Optimal Short Term Hydrothermal Scheduling

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***Abstract*— In this paper, short term hydrothermal scheduling is introduced. . The primary objective of the short term hydrothermal scheduling problem is to determine the optimal generation schedule of the thermal and hydro units to minimize the total operation cost of the system over the scheduling time horizon (typically one day) subjected to a variety of thermal and hydraulic constraints. The hydrothermal generation scheduling is mainly concerned with both hydro unit scheduling and thermal unit dispatching.**

Keywords: GENTIC ALGORITHM, LAGRANGE'S THEOREM.

I. INTRODUCTION

With extensive interconnection of the electric networks, the energy emergency on the planet and nonstop ascent in costs, it is exceptionally fundamental to lessen the running expenses of electric energy. A sparing in the operation of the power framework achieves a noteworthy decrease in the working expense and in addition in the amount of fuel expended. The principle point of current electric power utilities is to give fantastic solid power supply to the buyers at the least conceivable cost while working to meet the cutoff
Points and imperatives forced on the creating units and ecological contemplations.

The fundamental here and now hydrothermal scheduling case requires that a given measure of water be utilized as a part of such a path as to limit the cost of running the warm units. In the, here and now hydrothermal scheduling case the warm framework is spoken to by a comparable unit PS as done in the Fig 1 and a hydroelectric plant PH. It is expected that the Hydro-plant is not adequate to supply all the heap requests amid the period and that there is a

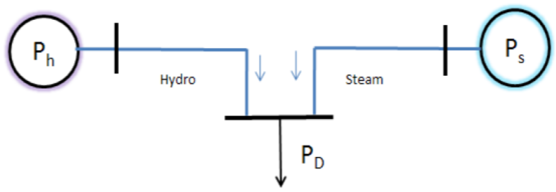

Figure: a general outline of a hydro warm plant

most extreme aggregate volume of water that might be released all through the time of T max hour

As hydro creating units don't results any fuel cost the hydrothermal scheduling issue is planned to limit the aggregate cost of warm plant while making utilization of the accessible hydro assets although much as could be expected. The target work and related constraints of the issue are detailed as take after:

Genetic algorithm

Genetic Algorithms (GA"s) are based on analogy, and are adaptive heuristic search algorithm based on , evolutionary ideas of natural selection and genetics. As such, they GA"s represent an intelligent exploitation of the random search used, to solve search and optimization problems. Although randomized, GA"s are by no means random, instead they are exploit historical information to direct the search in to the region of better performance with in the search space. The basic techniques of the GA are designed to simulate processes in natural systems necessary for evolution, especially those follow the principles first laid down by Charles Darwin of , "Survival Of The Fittest". Since in nature, competition among individuals for scanty resources, results in the fittest individuals dominating over the weaker ones.

The basic of genetic algorithm contains breeding process. The breeding process is the heart of the genetic algorithm. It is in this process, the search process creates new and hopefully fitter individuals.

The breeding cycle consists of three steps:

a. Selecting parents.

b. Crossing the parents to create new individuals (offspring or children).

c. Replacing old individuals in the population with the new ones.

Selection

Selection is the process of choosing two parents from the population for crossing. After deciding on an encoding, the next step is to decide how to perform selection i.e., how to choose individuals in the population that will create offspring for the next generation and how many offspring each will create

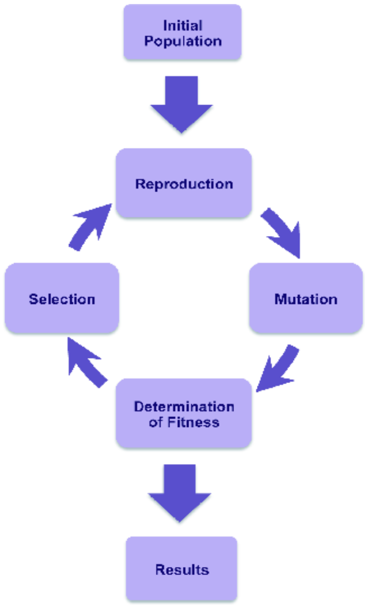

Figure: Breeding Cycle

Crossover (Recombination)

Crossover is the process of taking two parent solutions and producing from thema child. After the selection (reproduction) process, the population is enriched with better individuals. Reproduction makes clones of good strings but does not create new ones. Crossover operator is applied to the mating pool with the hope that it creates a better offspring.

