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A REAL VARIABLE GENETIC ALGORITHM FOR FIXED HEAD SHORT TERM HYDRO THERMAL GENERATION SCHEDULING

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Research Article

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ABSTRACT

In power system operation, short-term hydrothermal scheduling (STHTS) is a daily planning option. By properly scheduling the power outputs of all hydro and thermal units within study periods, given electrical demand and restricted water resources, the primary goal of hydro thermal generation scheduling is to reduce total operating costs and fulfill the provided limitations. The Real Variable Genetic Algorithm approach for the fixed head hydrothermal issue is presented in this research. Additionally, a hydro power input-output model with constant head was created for the Sewa hydroelectric power plant utilizing MATLAB 7.9 version software and curve fitting methods, including the least squares approach. For the case study under consideration, the genetic algorithm's control parameters have been improved.

Keywords: Real-variable evolutionary algorithm, hydro power input-output model, availability-based tariff, valve-point loading, and hydro-thermal scheduling

INTRODUCTION

For a power system to operate economically, short-term hydrothermal scheduling is an essential responsibility. A well-planned generating schedule maximizes reservoir energy capacity by making the most of the scarce water supply, lowers production costs, and improves system dependability. Finding the ideal quantity of power produced for hydro and thermal units in order to reduce the fuel cost of thermal units is the main goal of short-term hydro thermal scheduling. In order to accomplish this goal, a certain volume of water must be utilized, which is often much more difficult than arranging every thermal system. This is due to the fact that if the available water is used up in the current interval, there won't be any left for the subsequent interval, which will raise the price of operations in the future. Subject to a number of equality and inequality restrictions, it is challenging to coordinate the thermal generating system with electrically and hydraulically connected hydro plants to achieve the lowest possible overall system cost. In essence, the hydro thermal power system's optimum scheduling is a non-linear programming problem with a non-linear objective function and a combination of linear and non-linear constraints.

No nation or state has an abundance of nuclear fuel, coal, or water resources. Thermal generating should be kept to a minimum for both financial and environmental reasons. Therefore, a combination of thermal and hydroelectric power production is required. Large hydro-potential states may receive thermal electricity from other states during times of low water run-off and provide extra hydro-power to other states during times of high water run-off. The states may utilize the little hydropower to satisfy peak load needs since they have a huge coal reserve and a low hydro-potential. As a consequence, the thermal stations have lower installed capacity and run at high load factors, which leads to economy. In states with sufficient thermal and hydro In order to achieve the most economical operational condition, power producing capacity and power coordination are crucial. To preserve coal reserves and reduce environmental pollution, the full benefits of inexpensive hydropower should be used. Run-off river hydro-plants may provide all or part of the base load, while a suitable combination of thermal plants and reservoir-type hydro-plants can meet the peak or residual demand. The most cost-effective operating condition of a hydro-thermal system may be found by determining this using the appropriate mix. The hydro-plants are simple to start and may quickly be given a load. In thermal plants, on the other hand, it takes many hours to prepare the turbine system, boilers, and super heater to handle the load. Because of this, the hydro-plants are able to efficiently manage loads that change quickly. In contrast, the thermal plants react slowly [1].

As a result, hydro-plants may run at peak demand facilities whereas thermal plants are better suited to function at base load plants. When compared to hydroelectric facilities, thermal plants have relatively high operational costs but minimal capital costs. Because hydroelectric facilities have low operating costs and high construction costs, it is now both cost-effective and practical to operate thermal and hydroelectric plants on the same grid.

In addition to reservoir release objectives established by mid- and long-range planning models, short-term hydro-thermal coordination involves allocating the generation among the available units throughout a day or week, often on an hourly basis, in order to fulfill operational restrictions. Fixed water head is often assumed in short-range scheduling problems, and for reasonably large reservoirs, the net head fluctuation may be disregarded, in which case the water discharge is the only factor influencing power generation [1 and 2]. For many decades, hydro thermal scheduling has been the focus of much research as a daily planning problem in power system operation. In order to make the optimization issue more manageable, the majority of approaches that have been employed to tackle the hydrothermal coordination problem adopt a number of simplifying assumptions.

Mixed integer linear programming [3], dynamic programming [4], the Lagrange relaxation technique [5], the interior point method [6], and other traditional approaches to short-term hydrothermal scheduling issues have all been documented in the literature.

