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APPLICATION OF EVOLVED EVOLUTIONARY ALGORITHMS FOR THE SOLUTION OF DIFFERENT ASPECTS OF HYDROTHERMAL SCHEDULING – A COMPREHENSIVE OVERVIEW

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Hydrothermal Scheduling (HTS) presents highly complicated, non-linear and multi-constrained optimization problem. Usually very turbulent and non-convex search space is linked with Hydrothermal (HT) Scheduling problem. So rather a robust and powerful optimization tool is required to optimize this problem efficiently. In literature, so far, many powerful and robust optimization algorithms have been employed for the solution of HTS problem. Genetic Algorithm (GA) represents one of the most established while Bacterial Foraging Algorithm (BFA) represents one of the newest Evolutionary Algorithms. Both GA and BFA are being actively deployed to solve non convex optimization problems, where conventional approaches have rather failed to provide acceptable results. The aim of this research paper is to provide a comprehensive survey of literature related to both GA and BFA as effective optimization algorithms for the solution of various aspects of HTS problem. The outcomes alongwith both strengths and weaknesses of individual algorithms are also discussed.

Keywords: Hydrothermal Scheduling, Optimization Algorithms, Heuristic Algorithms, Bacterial Foraging Algorithm, Genetic Algorithm, Search Space

1. Introduction

HTS is an important aspect of not only determining the optimal usage of both hydro and thermal resources economically so as to meet the load demand alongwith minimization of net operational cost as much as possible but also satisfying a large number of coupling constraints related to both hydro and thermal power plants like generation limits, rate of water discharge, inequality constraints representing water reservoir and hydraulic continuity limitations etc. [1]. On the base of time intervals for which HTS has been performed, the problem can be classified as short term HTS (STHTS), mid term HTS (MTHTS) and long term HTS (LTHTS). Since energy production from water is the cheapest one and below minimal operational cost is usually related to hydro power generation so, minimizing the utilization of fossil based fuels in thermal power plant while exploiting the maximum amount of water resource for energy production is the main idea of problem.

In the nutshell, alongwith all constraints and limits HTS problem presents highly complicated and nonlinear search space for which our objective is the minimization of net operational cost. Without questions HTS problem is one of the most challenging and complicated problem of Power System Operation [1].

2. Mathematical Modelling of HTS Problem

The generalized mathematical modeling of HTS problem consists of defining both objective function and constraints related to thermal and hydropower plant [2].

2.1. Objective Function

The optimization of HTS problem includes the minimization of electric energy cost for thermal generation during predefined time intervals [3].

$$\text{minimize} \quad F_C = \sum_{t=1}^{T} \sum_{i=1}^{M} F_i\,(P_S(i,t)$$

Here, M defines the total no. of thermal power plants; T defines the scheduling intervals; $F_i(P_S(i,t))$ defines the fuel cost function of ith thermal power plant in respective time interval and

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F_C represents the total operational cost of all thermal power plants overall intervals. $P_S(i,t)$ represents power generation of i^{th} thermal power plant in respective time interval. Here fuel cost curve with valve point loading effect is a non-smooth, non-differentiable rectified sine model [4].

$$F_i(P_S(i,t))=a_i+b_iP_S(i,t)+c_iP_S^2(i,t)+ |d_i \sin\left\{e_i\left(P_S(i)^{min}-P_S(i,t)\right)\right\}|$$

Here, a_i, b_i, c_i, d_i and e_i are machine constants. $P_S(i)^{min}$ represents the lower limit of i^{th} thermal power plant.

2.2. Constraints

2.2.1. Load Balance

Out of all important equality constraints is the successful fulfillment of load demand [1].

$$\sum_{j=1}^{N} P_H(j,t)+\sum_{i=1}^{M} P_S(i,t)= P_D(t)+P_L(t)$$

Here, $P_D(t)$ is the load demand; $P_L(t)$ defines the line losses and $P_H(j,t)$ defines hydro power related to j^{th} hydro power plant in t interval, N defines the total number of hydro power plants. Here, the hydro plant power can be obtained by a nonlinear relation between water discharge, volume of water and hydro power generation [5].

$$P_H(j,t)=C_{1j}V_H(j,t)^2+C_{2j}Q_H(j,t)^2+C_{3j}V_H(j,t)Q_H(j,t) +C_{4j}V_H(j,t) +C_{5j}Q_H(j,t)+C_{6j}$$

Here, V is the respective volume; Q is the hydraulic parameter representing water discharge rate in corresponding time interval t and C is the coefficient related to hydro power plant.

2.2.2. Generation Capacity

The corresponding generation capacities of thermal as well as hydro power units have of course some limits [1].

$$P_S(i)^{min} \le P_S(i,t) \le P_S(i)^{max}$$

$$P_H(j)^{min} \le P_H(j,t) \le P_H(j)^{max}$$

Have to be satisfied as well. Here $P_S(i)^{min}$ represents lower limit of i^{th} thermal power plant. $P_S(i)^{max}$ represents upper limit of i^{th} thermal power plant. $P_H(j)^{min}$ is lower limit of jth hydro power plant and $P_H(j)^{max}$ is upper limit of jth hydro power plant.

2.2.3. Hydraulic Continuity Equation

Hydraulic continuity equation has to be satisfied for hydro power plants in case of interconnected or cascade network [2].

$$V(j,t)= V(j,t-1)+[I(j,t)- Q(j,t)- s(j,t)]n_t$$

Here n_t shows the scheduling intervals; $V(j,t)$ is the volume for corresponding hydro power plant in corresponding time; I(j,t) is the inflow; Q(j,t) is the discharge and $s(j,t)$ is the spillage.

2.2.4. Physical Limitations on Reservoir Parameters

There are some sort of physical limitations on both water discharge and volume of water that can be accommodated in reservoir [1].

$$Q_H(j)^{min} \le Q_H(j,t) \le Q_H(j)^{max}$$

$$V_H(j)^{min} \le V_H(j,t) \le V_H(j)^{max}$$

Here $Q_H(j)^{min}$ represents lower limit of discharge for j^{th} hydro power plant. $Q_H(j)^{max}$ represents upper limit of discharge for j^{th} hydro power plant. $V_H(j)^{min}$ is the lower limit of volume for j^{th} hydro power plant and $V_H(j)^{max}$ is the upper limit of volume for j^{th} hydro power plant.

2.2.5. Initial and Final Reservoir Storage Volumes

Usually there is some sort of boundary on how much volume of water can be accommodated in reservoir before and after the production of energy from water so, on base of that the initial and final storage volumes are defined from [1].

$$V_H(j,t)|^{t=0}= V_H(j)^{begin}$$

$$V_H(j,t)|^{t=T}= V_H(j)^{end}$$

Here $V_H(j,t)|^{t=0}$ represents starting or initial volume of j^{th} hydro power plant and $V_H(j,t)|^{t=T}$ represents ending or final volume of j^{th} hydro power plant.