Mutation

After crossover, the strings are subjected to mutation. Mutation prevents the algorithm to be trapped in a local minimum. Mutation plays the role of recovering the lost genetic materials as well as for randomly disturbing genetic information. It is an insurance policy against the irreversible loss of genetic material. Mutation has traditionally considered as a simple search operator.

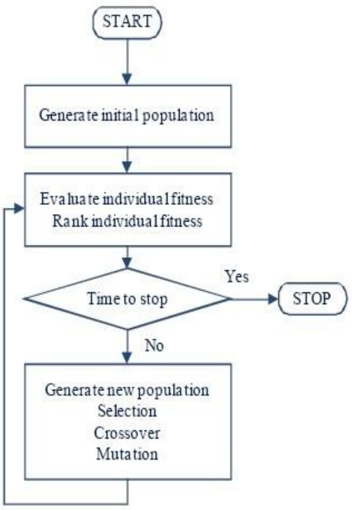

Figure: Genetic Algorithm

If crossover is supposed to exploit the current solution to find better ones, mutation is supposed to help for the exploration of the whole search space. Mutation is viewed as a background operator to maintain genetic diversity in the population. It introduces new genetic structures in the population by randomly modifying some of its building blocks. Mutation helps escape from local minima's trap and maintains diversity in the population. It also keeps the gene pool well stocked, and thus ensuring ergodicity. A search space is said to be ergodic if there is a non-zero probability of generating any solution from any population state.

There are many different forms of mutation for the different kinds of representation. For binary representation, a simple mutation can consist in inverting the value of each gene with a small probability. The probability is usually taken about 1/L, where L is the length of the chromosome. It is also possible to implement kind of hill-climbing mutation operators that do mutation only if it improves the quality of the solution. Such an operator can accelerate the search. But care should be taken, because it might also reduce the diversity in the population and makes the algorithm converge toward some local optima. Mutation of a bit involves flipping a bit, changing 0 to 1 and vice-versa.

Flipping

Flipping of a bit involves changing 0 to 1 and 1 to 0 based on a mutation chromosome generated. In mutation-flipping concept a parent is considered and a mutation chromosome is randomly

Generated. For a 1 in mutation chromosome, the corresponding bit in parent chromosome is flipped (0 to 1 and 1 to 0) and child chromosome is produced. In the above case, there occurs 1 at 3 places of mutation chromosome, the corresponding bits in parent chromosome are flipped and child is generate

Parent	**1** 0 1 1 **0** 1 0 **1**
Mutation chromosome	**1** 0 0 0 **1** 0 0 **1**
Child	**0** 0 1 1 **1** 1 0 **0**

Figure: Mutation flipping

Optimization Techniques

1. **Determinism**: A purely deterministic search may have an extremely high variance in solution quality because it may soon get stuck in worst case situations from which it is incapable to escape because of its determinism. This can be avoided, but it is a well-known fact that the observation of the worst-case situation is not guaranteed to be possible in general.

2. **Non determinism**: A stochastic search method usually does not suffer from the above potential worst case "wolf trap" phenomenon. It is therefore likely that a search method should be stochastic, but it may well contain a substantial portion of determinism, however. In principle it is enough to have as much non determinism as to be able to avoid the worst-case wolf traps

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Time (hr)	*PD (MW)*	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*	*PH (MW)*	*PL (MW)*	*Fuel cost Rs/hr*
1	*175(MW)*	*84*	*37*	*20*	*38.5*	*4.58*	*1.55e+003*
2	*190(MW)*	*75.3*	*37.7*	*37.6*	*41.8*	*2.56*	*1.60+003*
3	*220(MW)*	*65.15*	*37.71*	*72.25*	*48.4*	*3.5*	*1.75+003*
4	*280(MW)*	*67.15*	*43.78*	*114*	*61.6*	*2.01*	*2.08+003*
5	*320(MW)*	*89.99*	*54.92*	*114*	*70.4*	*9.31*	*2.31+003*
6	*360(MW)*	*112.57*	*65.82*	*114*	*79.2*	*11.59*	*2.56+003*

