to the use of Evolutionary Algorithms, (mostly Genetic Algorithms) both to Unit Commitment [9-25] as well as to the problem of Economic Dispatch [26-39].

As an approach on solving the Economic Dispatch problem, an Evolutionary Programming (EP) algorithm was used. Evolutionary Programming algorithms [5-7] try to emulate the natural evolutionary behavior of RNA (Ribonucleic Acid) coded entities such as viruses. They try to replicate the fact viruses adapt so fast to environmental changes. This is due to the fact that, unlike DNA (Deoxyribonucleic acid) coded creatures (as ourselves) who mainly rely on mating (crossover) as an evolution engine, viruses rely on heavy mutation to evolve. So, even though memory from their past evolution events is lost, a highly developed (and specially fast) evolution scheme is adopted.

Evolutionary Programming algorithms in Economic Dispatch (ED) have clear advantages over traditional methods due to their robustness, but also provide an edge over Genetic Algorithms, mainly because:

- They do not need any special coding of individuals. In the case of ED, since the desired outcome is the operating point of each of the dispatched units (a real number), each of the individuals can be directly presented as a set of real numbers, each one being the produced power of the unit it concerns.

- Since each of the individuals codes within itself its own mutation rate, and since it is itself mutated, the algorithms provide themselves a self-regulating adaptive scheme.

On the other hand, no special requirements are made regarding the objective function and constraints, which is a very interesting feature of Evolutionary Programming algorithms (and also of Genetic Algorithms) as compared to traditional methods. The methodology followed is detailed on the next section (see Fig. 1).

The algorithm was developed in an Object Oriented fashion, in the C++ programming language. This option was made given the high flexibility and ease of reconfiguration given by this approach.

III. GENERAL METHODOLOGY

The fitness function that was used for evaluation of the quality of individuals (dispatch solutions) was defined as following:

$$C_T = \sum_{i=1}^{NGen} C_i(P_i) + L * W_L + (D - \sum_{i=1}^{NGen} P_i)^2{}_{|if>0} * W_V$$

C_T	*Total Cost*
$NGen$	*Total of dispatched units*
C_i	*Operation* cost *of unit i*
P_i	*Active power output of generator i*
L	*Total apparent losses*
W_L	*Cost of losses unit*
D	*Total demand*
W_V	*Underdispatch penalty*

It can be seen that, in the case of the operating constraint that the demand is to be satisfied, a goal programming strategy was chosen, implicitly including the constraint in the fitness function using a penalty on the square of the difference between the demand and the dispatch in case of lack of generation. The constraints were related to generator operating limits as follows:

$$P_{i_{\min}} < P_i < P_{i_{\max}}$$

$$P_{i_{\min}}, P_{i_{\max}} \quad = \quad \textit{Operating limits of central } i$$

Mutation

Each of the elements of the population consists in a list of records, each record assigned to one unit. Each of those records has two fields:

- Field 1 with the current dispatched power of the generator.

- Field 2 with the current standard deviation of the mutation. This means that each individual has its own degree of mutation.

In each of the generations, and for each of the elements of the population, the value in field 1 for each generator is changed (mutated), adding a random amount with normal distribution, zero average and standard deviation given in field 2. The individual is then evaluated. If its new fitness is better, the *mutated* individual replaces the old individual. If fitness is worse, the *mutated* individual is accepted to replace the old with a given probability. Following this procedure, field 2 is also mutated, being added a random normal distributed number with 0 average and with a constant value of standard deviation that is an input to the algorithm. As referred in a previous section, this interesting feature inspired on a metaphor of nature allows the mutation to *adapt* itself in order to improve the efficiency of the algorithm.

After mutation is applied to all the individuals, the new population is sorted and the worst individual is replaced with a copy of the best. This process is known as *elitism*.

Dynamic model

The flowchart of the algorithm is presented in Fig. 1.