It is very clear that HTS problem is a very complicated and multi-constrained generation scheduling problem so rather a very robust and powerful optimization algorithm is required to optimize this problem successfully.

3. Adoptation of Various Optimization Methodologies for the Solution of Different Aspects of Hts Problem in Literature

Adaptation of huge number of optimization techniques to solve various aspects of HTS

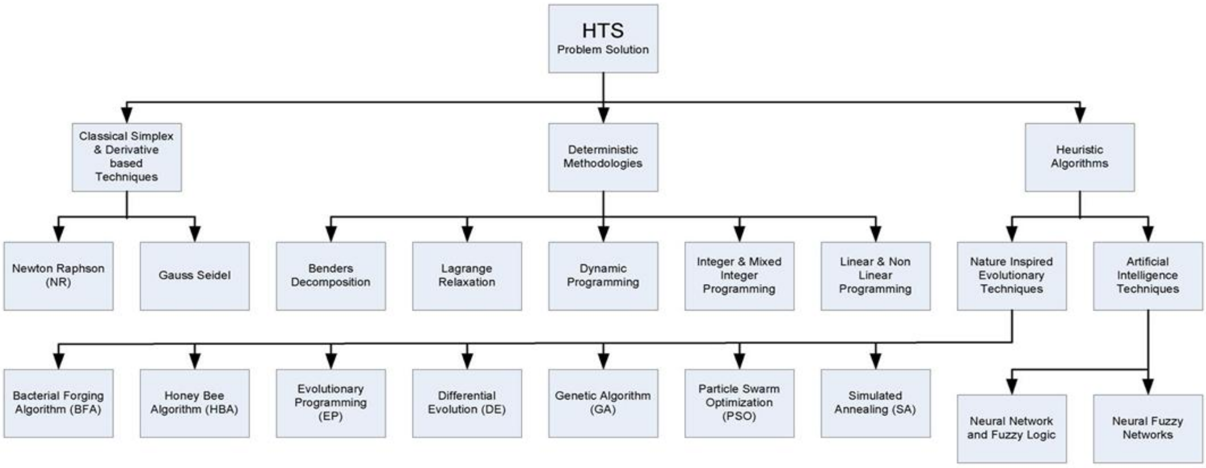

Figure 1. Categorized optimization techniques being used to solve HTS problem

problem manifests the importance and broadness of respective research area. Various categories of different optimization algorithms have been modified and hybridized to continuously reduce the operational cost of coordinated operation of HT power system. The roots of both HTS problem and adaptation of different basic optimization techniques for solution of HTS problem can be guessed by historical survey based research article being presented [6]. The earliest optimization methods were the base load procedures, best point loading and incremental cost criterion. Nowadays different optimization methods and algorithms are in use especially, in the recent years, Evolutionary Search Algorithms (EA) have aroused intense interest due to their flexibility, versatility and robustness in seeking a globally optimal solution for HTS problems [7-9].

Overall, the popular and mostly used optimization methods for the solution of different aspects of HTS problem can be further classified as below. Figure 1 shows the exactly similar categorized division of different methodologies being adopted in literature to solve complicated HTS problem. A very popular and efficient survey based research article regarding solution of STHTS problem has been presented [2]. The emphasis of our research article is to provide an enhanced and comprehensive survey of how HTS problem has been solved using different evolved Evolutionary optimization techniques. The adaptation of different algorithms, their merits and demerits regarding HTS and test systems being adopted alongwith outcomes being obtained are also discussed in this article (Most of the data being collected is based on IEEE/IET/Elsevier/ Springer/Taylor and Francis databases).

- Classical Simplex and Derivative based Techniques
- Deterministic Methodologies
- Heuristic Algorithms

3.1. Classical Simplex and Derivative Based Techniques

Classical category contains Gauss-Siedel and Newton-Raphson based simplex and derivative based mathematical optimization techniques which usually make use of single and multiple steps Derivative and Hessian operators. Conventional optimization techniques have usually been found to be suitable for relatively simpler, convex, differentiable and linear optimization problems with smooth search space.

For the solution of HTS problems the classical techniques although have proved to be very simpler to apply but were only suitable and productive for differentiable and smooth fuel cost curves for thermal production facilities [1] and also have the problem of trapping to local optima while never reaching global optimum for non smooth search space [6]. However, they have shown one great strength, that is to find the local optimum in due time. This particular strength of classical derivative based techniques has motivated different researchers to modify and cover weaknesses of other Heuristic and mathematical optimization algorithms by merging them with classical approaches. A very simple HTS problem with smooth fuel cost curves and limited energy

[10] has been solved via derivative based Newton Raphson (NR) method. Here due to native weakness of algorithm a smooth, differentiable and linear model has been optimized using NR approach while not considering the valve point loading effects. In [11] Gauss-Newton and Stationary Newton algorithms have been adopted alongwith Interior points (IP) based methodology to perform economical generation scheduling of HT power system using Jacobian Operator. According to authors the results being obtained have showed the accuracy of proposed hybrid approach.

For more realistic problems like HTS problem having non-smooth, non-differentiable fuel cost curves, classical techniques have usually been failed so the application of these techniques nowadays is limited to theory.

3.2. Deterministic Approaches

Deterministic approaches present a wide class of optimization search techniques based on deterministic transition rules and mathematical background, mostly optimizing the problem by decomposing it in sub problems and solving sub problems while relaxing or using multiple regression or bundled technique. Either way they solve the problem by linking sub problems in multiple iterative processes. Deterministic approaches can be further divided in Lagrangian Relaxation (LR), Benders Decomposition (BD), Integer and Mixed Integer programming (MIP), Dynamic Programming (DP), Linear and Nonlinear programming (NLP) techniques.

Solution of HTS problem using different deterministic approaches will be discussed here along with merits and de-merits of each technique against their application on HTS problem.

3.2.1. Lagrangian Relaxation (LR)

Probably the most used and well established mathematical programming approach from Deterministic algorithms to solve HTS problem is the LR technique. It is iterative based decomposition technique where multiple constraints are congested in main objective function using Lagrangian multipliers then main problem is divided in sub problems and each sub problem is solved individually while relaxing other sub-problems (constraints) to obtain dual solution. The corresponding difference between primal and dual solution triggers the termination criteria of LR technique [1]. The deficiencies related to Lagrangian based techniques are mainly trapping to local optima [1] and oscillations around global optima [12], so different modifications have been adopted to tackle with this flaw of LR technique like augmentation of multipliers in LR method and hybridization of LR based techniques with other Evolutionary and Deterministic algorithms [13] thus improving efficiency of LR based algorithms against complicated optimization problems.