Local determinism: A purely stochastic method is usually quite slow. It is therefore reasonable to do as much as possible efficient deterministic predictions of the most promising directions of (local) proceedings. This is called local hill climbing or greedy search according to the obvious strategies

Implementation Of Short-Term Hydrothermal Scheduling

The short term hydrothermal scheduling problem based on Lagrange Multiplier, simulated annealing and genetic algorithm has been tested on three different test systems. Three different test systems of thermal power plant and one hydro which share 22% of total load demand are taken to study the problem.

4.1 Case Study 1: Three Unit System [1]

(A) Lagrange Multiplier Method

The cost characteristics of the three units are given as

$F1=0.006P1^2+5.506P1+264.634$ Rs/hr

$F2=0.016P2^2+5.2P2+154.2$ Rs/hr

$F3=0.005P3^2+5.67P3+261.1$ Rs/hr

The unit operating constraints are-

$40MW \leq P1 \leq 225MW$

$20MW \leq P2 \leq 240MW$

$20MW \leq P3 \leq 114MW$

The B matrix of the transmission line loss coefficient is given by

B=1e-2.*[0.027251 -.003506 -.036788

-.003506 .030896 -.005653

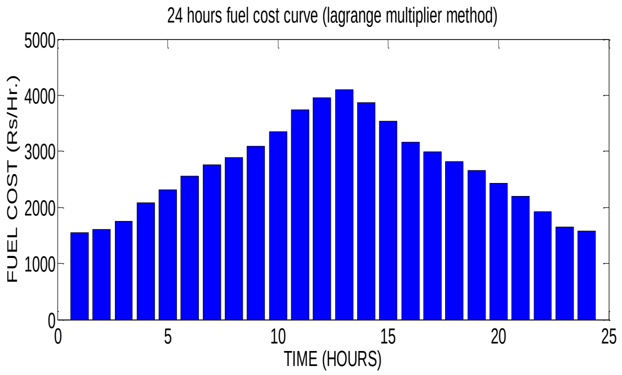
-.036788 -.005653 0.32295];

For the above system considering 24 hours loads

Hour	**P_D (MW)**	**Hour**	**P_D (MW)**	**Hour**	**P_D (MW)**	**Hour**	**P_D (MW)**
1	175	7	390	13	565	19	375
2	190	8	410	14	540	20	340
3	220	9	440	15	500	21	300
4	280	10	475	16	450	22	250
5	320	11	525	17	425	23	200
6	360	12	550	18	400	24	180

RESULTS: The result of Lagrange multiplier of short term hydro thermal scheduling shown below table 2 of 24 hour load. The Total Fuel Cost is 6.4557e+004 Rs/Hr