According to the aforementioned review, conventional/classical optimization techniques have a number of drawbacks, including difficulties with dimensionality, high memory requirements, lengthy computation times, an inability to handle nonlinear plus non-separable objective functions and constraints, an inability to handle global optimum, etc.

For hydro thermal scheduling, stochastic optimization methods including evolutionary programming [9], simulated annealing [8], genetic algorithms [7], and other hybrid methods [10] have recently become accessible.

In this research, a system consisting of one hydro and three thermal systems is used to evaluate the real variable genetic algorithm approach for the fixed head hydro thermal issue. Additionally, an experimental data set from the Sewa hydroelectric plant location in the Jammu & Kashmir area is used to construct a model for the hydro system.

The format of this document is as follows. The input-output model for hydro power is introduced in Section 2. Section 3 discusses the formulation of the short-term hydro-thermal issue. An summary of the actual programmed genetic algorithm is given in Section 4. The hydrothermal scheduling method and flow chart are described in Sections 5 and 6. Section 7 presents the hydro thermal scheduling test system findings and concludes.

HYDRO POWER INPUT-OUTPUT MODELLING

In Himachal Pradesh, the National Hydroelectric Power Corporation (NHPC) has supported a number of hydroelectric projects. Among them is the Sewa Hydroelectric Project Stage II (120MW), a run-off-the-river project situated in the Jammu and Kashmir region's Kathua district. The hydro power input-output model for the Sewa hydroelectric power plant is shown in this section. An essential component of a country's overall growth is electric power. It is a tool for shaping a nation's economic development. Planning and running a power system where hydro power production facilities account for a significant portion of the installed capacity heavily depends on the effective use of hydro resources. As a result, there has been a current demand for more and more power production in every nation on the planet. Compared to thermal or nuclear power plants, hydropower installations have far lower operating costs, and the hydraulic turbines may be turned on and off in a couple of minutes.

Since each hydroelectric plant is different depending on its location and needs, there is no standard modeling since it is a highly difficult process. Each of these designs must be modeled separately due to their variety. The modeling parameters are strongly reliant on the control variables and are nonlinear. In this case, hydro

The hydro units are combined to represent electric generation at the plant level. The hydroelectric

power produced
(PH)
relies on the water's specific weight (), the flow rate (q) through the turbine in m3/s, the net head (h) on the turbine in meters (m), and the plant's efficiency, taking pipeline head loss and turbine and generator efficiency into account. The power plant's output is shown below in (1), where the numerical factor converts the units from (m) and (m3/s) to MW while accounting for the acceleration caused by gravity and the water density [11].

$$P_H = \frac{qh}{1000} \quad (1)$$

where,

P_H =Available hydro power (MW)

η = Combined efficiency of turbine and generator set

 = Specific weight of water (N/m^3), and is the product of density of water (kg/m^3) and acceleration due to gravity (m/s^2)

q = Water flow through the turbine (Discharge) in (m^3/sec)

h= Net head of water in meters (the difference in water level between upstream and downstream of the turbine)

To model the input-output curve of the hydro power unit with constant head, experimental data has been obtained from the site of Sewa hydro electric plant of Jammu and Kashmir region. The input is in terms of water discharge rate (m^3s^{-1}) whereas output is in terms of hydro power (MW).

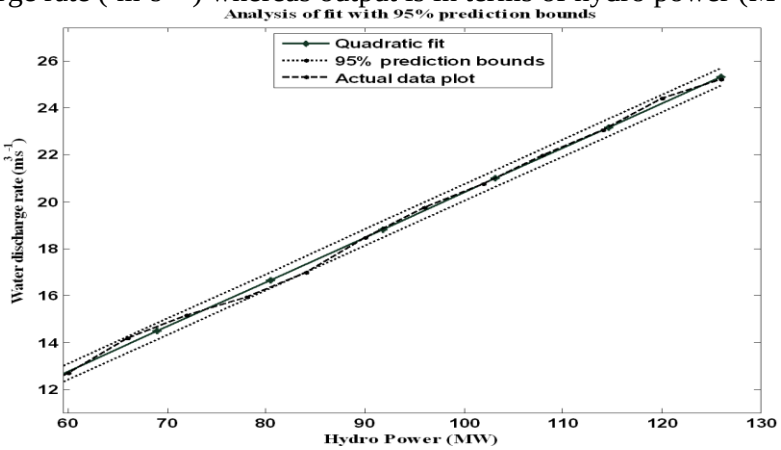


Figure1. Plot for actual and predicted results for water discharge rate versus power with constant head

Using curve fitting methods based on the least squares approach, the link between water discharge rate and hydro power has been established [12]. Figure 1 illustrates how effectively the second order quadratic equation (2) meets the relationship between produced power and water discharge rate based on site data. The real link between the water discharge rate and hydro power is shown in Figure 1 by the thick dotted line. Additionally, the experimental data's quadratic fit falls well within the 95% confidence range.