For HTS problem different flavors of LR based algorithms have been adopted like in [13] new multiplier updating augmented LR based hybrid approach has been adopted to optimize system containing HT and natural gas generation units. Hybrid approach not only nullified the native problems of LR but very efficient results have been obtained against HTS problem. In [14] LR has been adopted as hybrid approach together with Expert Systems (ES) to optimize STHTS problem. Results have shown the general accuracy of algorithm against complicated optimization problems like HTS itself.

In the nutshell LR based modified and hybrid algorithms performs at par with other robust algorithms being adapted for HTS problem optimization. The only problem which has to be controlled relating to LR based techniques is the severe oscillations around global optima.

3.2.2. Benders Decomposition (BD)

Just like LR based method of dual optimization, BD is another Deterministic approach. It also works on same principle as LR based techniques do i.e. dividing main problem in different sub problems then solving each sub problem individually while relaxation other sub-problems. It is basically a decomposition strategy for Lagrange based dual problem. Alongwith same working philosophy as LR based techniques the problems related to BD technique are also same like oscillations around global optimum, never quite reaching it. BD actually works by linking different stages of problem while discretizing each stage and solving using forward and backward iterative methodology. Sometimes, BD is also known as Dual Dynamic Programming (DDP) approach.

For HTS optimization problem BD technique is usually modified or adopted as hybrid approach like in [15] Multistage Benders Decomposition (MSBD) has been adopted to solve complicated HTS problem. MSBD is actually DDP based approach where problem is solved using iterative backward and forward recursion process. Results being obtained have shown strength of this technique against other programming techniques to solve HTS problem. In [16] Nested Benders

Decomposition (NBD) approach has been adopted to optimize HTS problem. The main problem has been decomposed in small sub problems and each sub problem has been further divided in small nano problems. Each nano problem has been solved using Benders approach. Thus whole technique has worked like a cage of NBD approach. Results being obtained have shown promising characteristics of corresponding algorithm against complex HTS problem. The adaptation of BD technique as hybrid approach is to cover problems like oscillations around global optima, never quite reaching optimum against the solution of complicated HTS problems [15, 16].

3.2.3. Integer and Mixed Integer Programming

This category of mathematical programming techniques present a wide class of Mixed Integer based optimization methodologies that are used as optimization algorithms for many complex problems like HTS problem. Integer based programming techniques usually work on variables which only take integer values. Linkage of present and past value is also one of the main steps of Integer Programming techniques. These optimization algorithms are further divided in the two parts

- Branch and bound Mixed Integer programming techniques
- Cutting plane Integer Programming techniques

Although problems like trapping to local minima and poor convergence are not related to Mixed Integer Programming techniques but due to huge dimensions of HTS problem programming based techniques take high computational times like in [17]. Mixed Integer Programming has been used to solve complicated HTS problem. To avoid premature convergence and long computational time taken by Mixed Integer Programming some of the constraints have been relaxed. In [18] Mixed Integer based Non-Linear Programming has been adopted to cope with native problems of Mixed Integer Programming against complex HTS problem. The main objective function has been optimized by Mixed Integer Programming along with satisfaction of constraints using Non-Linear Programming. Likewise the same Mixed Integer Non-Linear Programming approach has been adapted in [19] to solve more realistic HTS problem based on Portuguese network. Results being obtained are quite satisfactory.

3.2.4. Dynamic Programming (DP)

DP is one of the most popular Deterministic mathematical programming approaches for non-convex and very complicated optimization problems. DP has been extensively used for HTS problem solution. It divides main problem in different small sub problems, solving each problem in parallel with other problems and checking each possible state. As problem increases in size, states, due to increase in the dimensions of problem DP takes exceptionally high time which is also known as dimensionality curse [20]. DP is usually considered as an effective mathematical technique to resolve the complex optimization problems since its first formulation by Bellman in 1954. The long computation time and storage memory requirements are the main drawbacks of conventional DP, but with the course of time using Stochastic programming instead of conventional Deterministic programming they are reduced.

For HTS problem, which is very complex Dynamic problem, DP although have shown good results but takes exceptionally large computational time due to dimensionality curse so in [21] extended DP has been adapted to optimize HTS problem. The main problem has been divided in sub thermal and hydro problems. Then each sub problem has been further divided in nano problems. The algorithm has been further assisted by mixed coordination methodology between sub-problems to cope with the native problem of DP against complicated HTS problem. In [22] multi-pass DP has been used to solve HTS problem and to cover the problem of DP, Evolutionary Programming has been integrated in DP to solve HTS problem.

3.3. Heuristic Algorithms

The limitations and a bag of mix results regarding usage of Conventional search techniques against optimization of highly complicated and nonlinear problems have opened a wide research area toward more optimal and robust class of optimization algorithms. Heuristic computational methods represent the largest branch of optimization algorithms representing simulated nature inspired intelligent algorithms. Most of the algorithms from Evolutionary and Heuristic category follow Darwin's theory (natural selection or only fitter one will survive) thus copying some sort of natural process to seek the perfection in the process of optimization. Heuristic algorithms have found application in almost every field of science. From simpler mathematical problems to real time weather simulations, Evolutionary Heuristic algorithms have shown excellent results and robustness. In this article, we will only discuss the adoptability of most renowned Heuristic algorithms for optimization of HTS problem. Thus against HTS problem most used Heuristic algorithms are categorized as natures inspired Evolutionary and Knowledge based algorithms from Artificial Intelligence (AI) category. These algorithms are basically divided in to two parts.

- One part containing evolutionary algorithms like Genetic Algorithm (GA), Differential Evolution (DE), Evolutionary Programming (EP), Particle Swarm Optimization (PSO), Simulated Annealing (SA), Honey Bees Algorithm (HBA) and Bacterial Foraging Algorithm (BFA).
- Second part shadowing Fuzzy-Logic (FL), Neural Networks (NN) and Expert Systems.

Most of algorithms from Heuristic methodologies have been adopted to optimize HTS problems [23]. Heuristic algorithms follow path of nature to solve complex problems as nature does itself. Algorithms usage for optimization of HTS problems and their merits and demerits will be discussed one by one.

3.3.1. Simulated Annealing (SA)

SA is a very popular and well established Evolutionary algorithm based on the principle of metallurgical annealing process and has found to be suitable for optimization of complex problems. Annealing is the process where materials like glass, ceramics and different crystals are cooled gradually after heating them at very temperatures to attain perfected states. It follows the law of thermodynamics as when any metal is slowly iced in its melted state it attains the state of perfection but sometimes if non-perfected state is achieved whole process is restarted again to achieve perfection [24]. So if SA is not able to achieve global optimum, it takes exceptionally high time. For the perfect state to be achieved, cooling rate is an important decision. The algorithm was introduced by Metropolis in 1950 [25] based on Monte Carlo annealing process. The corresponding algorithm is also sometimes termed as probabilistic hill-climbing and stochastic relaxation [25]. Although SA has found numerous applications regarding optimization in different fields but the algorithm shows excellent results for power system operation like SA has been adopted in literature to perform HTS in [26, 27]. Overall algorithm consists of the following steps

- Production of candidate solution: Initialization of both temperature and solution. Next solution is found by perturbation of last solution.
- Acceptance criteria: The algorithm continues on the principle that next solution must have lower energy.
- Cooling schedule: The proper mathematical model is adopted for cooling criteria of next solution like exponential cooling selection (ECS).
- Stopping criteria: How the algorithm would stop i.e. either based on repetition of solution or fixed number of iterations etc.