Lagrange Method



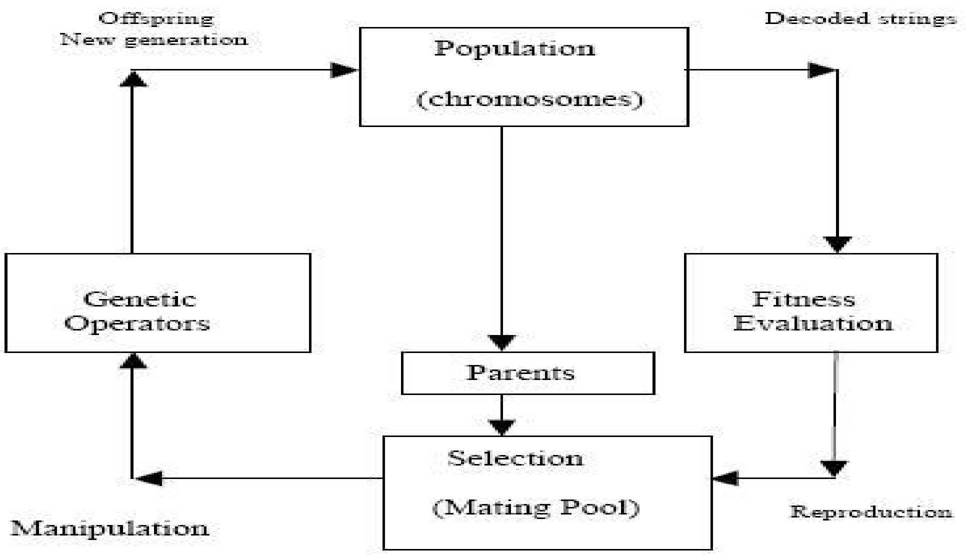


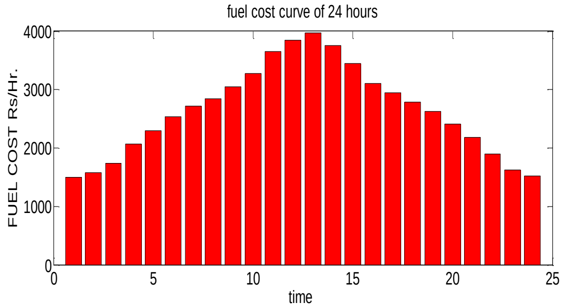
Figure: fuel cost curve for 3 unit system

Time (hr)	PD (MW)	P1 (MW)	P2 (MW)	P3 (MW)	PH (MW)	PL (MW)	Fuel cost Rs/hr
1	175(MW)	76.33	37.21	25.30	38.5	2.35	1.41 x10^3
2	190(MW)	83.31	40	27.65	41.8	2.8	1.57 x10^3
3	220(MW)	93.37	45.73	32.29	48.4	38	1.73 x10^3
4	280(MW)	123.86	57.39	41.40	61.60	6.26	2.06 x10^3
5	320(MW)	145.12	65.35	45.52	70.4	8.22	2.29 x10^3
6	360(MW)	164.59	73.47	47.34	79.2	10.45	2.53 x10^3

Genetic Algorithm

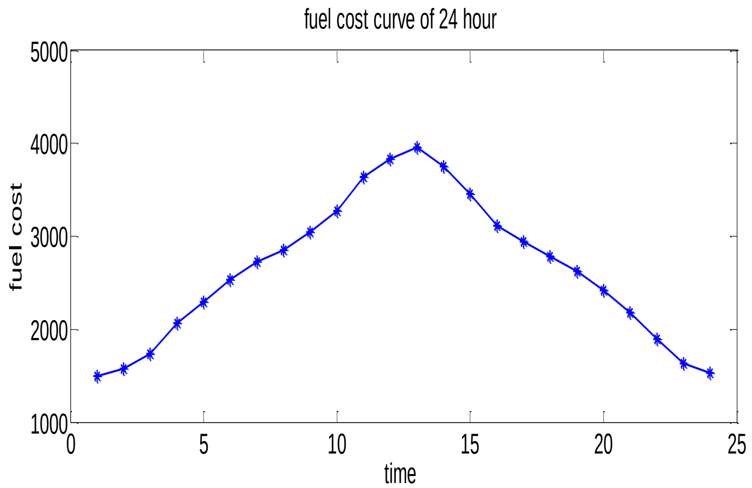
Time (hr)	PD (MW)	P1 (MW)	P2 (MW)	P3 (MW)	PH (MW)	PL (MW)	Fuel cost Rs/hr
1	175(MW)	74.66	39.05	25.11	38.5	2.33	1.41x10^3
2	190(MW)	83.14	40.52	27.29	41.8	2.76	1.57 x10^3
3	220(MW)	96.82	46.50	32.04	48.4	3.77	1.74 x10^3
4	280(MW)	127.12	56.67	40.92	61.60	6.2	2.06 x10^3
5	320(MW)	144.23	67.75	45.52	70.4	7.91	2.29 x10^3
6	360(MW)	162.23	76.46	51.89	79.2	10.18	2.53 x10^3
7	390(MW)	183.94	76.30	56.05	85.8	12.91	2.72 x10^3

The total fuel cost is 6.2389e+004 Rs/Hr.