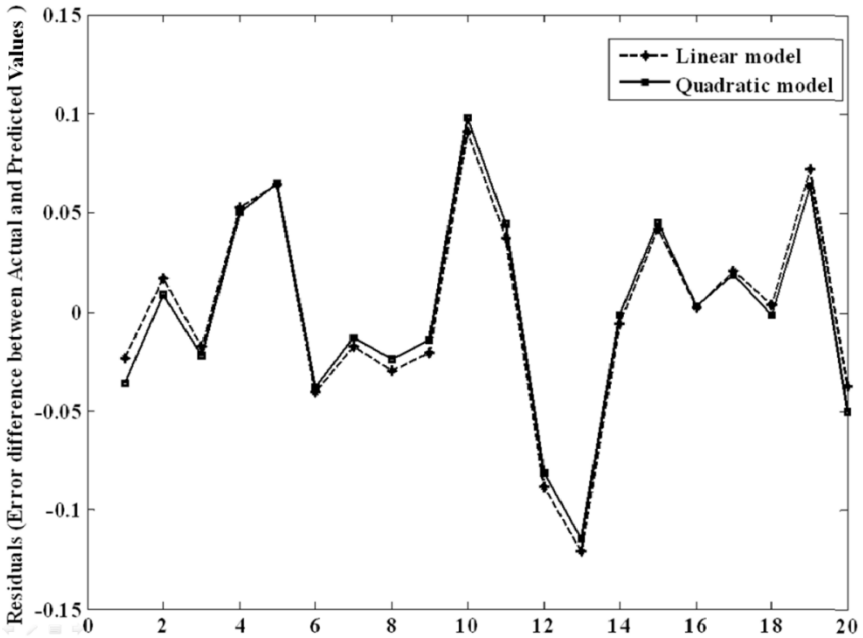


Figure 2. Residual plot for linear and quadratic regression models for water discharge rate versus power (MW) with constant head

The linear and quadratic models are compared in Figure 2, and it is discovered that the quadratic model performs better in terms of residual magnitude at various places. The R-square value and sum of squares owing to errors (SSE) are shown in Figure 3. A model with a tiny random error component and a matching fit that may be used for prediction is indicated by an SSE value that is closer to zero.

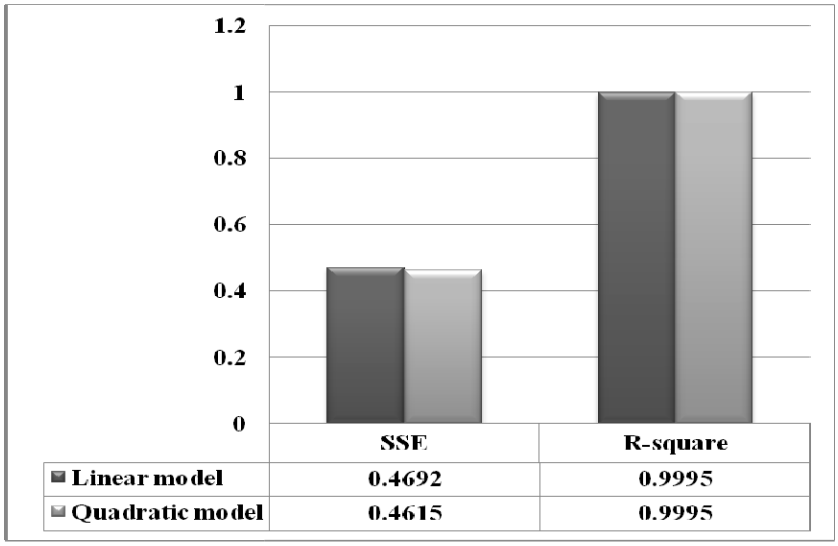


Figure 3. Plot for SSE and R-square value

The model's proximity to real values is shown by R-square values. Put otherwise, it gives an indication of how effectively the model is expected to forecast future events. Therefore, it is ideal for R-square values to be very high, that is, around 1. According to the model, the independent variable accounts for 99% of the variance in the dependent variable. According to the graphical findings, the SSE value is 0.4615, which is within acceptable bounds and was lowest for the quadratic model. The optimal link between produced hydro power (PH) and water discharge rate (q) for the second stage

of the Sewa hydroelectric project is represented by the input output model.