For HTS problem SA has been used mainly with some modifications or as hybrid approaches like in [28] a comprehensive comparison between SA and GA has been performed against solution of complex medium term HTS problem. Both techniques have been found to be equally suitable for HTS problem. The prime reason to use hybrid approach is to cope with native problems of SA and to support SA against complex problems like HTS problem.

3.3.2. Particle Swarm Optimization (PSO)

PSO is probably the most popular population based Evolutionary algorithm optimizing non convex and nonlinear problems using social, cultural and intelligent swarming behavior of different animals like flock of birds and school of fish. It was first introduced by Kennedy and Eberhart in 1995 [29] for continuous mathematical optimization problems. Perhaps it represents the simpler algorithm having small number of parameters. PSO basically belongs to mathematical background where it is considered as a very poor technique but for power system optimization problem this algorithm is very suitable due to its random nature [23].

In PSO algorithm, a particle is accelerated in search space. The particle moves toward global optimum by evaluating both its own and others favorable paths in each next iteration. From whole class of Heuristic algorithms, PSO is the most successful algorithm for HTS problems [7]. A broad research area is linked with PSO like reactive power and voltage control [30], voltage stabilizer [31], economic dispatch (ED) with valve point loading effects [32] and short term HTS scheduling. The whole algorithm works as follows

- Initialization of particle's velocity and position in nth dimensional space.
- Update the velocity and position using Pbest and Gbest in each subsequent generation.
- Termination criteria.

However, PSO needs some tuning related to parameters so as to perform optimally particularly for HTS problems. So far HTS problems, PSO is mostly used in modified form like in [7] small population based PSO has been used to optimize STHTC problem. Here small population has been taken to help PSO to find global optima in minimum time and to cope with the problems related to small population different operators have been used. In [33] modified PSO has been adapted to optimize HTS problem and the results being obtained have found to be better than SA. Hybrid approach has been applied in [34] where Differential Mutation operator has been used to assist PSO to find optimum best against HTS problem thus quantum behaved PSO (QPSO) has been found to be suitable against both PSO and Differential Evolution (DE) individually.

3.3.3. Evolutionary Programming (EP)

EP presents a huge class of Evolutionary optimization algorithms applied directly to solve many complex optimization problems like HTS problem. Works on same philosophy as GA like random initialization of strings of solutions across search space and modifying strings in each next iteration but EP based techniques e.g. infamous Differential Evolution (DE) differs in operators used [35]. The whole algorithm can be described as follows:

- Initialization
- Mutation
- Selection
- Termination

EP has been adopted to optimize HT power system like in [36] where EP has been modified by inserting Cauchy mutation in basic EP to show acceptable results against HTS problem. Generally both EP and DE have merits and demerits similar to GA like taking exceptionally high computational time to solve complex problems like HTS. So, to cope with these problems DE is used as hybrid approach alongwith other Heuristic and Deterministic approaches to solve HTS problems e.g. in [37] Chaotic Local Search (CLS) has been used to cover problems like long computational time and poor convergence of DE against complex STHTC problem. The results being obtained are comparable to both PSO and DE individually. In [38] Sequential Quadratic Programming (SQP) has been adapted to assist DE to cover its poor convergence characteristics and tracking to local optima against complex STHTC problem.

3.3.4. Honey Bee Algorithm (HBA)

HBA is the newest social behavior based Heuristic algorithm converting both foraging and social behavior of honey bees in excellent optimization methodology.

Despite the young age of HBA, it is well-defined algorithm and has found to be suitable for optimization of complex problems like economic dispatch (ED) and HTS. In [39] BA has found to be better than modern Heuristic algorithms for the solution of ED problem which is much similar to HTS problem. If we compare this algorithm with old and famous nature inspired Evolutionary algorithms like GA, PSO and SA, HBA has showed more promising results for complex power system optimization problems [39].

3.3.5. Neural Networks and Fuzzy Logic Based Techniques

Neural Networks (NN) is basically a huge distributed processor just like human brain which has the ability of learning, storing, linking and generation of some sort of information. Learning is specialized through weight-tune procedure alongwith storing and linking of inputs-information. Once learning is done, processor has the ability to develop outputs i.e. Generation. This algorithm has no limitations just like most other techniques except the difficulty of designing NN processor itself and then training it for specific problem. For power system optimization problems especially HTS problem although NN shows itself as very powerful tool but has seldom used primarily due to difficulty in application of NN to solve HTS problem. In [40] Hopfield Neural Network has been used alongwith LR methodology to solve STHTC problem. Test system being adopted contained multiple pumped storage hydro and thermal machines. The results being obtained have been compared with both LR and Quadratic Programming (QP) based approaches and this particular technique has been found to be suitable for STHTC.

Alongwith NN, Fuzzy-Logic (FL) based technique is also another popular technique from artificial systems. It has found to be suitablefor very complex problems having inaccurate data and