Simulated Annealing

Total fuel cost is 6.3352e+004 Rs/Hr.



Case Study 2: Six Unit System

S.NO	A	B	C	Pmin	P max
1	0.15247	38.53973	756.79886	10	125
2	0.10587	46.15916	451.32513	10	150
3	0.02803	40.3965	1049.9977	35	225
4	0.03546	38.30553	1243.5311	35	210
5	0.02111	36.32782	1658.5596	130	325
6	0.01799	38.27041	1356.6592	125	315

Table: 7 Transmission loss (B-coefficients) six bus system

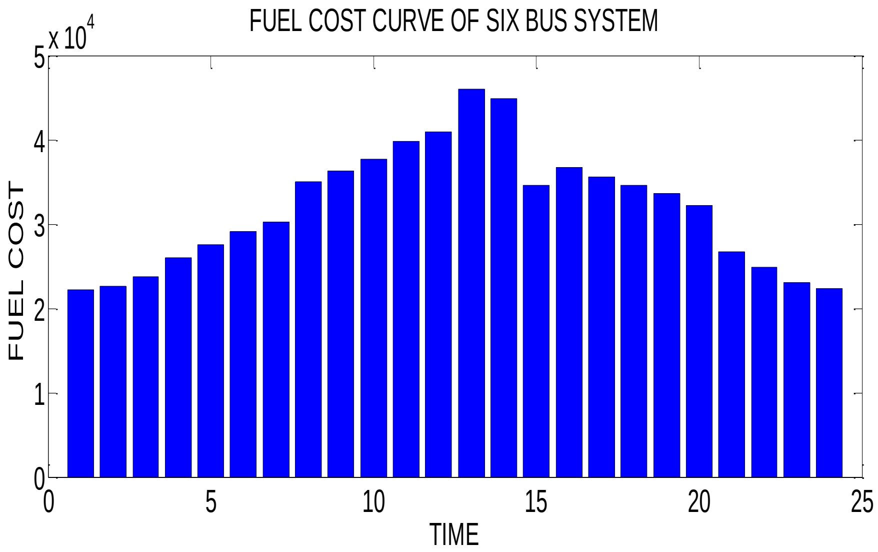
1.4 x 10^{-4}	*0.17 x10^{-4}*	*0.15 x10^{-4}*	*0.19 x10^{-4}*	*0.26 x10^{-4}*	*0.22 x10^{-4}*
0.17 x10^{-4}	*0.6 x10^{-4}*	*0.13 x10^{-4}*	*0.16 x10^{-4}*	*0.15 x10^{-4}*	*0.2 x10^{-4}*
0.15 x10^{-4}	*0.13 x10^{-4}*	*0.65 x10^{-4}*	*0.17 x10^{-4}*	*0.24 x10^{-4}*	*0.19 x10^{-4}*
0.19 x10^{-4}	*0.16 x10^{-4}*	*0.17 x10^{-4}*	*0.71 x10^{-4}*	*0.30 x10^{-4}*	*0.25 x10^{-4}*
0.26 x10^{-4}	*0.15 x10^{-4}*	*0.24 x10^{-4}*	*0.30 x10^{-4}*	*0.69 x10^{-4}*	*0.32 x10^{-4}*
0.22 x10^{-4}	*0.20 x10^{-4}*	*0.19 x10^{-4}*	*0.25 x10^{-4}*	*0.32 x10^{-4}*	*0.85 x10^{-4}*

(A) Lagrange Method

Time (hr)	*PD (MW)*	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*	*P4 (MW)*	*P5 (MW)*	*P6 (MW)*	*PH (MW)*	*PL (MW)*	*Fuel 10^4 rs/hr*
1	*475*	*13.01883*	*10*	*38.46605*	*56.42657*	*133.1914*	*125*	*104.5*	*5.6029*	*2.2128*
2	*490*	*13.72726*	*10*	*42.19526*	*59.34304*	*137.8494*	*125*	*107.8*	*5.9149*	*1.2515*
3	*520*	*15.14728*	*10*	*49.66613*	*65.1853*	*147.1738*	*125*	*114.4*	*6.5725*	*1.3465*
4	*580*	*17.43105*	*10*	*61.71297*	*74.53497*	*161.9362*	*134.8889*	*127.6*	*8.1040*	*1.5411*
5	*620*	*18.77937*	*10*	*68.83644*	*80.03385*	*170.5482*	*144.6527*	*136.4*	*9.2505*	*1.6743*
6	*660*	*20.13339*	*10*	*75.98542*	*85.55064*	*179.1776*	*154.4299*	*145.2*	*10.4769*	*1.8104*