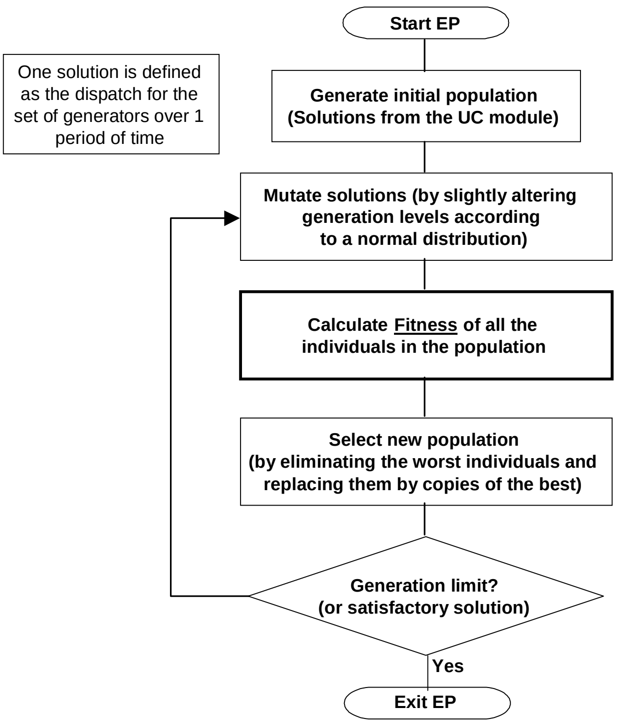

Fig. 1 - General algorithm for the Economic Dispatch module

The evaluation process, where the fitness (or quality) of each of the individuals is assessed, includes a Newton-Raphson load flow routine to evaluate the losses associated with the individuals dispatch and to calculate the dispatch of the compensation bar generator. The flow chart depicting the steps of the evaluation of each of the individuals is presented in Fig 2.

Note that the cost of Power Losses may be included in the total costs in the fitness function. Normally we should not include these costs since the fuel cost of power losses is already included in the generation costs. However one might be interested in operating with minimum network losses (e.g. in liberalized environments) in which case this strategy could be considered.

It is also important to stress that the fitness of a solution is not just given by the generation costs but also includes costs related to quality, in this case, voltage level and thermal limits costs. Any other type of quality evaluation may easily be included in the fitness function (e.g. reliability costs).

The corrected power losses and voltage levels will be used as an estimate on the next evaluation of the solution.

Input Data

The input information of this module includes both algorithm parameters and network data. Since the evaluation function needs a load flow to be run, this module needs all the information on the required electrical parameters.

The user can set the following parameters related to the algorithm:

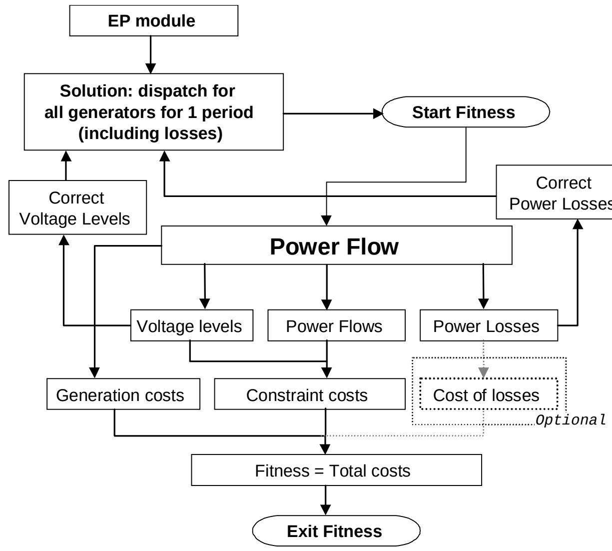

Fig. 2 - Fitness function

- Population size.
- Number of generations.
- Penalty for overload (the parameter W_V on the fitness function)
- Penalty for power losses (the parameter W_L on the fitness function)

IV. CASE STUDY

The algorithm was tested on the network on Fig. 3.