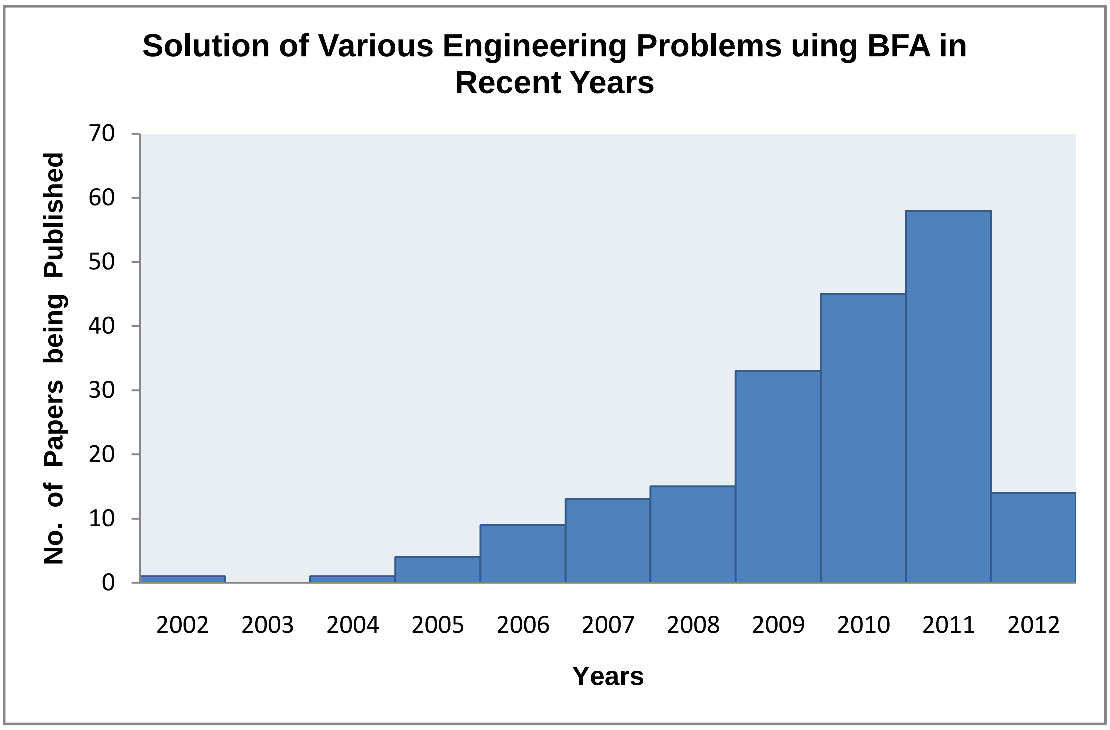

Figure 2. Survey on application of BFA to solve various engineering problems.

stochastic nature. It basically operates on some definite rules and rules are operated based on fuzzy membership functions and fuzzy logic data. It works on fuzzy variables (not clearly defined) i.e. set of variables like between 1 and 0. If each member of fuzzy set is well defined it contains all the necessary information of solution set and if it is not, problems related to huge computational time and poor convergence occur. The process usually contains following three steps.

- Fuzzification of data structure.
- Conversion of data structure to solution set.
- Defuzzification of solution set.

FL has been adopted to optimize HT power system operation like in [41] to solve complicated and non-linear LTHTC problem open loop feedback controller using Neural Fuzzy based forecasting system has been used. The algorithm has been tested on test system containing 19 hydro power plants with cascaded reservoirs. Results being obtained are found to be comparable to those obtained after the application of DP on similar test system. Fuzzy-systems has also been applied as hybridization approach to solve HTS problem like in [42] Fuzzy based hybridized PSO based approach has been used to solve HTS system to cover premature convergence related to PSO against complex problems. Results have showed that respective algorithm is fast with respect to convergence speed against both PSO and DP individually.

4. Bacterial Foraging Algorithm (BFA)

4.1. Working Philosophy

BFA is one the newest natures inspired optimization algorithm. It uses the foraging activity of bacteria, E. coli, as an optimization process. Bacterial foraging process was presented as an efficient optimization process in [43] where it was used to optimize distributed controller. It has also been used in the harmonic estimation [44], optimal power flow [45] and optimal design of power system stabilizers [46]. However for very complex dynamic optimization problems, BFA shows poor convergence characteristics due to very high amount of randomization in the algorithm. Likewise for HTS problem this algorithm again showed poor convergence results so some sorts of modifications were adopted in this algorithm [47]. BFA can be used as hybrid approach with other such algorithms like PSO [48]. The whole foraging process is divided in

- Chemo-taxis
- Reproduction
- Elimination and Dispersal

Chemo-taxis is the main part of foraging behavior of E. coli bacteria where the bacteria first tumbles (A very small step) checking which direction is most suitable for him based on concentration of edible materials and then swimming in same direction thus maximizing the amount of food in the end of foraging. Swim is usually performed in the form of steps and at each step concentration of food is checked so swim continues on the base of increasing concentration of food. The chemo-taxis process is applied on whole amount of bacteria in population. For engineering and science problems, a brief survey of usage of BFA from 2002 to 2012 is presented below in Figure 2.

On base of food collected bacteria divides keeping the population constant thus whole algorithm from [43] can be plotted as below

4.2. BFA as an Optimization Algorithm

Step-1

To initialize the main parameters

P// Dimensions of search area (Population)

S// Amount of bacteria in each population

n_C // Chemo-taxis steps of each bacteria

n_S // Swim length in the form of steps

n_{re} // Number of reproduction events

n_{ed} // Number of elimination-dispersal loops

p_{ed} // Probability of elimination-dispersal

$c(i,j)$ // Swim-step length

θ^i // initialized location of bacterium (random)

//parameters for swarming

$x_{repellant}$ // Height of repellant effect

$z_{repellant}$ // Width of repellant effect

$x_{attractant}$ // Depth of attractant effect

$z_{attractant}$ // Width of attractant effect

//Initialization of events loop

Step-2

$ed = ed + 1;$ // Elimination/dispersal loop

Step-3

$r = r + 1;$ // Reproduction loop

Step-4

$j = j + 1;$ // Chemo-taxis loop

//Start Chemo-taxis

for $i = 1, 2, \ldots s;$

- Evaluate the cost function $J(i, j, r, ed)$ of each bacterium at initialized random position using

$$J(i,j,r,ed)=J(i,j,r,ed)+J_{cc}(\theta,P(j,r,ed)) \quad (1)$$

Here,

$$J_{cc}(\theta,P(j,r,ed))=\sum_{i=1}^{s} J_{cc}^{i}\left(\theta,\theta^{i}(j,r,ed)\right)$$

$$=\sum_{i=1}^{s}[-x_{attractant}\exp\{-z_{attractant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\}]$$

$$+\sum_{i=1}^{s}[x_{repellant}\exp\{-z_{repellant}\sum_{m=1}^{p}(\theta_m-\theta_m^i)^2\}]$$

- Let $J_{last} = J(i, j, r, ed)$ so that the cost can be minimized by moving to new locations.
- Generate a random vector $\nabla(i)$ in [-1; 1] range.
- Compute $\partial(i)$ which shows direction and small displacement to check concentration of food using

$$\partial(i)=\frac{\nabla(i)}{\sqrt{(\nabla^T(i)\nabla(i))}}$$

Tumble using

$$\theta^i(i,j+1,r,ed)=\theta^i(i,j,r,ed)+c(i,j)\partial(i) \quad (2)$$

- Compute $J(i, j + 1, r, ed)$ at new position using (1)
- Start swimming, let w = 0 (swim step counter)

While w < n_s (until steps of swim are not over)

Let w =w + 1

- For each step w, position of bacteria θ^i will change using (2)
- At each new position after swim, calculate cost function using (1)
- If $J_{last} < J(i, j, r, ed)$ // Reducing strategy

Let $J_{last} = J(i, j, r, ed)$

- Continue swimming in same direction (at each step cost gets lowered) and calculate new $J(i, j, r, ed)$ using (1) in the end of swim

else let w=n_s //stop counter for swim

- Repeat the whole process for each bacterium (i=i+1 if $i \neq s$)

Compute best (lower) cost obtained ($J_{best}(j)$)

- If $j < n_c$ go to *Step-4* ($j = j + 1$). Else end chemo-taxis loop

//Start Reproduction

Step-5

- Evaluate the total health of each bacterium in the end of chemo-taxis loop as follows

$$J^i_{health} = \sum_{j=1}^{n_c+1} J(i,j,r,ed) \quad (3)$$

The health of bacterium notifies us about the amount of nutrients it has got over its entire lifespan. On base of this collection bacterium will either reproduce or destroy in reproduction loop.