$q(P_H) = 0.065844P_H^2 - 675.36P_H + 5122.8$ m^3/ hr (2)

PROBLEM FORMULATION

Finding the best schedule for a power system's hydro and thermal plants in order to reduce the overall cost of thermal production is the primary goal of the hydro thermal scheduling challenge. The load demand and operating restrictions placed on the hydro and thermal plants must be satisfied by this overall timetable.

Thermal model

The objective function is to minimize the total operating cost ($C_{Thermal}$) represented by the fuel cost of thermal generation over the optimization interval (k).

$$C_{Thermal} = \sum_{i=1}^{N_g} Min \sum_{k=1}^{N_T} t_k C(P_{Tk}); N_T = 96;\ i = 1,2 and 3 \quad (3)$$

where, t_k is number of hours in k^{th} time block.

Ng is number of generating units

Here, the problem is to schedule the power generation of hydro-thermal units for k sub interval in order to minimize the fuel cost. The fuel-cost function without valve-point loadings of i^{th} generating units.

$C(P_{Tki}) = \alpha_i P_{Tki}^2 + \beta_i P_{Tki} + \gamma_i$ Rs/hr (4)

where, α , β and γ are cost coefficients of thermal plant.

While considering valve point effect [13-14] in the input output curve, the possibility of non-convex curves must be accounted for if extreme accuracy is desired. If non-convex input-output curves are to be used, equal incremental cost methodology cannot be used, since there are multiple outputs for any given value of incremental cost. As the introduction of valve point results in ripples. Thereby the effects of valve-point loading is modeled as a recurring rectified sinusoid contribution and added to the basic quadratic cost function and the fuel-cost function considering valve-point loadings of the generating units is expressed as

$$C(P_{Tki}) = \alpha_i P_{Tki}^2 + \beta_i P_{Tki} + \gamma_i + |e_i \sin(f_i (P_{Ti}^{min} - P_{Ti}))| \quad (5)$$

where , α , β and γ and are the fuel-cost coefficients of the unit, and e and f are the fuel cost-coefficients of the unit

with valve-point effects. However, the cost function of a generator is not always differentiable due to the valve-point effects and/or change of fuels.

Hydro model

In hydro system, there is no fuel cost incurred in the operation of hydro units. According to Kothari and dhillon [15], discharge is a function of power output and the head. For short term scheduling, not much variation in head takes place as available water is limited, released over a day as long as there is not much influence of inflows on head of reservoir. Thus $q(P_H)$ is the rate of discharge of Sewa hydro electric power plant as obtained in equation (2) which is a quadratic equation represented by:

$q(P_H) = aP_H^2 + bP_H + c$ m^3/hr (6)

where, a, b and c are water discharge rate coefficients of hydro plant.

Water availability constraint

The total water discharge is

$$q_{total} = \sum_{k=1,2,3,...,T} t_k \quad q_k ; \quad k = 1 \quad NT \tag{7}$$

Here in this study, constant head operation is assumed and the water discharge rate, q_k is assumed to be a function
of the hydro generation, P_{Hk} as in
$q_k \square q_k(P_{Hk})$
where, t_k is number of hours in k^{th} time block and q_k is the water discharge rate for k^{th} time block.

Power balance equation
Total generated power is equal to the total demand P_{Dk} including losses P_{Lk} in each time interval. Mathematically,

$$\sum_{i\square 1}^{N_g} P_{Tki} \square P_{Hk} \square P_{Dk} \square P_{Lk}; \quad k \square 1,2,,T; \tag{8}$$

where, P_{Dk} is the load demand for k^{th} sub-interval and P_{Lk} are the transmission losses for k^{th} sub-interval. P_{Tk} P_{Hk} are thermal and hydro power generation for k^{th} sub-interval. The transmission loss is function of P_{Hk} and P_{Tk}.

Thermal and hydro power limits
Thermal and hydro units can generate power between specified upper and lower limits

$$P_{Ti}^{min} \square P_{Tki} \square P_{Ti}^{max}; \quad k \square 1,2,...,T \tag{9}$$

$$P_H^{min} \leq P_{Hk} \leq P_H^{max}; \quad k \square 1,2,...,T \tag{10}$$

where, P_{Tk} and P_{Hk} are Power output of the thermal and hydro generating units in MW for k^{th} sub- interval and
$P^{min}_T, P^{min}_H, P^{max}_T$ and P^{max}_H represents minimum and maximum power limits of thermal and hydro plant respectively.