This network includes 25 buses, 5 synchronous generators (on bars 0, 1, 2, 3, 4, 5, 7), 8 asynchronous generators (on bars 17, 18, 19, 20, 21, 22, 23, 34), each with capacitor bank (not shown) and 6 transmission lines. Loads are also assigned to bars 6, 8, 13, 14, and 15. The tests were performed on an Intel Pentium II 333MHz computer with 64Mb main memory.

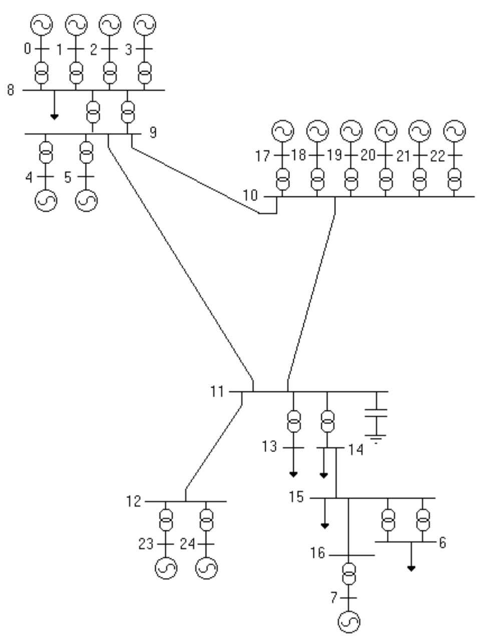

Fig. 3 - Test Network

The asynchronous generators were considered to have cost functions of the form:

$$GC = 0.5.P_i^{\ 2} + 100.P_i + 25 \quad \texttt{Fuel cost.h}^{-1}$$

In the case of synchronous generators, the cost functions are the following:

$$GC = P_i^{\ 2} + 85.P_i + 400 \quad \texttt{Fuel cost.h}^{-1}$$

The population sizes tested were of 5, 10 and 20 individuals. The following tests were made:

- (A) A test with a run of 1000 *evaluations* (number of fitness function calls. The number of evaluations is equal to the population size times the number of generations).
- (B) A test with a run of 2000 evaluations.

Th evolution of the fitness of the best-so-far solution for a typical run of the EP algorithm is presented in Fig. 4 for the 1000 evaluations case, and in Fig. 5 for the 2000 evaluations case.

For the 1000 evaluations case, the results found were the following:

- Run time: 71 seconds.
- The best solution was found with a population of 5 (200 generations).

For the 2000 evaluations case, the results were the following:

- Run time: 142 seconds. This execution time is fairly acceptable since the CARE system operates on 20 minute windows. In fact, the algorithm followed by the CARE system allows the Economic dispatch module to be permanently improving on the dispatch solution.
- The most efficient algorithm had a population of 10 and 200 generations.

Figs. 6 and 7 depict the best solution for two cases. The first situation (base case) considers only fuel costs, i.e. the usual dispatch with losses, and leads to a total fuel cost of 1616.1 units, with 3.26% losses. In the second situation, minimization of losses was also considered (3.21%), although the total fuel cost is higher (1634.1 cost units).

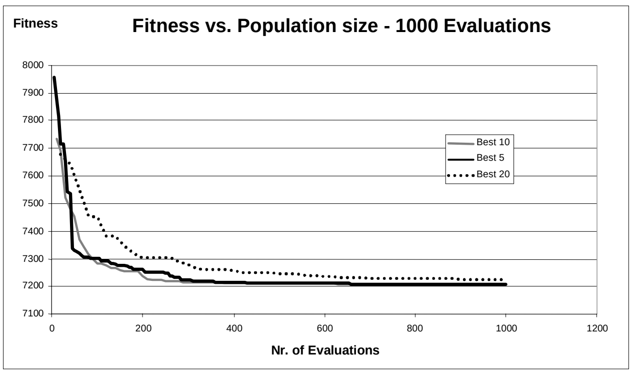

Fig. 4 - Fitness Evolution (1000 evaluations)