- Sort bacteria according to amount of nutrients they have collected i.e. on the base of their health J^i.
- The bacteria having higher number of nutrients will pass through reproduction where they will split and other bacteria having lower number of nutrients will die out eventually.

Step-6

- If $r < n_{re}$, go to *Step-3* $(r = r + 1)$

Else end reproduction loop

//Start Elimination/Dispersal

Step-7

- On the base of probability p_{ed}, either eliminate or disperse selected amount of bacteria to keep the population constant.

Step- 8

- If $ed < n_{ed}$, go to *Step-2* $(ed = ed + 1)$, otherwise end algorithm.

5. Hydrothermal Scheduling Using BFA

BFA has showed satisfactory results against optimization of complicated HTS problems like optimization of short term variable head HT problem and multi-objective optimization of HTS problem [47], although some modifications are always adopted to optimize these complex problem. Mostly chemo-taxis step has been modified as decreasing function with respect to time. Beside HTS problem, BFA is also used to solve complex ED problems where efficiency of this algorithm has been found to be on par with other such nature inspired Meta-Heuristic algorithms [49]. Brief review of stances when BFA has been used for HTS problem is described below. Figure 2 contains graph representing no. of papers published relating to BFA application to solve different aspects of HTS problem in recent years. Here data being collected mostly belongs to IEEE, IET, Science Direct, Taylor & Francis and Springer.

I.A. Farhat and M. E. El-Hawary in [50] have devised nature inspired Enhanced Bacterial Foraging (EBFA) optimization algorithm to solve dynamic, highly nonlinear and multi-constrained variable head short term HT coordination (VHSTHTC) problem. The variable nature of head of water in this problem has made corresponding problem even more beefy and complex. Authors also have considered real-time constraints related to both hydro and thermal power plants. Only smooth fuel cost curves for thermal machines have been considered here. According to authors, raw BFA technique has showed poor convergence criteria along with long computational time required to solve STHTC problem so some type of critical change in infrastructure of BFA (in the form of change in chemo-taxis step $C(i, j)$) has been used to show optimum results for STHTC problem. The accuracy of proposed enhanced BFA has been tested by applying EBFA on two test systems. One test system contained two thermal and two hydro machines and other test system contained five thermal and four hydro machines. According to authors EBFA has showed promising results against solution of complex VHSTHTC problem.

I.A. Farhat and M. E. El-Hawary in [51] have solved a system containing 4 hydro units and 3 thermal units. The test system presented highly nonlinear, complicated and dynamic multi-reservoir cascaded short term HT coordination (STHTC) problem (scheduling from 1 day to 1 week). Real-time constraints from both hydro and thermal power plants have been realized and non-smooth fuel cost curves for corresponding thermal generation units have been considered. The problem has been optimized by authors using modified Bacterial Foraging Algorithm (MBFA) where according to authors basic BFA has failed to converge and been trapped in local minima. Here the critical change in algorithm of raw BFA (dynamically decreasing chemo-taxis step) has managed to show good results for the solution of STHTC problem.

I.A. Farhat and M. E. El-Hawary in [52] have modified BFA which they then have termed as Improved Bacterial Foraging Algorithm (IBFA), to solve complicated, dynamic and highly nonlinear STHTC problem considering environmental aspects. As a bi-objective optimization problem,

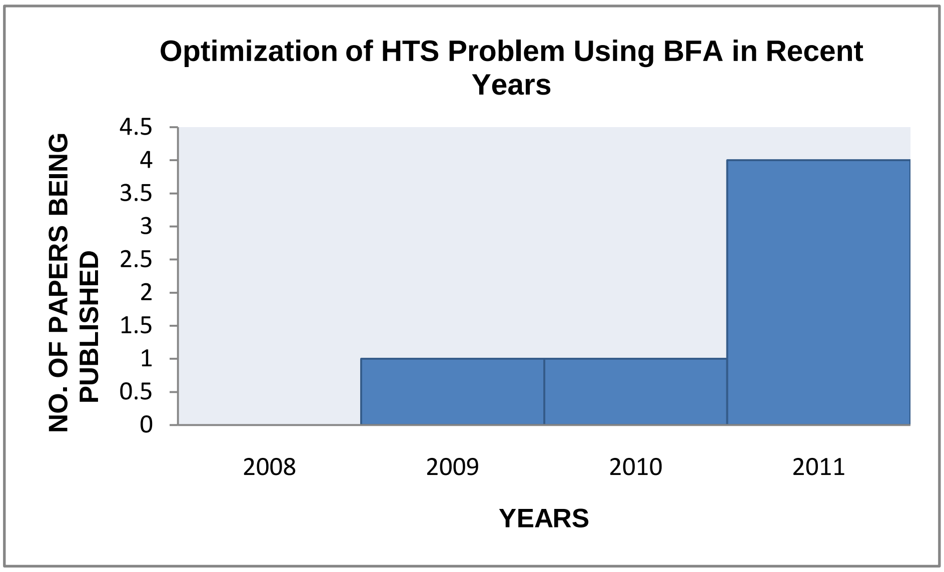

Figure 3. No. of Papers using BFA to solve HTS problem in corresponding years.

one has to minimize both cost and pollution in this problem. So this flavor of STHTC problem has presented dual objectives and multiple constraints which have made this problem very unique of its own nature. Basic BFA has been modified by authors, an improved BFA to solve this bi-objective problem successfully. Real-time constraints and smooth fuel cost curves for thermal machines have been considered here. Algorithm has been tested on test system containing two thermal and two hydro machines. According to authors IBFA has showed promising results while optimizing bi-objective STHTC problem.

I.A. Farhat and M. E. El-Hawary in [53] have devised a strategy to perform simultaneous unit commitment (UC) and ED of highly nonlinear and dynamic fixed head short term hydrothermal coordination (FHSTHTC) problem using nature inspired BFA algorithm to obtain optimum cost of net unit of electric energy alongwith satisfactory solution of constraints. In fixed head problem, virtually a large reservoir has been presented so no effect on head of water hence constant head. Although here authors have approximated fixed head opposed to [50] but still system is complex one because real-time constraints have been considered alongwith smooth fuel cost curves. BFA has showed excellent characteristics to solve this type of multi-constrained complex problem except some deficiencies like trapping to local minima and poor convergence. To cope with this problem of raw BFA authors have modified the chemo-taxis step of BFA to solve FHSTHTC problem, they have termed this version of BFA as modified Bacterial Foraging Algorithm, MBFA. To test the accuracy of algorithm, MBFA has applied on two fixed head test systems. First system contained one thermal power plant and two fixed head hydro machines while second test system contained one fixed head hydro and three thermal machines. Results being obtained from implementation of algorithm on actual test systems have showed accuracy of modified BFA.