Expected Transmission Losses
To model transmission losses in the system is to use Kron's loss formula through B-coefficients [15].

$$P_{Lk} \square \sum_{i\square 1}^{Ng\square 1\square NH} \sum_{j\square 1}^{Ng\square 1\square NH} P_{ik} B_{ij} P_{jk} \square \sum_{i\square 1}^{Ng\square 1\square NH} B_{io} P_{ik} \square B_{oo} \tag{11}$$

where P_{Lk} is the transmission loss during k^{th} subinterval. B_{ij}, B_{io} and B_{oo} are B-coefficients.
P_{ik} represents the power generation of i^{th} plant at k^{th} sub interval.

Calculation for Slack Thermal Generator:

Let *Ng* committed generating units deliver their power output subject to the power balance constraint (8) and the respective capacity constraints (9 & 10). Assuming the power loadings of *Ng-1* generators are known [15-16], the power level of N_g^{th} generator (called slack generator) is given by

$$P_{Ng} = P_{Load} + P_{Loss} - \sum_{i=1}^{NH} P_i \quad (12)$$

The transmission loss is a function of all the generator outputs including the slack generator and it is given by

$$P_L = P_i^T [B] P_i \quad (13)$$

$$P_{Loss} = \sum_{i=1}^{Ng-1} \sum_{j=1}^{NH} P_i B_{ij} P_j + 2 \sum_{i=1}^{Ng-1} B_{iNg} P_i + B_{NgNg} P_{Ng}^2 + \sum_{i=1}^{Ng-1} B_{0i} P_i + B_{00} \quad (14)$$

Expanding and rearranging, (12 & 14) becomes

$$\sum_{i=1}^{Ng-1} \sum_{j=1}^{NH} P_i B_{ij} P_j + 2 \sum_{i=1}^{Ng-1} B_{iNg} P_i + B_{NgNg} P_{Ng}^2 - P_{Load} + \sum_{i=1}^{NH} P_i + B_{00} = 0$$

or,

$$B_{NgNg} P_{Ng}^2 + \left(2 \sum_{i=1}^{Ng-1} B_{iNg} P_i - 1 \right) P_{Ng} + \left(\sum_{i=1}^{Ng-1} \sum_{j=1}^{NH} P_i B_{ij} P_j + \sum_{i=1}^{NH} B_{0i} P_i - P_{Load} + B_{00} \right) = 0 \quad (15)$$

The loading of the dependent generator (i.e.,N^{th}) can then be found by solving (15) using standard algebraic method. The above equation can be rewritten in quadratic form as:

2_{XP}
Ng
where
YP_{Ng}
$Z \square 0$

(16)

$X = B_{NgNg}$
$\left(Ng \square 1 \square NH \right.$
$Y = \left| 2 \sum B_{Ngi} P_i \right| \square B_{0N} - 1 \left| \right.$
$\left. \right)$
$Ng \square 1 \square NH \quad Ng \square 1 \square NH \qquad Ng \qquad \square 1 \square Ng \square 1 \square NH$
NH
$Z = P_{Load} + \sum_{i \square 1} \sum_{j \square 1} \sum_{i \square 1} P_i B_{ij} P_j + \sum_{i \square 1} B_{0i} P_i - \sum P_i \square B_{00}$

The positive roots of the equation are obtained as

$$\square Y \quad P_{Ng} \quad \square \frac{-Y \pm \sqrt{Y^2 - 4XZ}}{2X} \square \quad \text{—} \quad \square \frac{\sqrt{Y^2 - 4XZ}}{2X} \qquad (17)$$

where $Y^2 \square 4XZ \square 0$
The positive valued roots are considered.
To satisfy the equality constraint (12), the positive root of (17) is chosen as output of the N^{th} generator. If the positive root of quadratic equation violates operation limit constraint of (9 & 10) at the initialization process of the algorithm, then Generation value of first (Ng-1) generators is reinitialized until the positive root satisfies the operation limit and other constraints. If the positive root of quadratic equation violates operation limit constraint of (9 & 10) at the later stage of the algorithm that means when the modified generation value is obtained after applying necessary steps of the algorithm, then that modified generation set is discarded and different steps of the algorithm are reapplied on its old value until it satisfies the operation limit and other constraints.