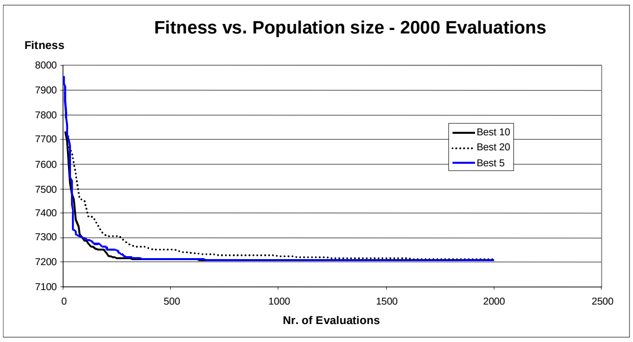

Fig. 5 - Fitness Evolution Chart (2000 evaluations)

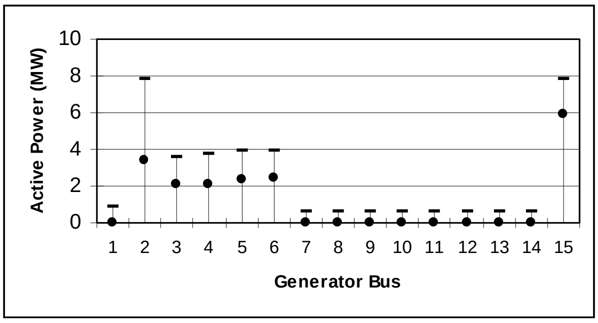

Fig. 6 - Best solution for the dispatch (base case).

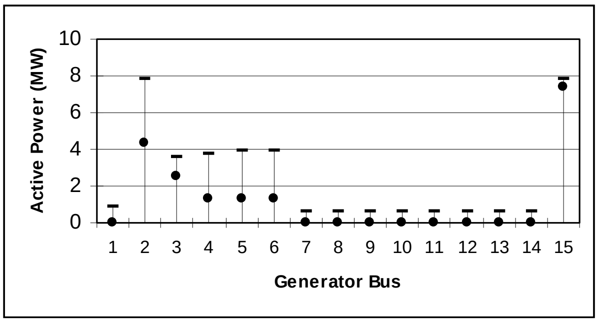

Fig. 7 - Best solution for the dispatch minimizing power losses.

V. CONCLUSIONS

Evolutionary Programming has proven to be an efficient tool for the Economic Dispatch problem, mainly because it allows for the network losses and non-linear cost function to be included directly in the model without significant increase in model complexity. Even though several load flows have to be performed during the run of the algorithm, its run time is still low enough to satisfy the real-life requirements of a real-time application such as the CARE system. Furthermore, the algorithm is extremely robust, always providing a consistent solution. The module ED module developed by INESC is now integrated in the CARE system.

VI. REFERENCES

[1] W. Ebeling, “Applications of Evolutionary strategies”, System Analysis Modeling Simulation, Vol 7, Iss, 1, 3-16., 1990.

[2] E. Goldberg, "Genetic Algorithms In Search, Optimization And Machine Learning", 1989 Addison-Wesley

[3] H. Holland, "Adaption in Natural and Artificial Systems", The University of Michigan Press, 1975 Ann Arbor

[4] Hoffmeister, T Bäck, “Genetic Algorithms And Evolution Strategies: Similarities And Differences”, Parallel Problem solving from Nature, Proceedings of the first workshop PPSN I, Dortmund, October 1991, Berlin: Springer. 455-469

[5] B. Fogel, A. J. Owens, M. J. Walsh, “Artificial Intelligence through Simulated Evolution”, New York, John Wiley & Sons, 1966

[6] B. Fogel, “Evolving Artificial Intelligence”, Doctoral Dissertation, University of California at S. Diego.