I. A. Farhat and M. E. El-Hawary in [54] have proposed a modified bacterial foraging algorithm, an Improved Bacterial Foraging Algorithm, IBFA to solve dynamic, nonlinear and multi-constrained multi-objective STHTC problem. Critical improvements have been introduced in basic BFA like changes in chemo-taxis step to optimize this bi-objective STHTC problem where both fuel costs and pollution have been minimized at the same time. Weighting factors have been adapted to have an acceptable compromise between both objective functions. Real-time constraints alongwith smooth fuel cost curves have been considered here. The algorithm has been tested on test system of two thermal and two hydro machines. According to authors this improved flavor of BFA has showed promising results against complex bi-objective optimization problems like MOSTHTC problem itself.

I. A. Farhat and M. E. El-Hawary in [47] have optimized very complicated, highly non-linear and multi-constrained scheduling of HT power system for 1 day to one week, short term hydrothermal coordination (STHTC) problem. STHTC problem presents highly non-linear search space where both UC) and ED problems have been performed simultaneously. In the nutshell successful optimization of STHTC problem requires very robust algorithm. BFA is one of the newest and efficient Evolutionary algorithms. In literature it has been used to solve complex optimization problems [54]. However for multi-dimensional problems like STHTC, this algorithm has shown poor convergence characteristics so some sort of critical improvements have been introduced by authors and they termed that improved version, an IBFA. STHTC problem has been solved using IBFA and accuracy of algorithm has been proved by applying this algorithm on test system having one hydro and one thermal machine.

6. Genetic Algorithm

6.1. Working Philosophy

Genetic algorithm (GA) is rather most established and popular population based Heuristic optimization algorithm. GA was first introduced by Goldberg (2000) as a tool for global optimization of complex, non-differentiable and non-linear problems with turbulent search space and multiple constraints [55]. The trapping to local minima is no longer a problem for GA as the algorithm randomly takes the set of solutions all over search space and optimize those sets with each next iteration (generation) using different operators.

If we have a look at the brighter side, GA is very suitable for the optimization of complex problems but if we have a look at darker side of GA, it suffers from high computational time and repetition of solution sets in large no. of iterations [56]. To solve these problems related to GA, it is mostly used in modified form like real coded GA [57], hierarchical GA or as hybrid approach. Just like other stochastic Evolutionary algorithms GA is a global optimizer and performance of GA is mainly associated with the configuration of following operators

- Initialization
- Random generation of population
- Fitness evaluation
- Selection
- Cross-over
- Mutation
- Termination

7. Hydrothermal Scheduling Using GA

In case of HTS problem GA has shown excellent performance [58]. However it is not a complete algorithm like it takes exceptionally high computational time once reaching optimum region. So to solve this problem related to GA, hybridization of GA with other optimization techniques like classical derivative based techniques has proved to be very favorable for HTS problems optimization like in [59] both GA and classical lambda iterative technique have been hybridized to optimize short-term oriented complicated problem consisting of HT power system and results obtained are quite fruitful. HTS using different flavors of GA as optimization methodologies will be discussed here. Figure 4 represents a survey on adaptation of GA as an optimization algorithm to solve HTS in recent years.

In [60] Carneiro, A. A. F. M., P. T. Leite, et al. have adapted GA based approach as an alternative to classical methods for the optimization of operational planning of HT power system. Previous work on the same problem suffered from convergence, over simplification and approximation of the problem. The results being obtained from GA based approach have showed that this approach can be one of the best alternative to classical techniques in terms of its parallelize operation, simplicity, less processing time, dealing various plants of different behaviors.

Orero and M.R. Irving in [55] have suggested the solution of HTS problem using GA framework considering various constraints. The problem being considered here is a multi reservoir cascaded hydro system having complex relationships amongst various variables of the function. The problem under consideration has been successfully implemented using GA due to its capability of handling such a multi-constraint problem, simplicity, and robustness.

In [61] STHTS problem has been solved using SA and GA and two hybrid techniques. All equality, inequality constraints have been taken into account. The advantage of the proposed algorithm is that unlike other algorithms, the thermal generators have not been considered as single unit and the proposed algorithm has reflected the characteristics of individual generator. The results being obtained have shown that the new proposed algorithms can be more efficient and reliable.

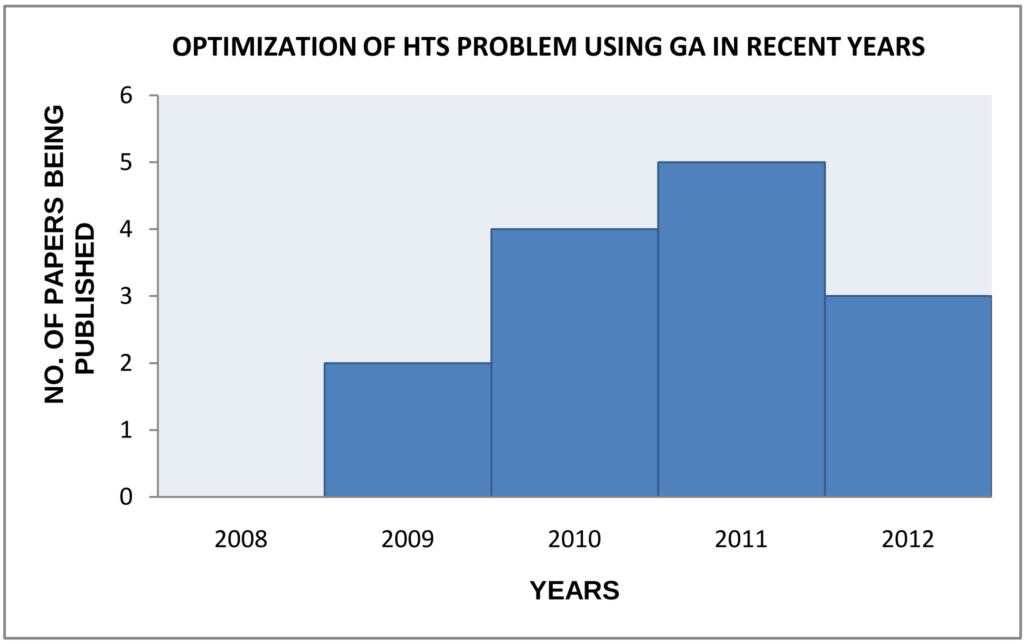

Figure 4. No. of Papers using GA to solve HTS problem in recent years

Xiangping, M., Z. Huaguang, et al. in [62] have addressed the main drawbacks of the GA that are slow speed and premature convergence and have tried to avoid these drawbacks using newly proposed algorithm called Fast Synthetic Genetic Algorithm (FSGA). The new algorithm has the advantages like fast speed of convergence, higher precision and most important one is reduction in population size. A hybrid algorithm has been developed by combining FSGA with Back propagation (BP) and applied for short term economic dispatch of HT power system. Hybrid algorithm also has solved the problem of long training time of BP. The proposed algorithm has been tested using three units and six buses test system. The results being obtained have been compared with classical methods and comparisons have shown that run time has reduced.