Table: 8 six unit system result by Lagrange multiplier

TOTAL FUEL COST =7.6570x10^5

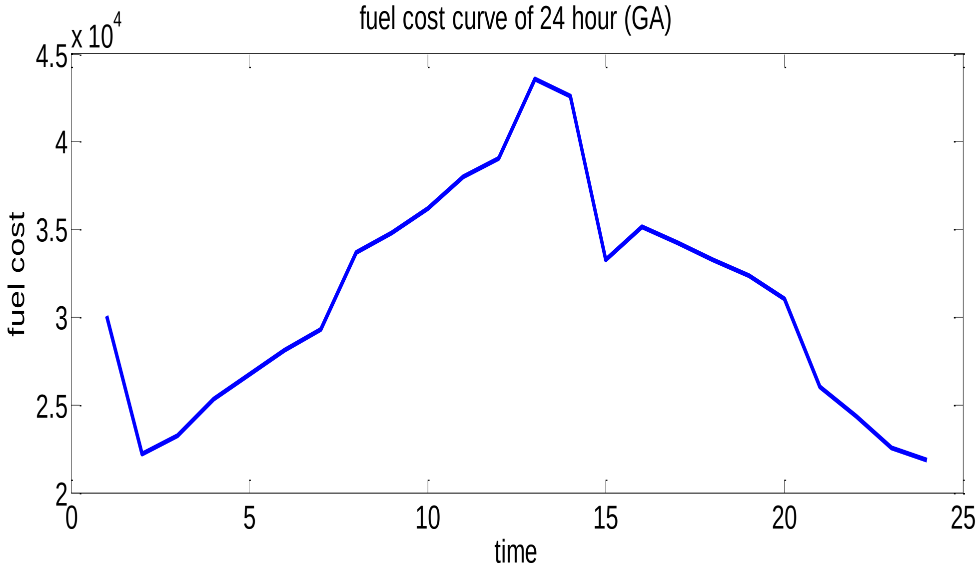


(A) Genetic Algorithm

Table: 9 six unit system result for genetic algorithm

Time (hr)	*PD (MW)*	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*	*P4 (MW)*	*P5 (MW)*	*P6 (MW)*	*PH (MW)*	*PL (MW)*	*Fuel rs/hr*
1	*475*	*10*	*11.45464*	*38.83362*	*38.99379*	*151.4424*	*133.9001*	*104.5*	*6.086173*	*30089.87*
2	*490*	*15.52055*	*16.72736*	*53.41049*	*44.0457*	*132.336*	*125.9075*	*107.8*	*5.747647*	*22227.95*
3	*520*	*17.18647*	*11.28117*	*44.92188*	*79.00682*	*133.5426*	*126.1406*	*114.4*	*6.479622*	*23218.96*
4	*580*	*11.17607*	*12.86876*	*88.90236*	*72.65718*	*142.0984*	*132.4732*	*127.6*	*7.775892*	*25335.33*
5	*620*	*25.94088*	*10.46391*	*88.39069*	*75.07086*	*132.6921*	*159.9954*	*136.4*	*8.953903*	*26754.69*
6	*660*	*21.41168*	*12.71691*	*89.26969*	*81.08579*	*158.7875*	*161.7658*	*145.2*	*10.23743*	*28147.11*