[7] H. Holland, K. J. Holyoak, R. E. Nisbett, P. R. Thagard, “Induction: Processes Of Inference, Learning And Discovery”, Cambridge, Mass.: MIT press., 1986.

[8] V. Miranda, S. Srinivasan, L. M. Proença, “Evolutionary computation in Power Systems”, Electric Energy Systems Review, Jan 1998.

[9] “Optimization of the unit commitment problem by a coupled gradient network and a genetic algorithm”, Technical Report TR-103697, EPRI, 1994.

[10] A. J. Adderman (1985) “Treatment of Integral Contingent Conditions in Optimal Power Plant Commitment”, in H. J. Wacker (ed.) : Applied Optimization Techniques in Energy Problems, Stuttgard.

[11] D. Dasgupta, D. R. McGregor, "Thermal unit commitment using genetic algorithms", IEE Proceedings Part C - Generation, Transmission and Distribution, Vol. 141, 1994, pp. 459-465.

[12] G. B. Sheble, T. T. Maifeld, "Unit commitment by genetic algorithm and expert system", Electric Power Systems Research, Vol. 30, 1994, pp. 115-121.

[13] H. Saitoh, K. Inoue, J. Toyoda, "Genetic algorithm approach to unit commitment problem", Proceedings of International Conference on Intelligent Systems Applications to Power Systems (ISAP’94), France, September 1994, pp. 583-589.

[14] H. T. Yang, P. C. Yang, C. L. Huang, "A parallel genetic algorithm approach to solving the unit commitment problem: Implementation on the transputer networks", p. n.: 96 WM 292-3-PWRS, IEEE-PES Wt P. M., Baltimore, USA, Jan 21-25, 96.

[15] H. T. Yang, P. C. Yang, C. L. Huang, "Applications of the genetic algorithm to the unit commitment problem in power generation industry", Proceedings of the Fourth IEEE International Conference on Fuzzy Systems, Part 1, Yokohama, Japan, 1995, pp. 267-274.

[16] H. Wagner, “Procedures for the Solution of the Unit commitment Problem”, in H. J. Wacker (ed.) : Applied Optimization Techniques in Energy Problems, Stuttgard, 1985.

[17] S. J. Huang, C. L. Huang, "Application of genetic based neural networks to thermal unit commitment", paper no. 96 WM 203-0 PWRS, presented at IEEE-PES Winter Power Meeting, Baltimore, USA, Jan 21-25, 1996.

[18] S. Kazzrlis, A. Bakirtzis, V. Petridis, "A genetic algorithm solution to the unit commitment problem", IEEE PES Winter 94-95 Meeting, 1994, New York.

[19] T. Ohta, T. Matsui, T. Makata, M. Kato, M. Aoyagi, M. Kunugi, K. Shimada, J. Nagata, "Practical Approach to Unit Commitment Problem using genetic Algorithm and Lagrangian Relaxation Method", Proc.of ISAP’96, Orlando, USA, 29 January-2 February, 1996, pp. 434-440.

[20] T. T. Maifeld, G. B. Sheble, "Genetic-based unit commitment algorithm", paper no.: 95 SM 548-8-PWRS, presented at IEEE-PES Summer Meeting at Portland, USA, July 23-27, 1995.

[21] X. Ma, A. A. El-Keib, R. E. Smith, H. Ma, "Genetic algorithm based approach to thermal unit commitment of electric power systems", Electric Power Systems Research, Vol. 34, No. 1, July 1995, pp. 29-36.

[22] D. C. Walters, G. B. Sheble, "Genetic algorithm solution of economic dispatch with valve point loading", IEEE Transactions on Power Systems, Vol. 8, 1993, pp. 1325-1332

[23] D. Srinivasan, A. Tettamanzi, "An evolutionary algorithm for evaluation of emission compliance options in view of the Clean Air Act Amendments", paper no. 96 WM 294-9-PWRS, presented at IEEE PES Winter Power Meeting, Baltimore, USA, January 21-25, 1996.