In [56] GA based model has been proposed for STHTS problem. The proposed algorithm has divided the problem into two sub problems which are UC and ED. Future cost curve has been used to optimize the hydro energy required during that specific period. The performance of the proposed model has been improved by new technique used for representations of candidate solution and applying a set of expert operators. Results being obtained have been compared with the result obtained previously from the same problem when solved with LR, Mimetic algorithm, and GA and the results being obtained are competitive with the previous results.

Zoumas, C. E., A. G. Bakirtzis, et al. in [8] have solved HTS for economic dispatch using Enhanced Genetic Algorithm (EGA) and Priority List method. HTC problem is divided into two sub problems, Hydro part has been solved using EGA and is formulated as nonlinear, mixed integer optimization problem. Where thermal part has been solved using priority list method. Hydro as well as thermal constraints have been taken into consideration while applying the proposed algorithm. For improving GA performance problem specific genetic operators have been adapted. The main advantage of EGA over simple GA being demonstrated is the flexibility in modeling.

Leite, P. T., A. A. F. M. Carneiro, et al. in [63] have used a hybrid GA for the optimal operation of Brazilian HT power system. In this paper a comparison has been presented between Gradient method and GA based on Gradient method (Hybrid method). All equality and inequality constraints have been taken into account. Two new genetic operators, gradient mutation and gradient direct mutation have been used in the proposed new hybrid algorithm. Results being obtained from hybrid technique are quite promising and it has been shown that the proposed method can be used for planning also.

Kumar, S. and R. Naresh in [64] have solved STHTS problem with continuous and non smooth/ non convex cost function using an efficient real coded Genetic Algorithm (RGA) technique considering travel time between cascaded reservoirs and valve point effect in addition to all equality and inequality constraints. A comparison between real coded and binary coded GA (BGA) has been demonstrated when implemented for the same multi chain, cascaded HT power system. The comparison has shown that RGA is better than BGA in its simplicity, ease of implementation, efficiency, small population size and effective constraints handling without penalty parameters.

In [65] STHTS has been solved using decomposition and GA based optimal power flow (OPF). The problem has been divided into two sub problem, Hydro sub problem has been solved using Discharge Proportional to Demand Method (DPDM), and Lambda iteration technique has been used to solve the thermal sub problem including line losses. To control line losses GA based optimal power flow has been used. Results being obtained from DPDM have been compared with that obtained from Average Inflow method (AIFM) and it has been found that DPDM is simple, reliable and efficient.

Ozyon, S., C. Yasar, et al. in [66] have proposed GA based solution to environmental economic power dispatch problem of a HT power system. The paper aims to reduce NOx emission besides the reduction of total thermal cost. Weighted Sum Method (WSM) has been adapted to convert the multi objective environmental ED problem into single objective optimization problem. GA has been then used to solve the single objective ED optimization problem.

In [67] Basu, M. has proposed Non Dominated sorting Genetic Algorithm-II for the economic environmental dispatch of fixed head hydro thermal (FHHTS) power system. Non Dominated Sorting GA-II has been used to handle the problem as multi objective problem as the said problem is nonlinear, constrained multi objective problem. The GA been implemented here is the real coded and all constraints have taken into account. The objective of the paper is to reduce SOx and NOx emission alongwith the reduction of fuel cost. Results being obtained are compared with the results obtained from previously used techniques; strength Pareto Evolutionary algorithm 2 and multi objective DE and some others and found better than previous results.

Sasikala, J. and M. Ramaswamy in [58] have introduced a new Optimal Gamma based technique using GA for the improvement of the computational speed, robustness and accuracy in scheduling of large HT power system problems. The simulation results being obtained from the proposed technique have showed that this technique is fast, has lower population size and is accurate as compared to previously used techniques.

In [68] Mid-Long term hydrothermal scheduling has been solved using a Hybrid GA considering the final water storage and effects of water head also. The problem has been decomposed into two sub problem thermal and hydro as usual. The GA has been used only to solve Hydro problem where the mathematical programming algorithm has been used for thermal problem. Results and comparison show that Hybrid GA is much better than GA in case of large non linear system and is because in large system GA technique solves both hydro and thermal sub problem using GA so the search become more stochastic. Hybrid GA has higher computational speed and accuracy.

Kumar, V. S. and M. Mohan in [59] have proposed short term HT scheduling solution using GA. As usual problem has been divided into two sub problem; hydro and thermal sub problems. Thermal sub problem has been solved using lambda iterative technique while GA has been adapted for hydro sub problem. Line losses and line flow constraints have also taken into account for GA based optimal power flow (OPF). Whenever line flow constraints are violated the GA based OPF has been applied. Line losses have been computed using Fast Decoupled Load Flow (FDLF). The proposed technique has reduced complexity that is introduced due do calculation of line losses in each step, reduces computational speed and gives near optimal global solution.

In [57] STHTS has been solved considering the uncertainty involved in this process. The scheduling of HT system is probabilistic in many aspects like stochastic operating cast curves of thermal units, Load demand is also uncertain, inflow in the reservoir is also probabilistic. These uncertain parameters have been treated as random variables. RGA has used with special arithmetic-average-bound-blend crossover and wavelet mutation operators. All equality and inequality constraints have been taken into account. Operation limits violations have also been taken into account using exterior penalty method. The results obtained are promising.

8. Conclusions

This paper not only provides a brief survey on how both well established and newly developed Evolutionary algorithms, both GA and BFA stands for solution of different aspects of very complicated and highly non-linear HTS problem but also a brief survey on how this HTS problem has been solved using different other methodologies in literature is presented. The merits and de-merits of nearly each methodology has been discussed on the behalf of HTS problem. Most of the time BFA algorithm fails to converge successfully against HTS problem but with some minor modifications BFA stands equally with other famous algorithms showing quite promising results while GA has already shown itself as very robust and versatile optimization algorithm where many modifications and different hybrid flavors of GA have been adapted by various researcher to optimize the economical scheduling of HT power system. Despite the young age of BFA, it shows its strength against complex HTS problem compelling other researchers to at least have a single look on both BFA and GA algorithms against their complicated optimization problems.

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