Total fuel cost =7.31x10^5 Rs/Hr



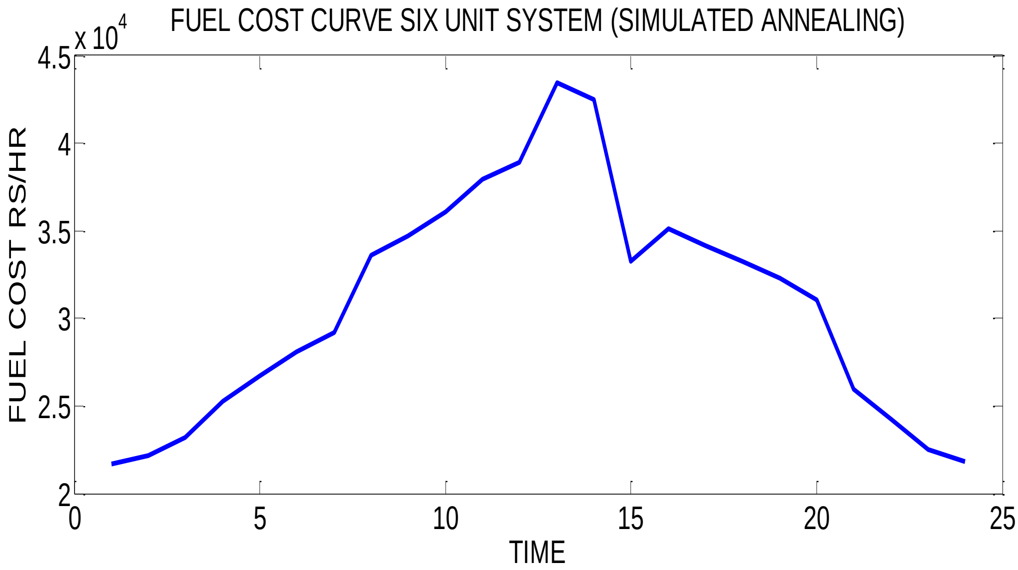
(A)

Simulated Annealing

Table: 10 six unit system result for simulated annealing

Time (hr)	*PD (MW)*	*P1 (MW)*	*P2 (MW)*	*P3 (MW)*	*P4 (MW)*	*P5 (MW)*	*P6 (MW)*	*PH (MW)*	*PL (MW)*	*Fuel rs/hr*
1	*475*	*13.02373*	*10.00004*	*38.46789*	*56.41934*	*133.1918*	*125.0001*	*104.5*	*5.602829*	*21664.3*
2	*490*	*13.72762*	*10.00002*	*42.20105*	*59.34261*	*137.8434*	*125.0001*	*107.8*	*5.914838*	*22173.13*
3	*520*	*15.1432*	*10.00001*	*49.66808*	*65.18661*	*147.1745*	*125.0001*	*114.4*	*6.572494*	*23199.57*
4	*580*	*17.42948*	*10*	*61.71116*	*74.53743*	*161.9387*	*134.8873*	*127.6*	*8.104057*	*25284.96*
5	*620*	*18.77888*	*10.00006*	*68.83556*	*80.03188*	*170.5451*	*144.6591*	*136.4*	*9.250587*	*26695.04*
6	*660*	*20.13047*	*10.00002*	*75.98726*	*85.54723*	*179.1745*	*154.4376*	*145.2*	*10.477*	*28120.77*

Total fuel cost=7.3722×10^5



IV.SIMULATION RESULTS

fuel cost comparison for three unit system

Method	*Fuel cost*
Lagrange method	*6.4557×10^4 Rs/Hr.*
Simulated annealing	*6.3352×10^4 Rs/Hr*
Genetic algorithm	*6.2389×10^4 Rs/Hr.*

Fuel cost comparison for six unit system

Method	*Fuel cost*
Lagrange method	*7.6570 x10^{5}Rs/Hr.*
Simulated annealing	*7.37 x10^{5}Rs/Hr*
Genetic algorithm	*7.31 x10^5 Rs/Hr.*

CONCLUSION

In order to optimize the optimal hydro thermal generation scheduling carried out by lagrange simulated annealing and GA was employed to solve the problem while considering the constrains. These problem has been verified on the three different cases , three unit system six unit system and 15 unit system. The comparison of results for the test cases of three unit and six unit system and 15 unit system clearly shows that the GA method is more capable of obtaining higher quality solution. For the same power demand the fuel cost is minimized by employing GA method

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