[24] D. Srinivasan, A. tettamanzi, "An integrated framework for devising optimum generation schedules", Proceedings of the IEEE International Conference on Evolutionary Computation (ICEC’95), Perth, Australia, December 1995, Vol. 1, pp. 1-4.

[25] F. Li, R. Morgan, D. Williams, Y. H. Song, "Handling constrained power dispatch with genetic algorithms", Proceedings of the First IEE/IEEE International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications (GALESIA’95), Sheffield, UK, 12-14 September 1995, pp. 181-187.

[26] G. B. Sheble, K. Brittig, "Refined genetic algorithm - Economic dispatch example", IEEE Transactions on Power Systems, Vol. 10, 1995, pp. 117-124.

[27] H. C. Chang, P. H. Chen, "A novel economic dispatch approach - Implementation of genetic algorithm", Proceedings of IEEE/KTH Stockholm Power Tech Conference, Stockholm, Sweden, June 18-22, 1995, pp. 48-54.

[28] H. Ma, A. A. El-Keib, R. E. Smith, "Genetic algorithm-based approach to economic dispatch of power systems", Proceedings of the IEEE SOUTHEASTCON’94, Miami, FL, USA, 1994, pp. 212-216.

[29] H. Mori, T. Horiguchi, "A genetic algorithm based approach to economic load dispatching", Proceedings of the Second International Forum on Applications on Neural Networks to Power Systems (ANNPS’93), Japan, 1993, pp. 145-150.

[30] H. T. Yang, 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. 10, 1995.

[31] K. P. Wong, Y. W. Wong, "Genetic and genetic/simulated annealing approaches to economic dispatch", IEE Proceedings Part C - Generation, Transmission and Distribution, Vol. 141, 1994, pp. 507-513.

[32] K. P. Wong, Y. W. Wong, "Thermal generator scheduling using hybrid genetic/simulated annealing approach", IEE Proceedings Part C - Generation, Transmission and Distribution, Vol. 142, No. 4, July 1995, pp. 372-380.

[33] K. S. Swarup, M. Yoshimi, Y. Izui, N. Nagai, "Genetic algorithm approach to environmental constrained economic dispatch", Proceedings of International Conference on Intelligent Systems Applications to Power Systems (ISAP'94), France, September 1994, pp. 707-714.

[34] M. Salami, G. Cain, "Multiple genetic algorithm processor for the economic power dispatch problems", Proceedings of the First IEE/IEEE International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications (GALESIA'95), Sheffield, UK, 12-14 September 1995, pp. 188-193.

[35] M. Yoshimi, K. S. Swarup, Y. Izui, "Optimal economic power dispatch using genetic algorithms", Proceedings of the Second International Forum on Applications on Neural Networks to Power Systems (ANNPS'93), Japan, 1993, pp. 157-162.

[36] P. H. Chen, H. C. Chang, "Large-scale economic dispatch by genetic algorithm", ", IEEE Transactions on Power Systems, Vol. 10, 1995.

[37] S. O. Orero, M. R. Irving, "Scheduling of generators with a hybrid genetic algorithm", Proceedings of the First IEE/IEEE International Conference on Genetic Algorithms in Engineering Systems: Innovations and Applications (GALESIA'95), Sheffield, UK, 12-14 September 1995, pp. 200-206.

[38] Y. H. Song, F. Li, R. Morgan, D. T. Y. Cheng, "Effective implementation of genetic algorithms on power economic dispatch", Proceedings of the International Power Engineering Conference (IPEC'95), Singapore, March 1995, pp. 268-274.

[39] J. H. Park, S. O. Yang, H. S. Lee, Y. M. Park, "Economic Load Dispatch Using Evolutionary Algorithms", Proc. of ISAP'96, Orlando, USA, 29 January-2 February, 1996, pp. 441-447.