Calculation for Slack Hydro Generator:
Slack hydro units [15-16] are selected arbitrarily from committed units to meet the water balance constraint for the whole period. The power output of the slack hydro units during 'k' time is computed by rewriting the water energy balance Equation (7):

$$q_{total} \square t_d q_d \sum_{k \square 1 \ k \square d}^{NT} \square t_k q_k$$

$$t_d q_d \square q_{total} \sum_{k \square 1 \ k \square d}^{NT} \square t_k q_k$$

$$q_d \square \frac{1}{t_d} \left| q_{total} \square \sum_{k \square 1 \ k \square d}^{NT} t_k q_k \right|$$

From Equation (6) we can also write

$$q_d = aP_{Hd}^2 + bP_{Hd} + c$$

$$aP_{Hd}^2 + bP_{Hd} + (c - q_d) = 0$$

$$aP_{Hd}^2 + bP_{Hd} + \left(c - \frac{1}{t_{total}} \left[q_d - \sum_{k=1}^{N_T} t_k q_k \right] \right) = 0$$

$$2aP_{Hd} + bW = 0 \qquad (18)$$

where

$U = a$

$V = b$

$$W = \left(c - \frac{1}{t_{total}} \left[q_{total} - \sum_{k=1}^{N_T} t_k q_k \right] \right)$$

$$\left(\left| \frac{t_d}{L} \right| \right)^{k=1}_{k=d} \Big]$$

The roots of the equation are obtained as

$$P_{Hd} = \frac{-V - \sqrt{V^2 - 4UW}}{2U}, \quad \frac{-V + \sqrt{V^2 - 4UW}}{2U} \tag{19}$$

where $V^2 \square 4UW \square 0$

The positive root is selected as a solution of (18). In this way power generation level of the hydro-generator during slack time interval'd' is calculated.

REAL VARIABLE GENETIC ALGORITHM

In the 1970s, John Holland developed the Real Variable Genetic Algorithm (RVGA), a stochastic search algorithm [14], as a unique method for function optimization [17]. It creates a strong system that is very successful at identifying the best answers to challenging real-world issues by combining an artificial concept—the Darwinian Survival of the Fittest principle—with genetic operations that are abstracted from nature. Genetic algorithms continuously concentrate their search on the regions with the observed greatest performance while simultaneously searching for many places in the search space. Reproduction, crossover, and mutation are the fundamental components of real variable genetic algorithms. Individuals are chosen for reproduction depending on how fit they are in comparison to the population. In the crossover procedure, two distinct strings are chosen at random from the mating pool, and mathematical relations are used to accomplish a crossover. Mutation is the sporadic, random modification of a population member. From now on, we call it the classical GA (CGA). When it comes to resilience and global search for any non-linear function, CGA outperforms conventional optimization techniques. Nevertheless, it has a premature convergence issue and often takes a long time to compute.

In the CGA, the reproduction and crossover operations—also known as the exploitation operations—are primarily responsible for the local search capacity, while the mutation operation—also known as the exploration operation—guarantees the worldwide search capability. In general, as the likelihood of crossover grows, so does the pace of local search. In a similar vein, as the likelihood of mutation rises, so will the capacity of global search. To provide an acceptable degree of local search capacity, the mutation probability must be decreased in order to raise the crossover probability since the total of the probabilities of all the generic operations must equal unity. This adds to the very low risk of mutation in CGA, which typically ranges from 0.1 to 5%. However, in order to enhance the likelihood of mutation, the probabilities of reproduction and crossover must be reduced in order to reach a desirable level of global search capacity. This will significantly impair local search capabilities, slow down the pace of convergence, and ultimately render global search capabilities unattainable. It is difficult to reach a win-win scenario for both parties at the same time when balancing exploration and exploitation based on reproduction/crossover and mutation operations for a given population. As a result, many researchers continue to find it challenging to strike a balance between exploration and exploitation in GA-type algorithms [18–19].

A good GA must strike a balance between the amount of information explored via recombination and mutation operators up to the current generation and the amount of information exploited through the selection operator. Premature convergence is anticipated if the solutions are overused. However, if a search (i.e., exploration) is overemphasized, the knowledge gathered so far has not been used appropriately. As a result, the search behaves similarly to a random search and the solution time may be quite long. A recombination and mutation operator depends on the selection operator used for a successful GA run due to the problem of exploration and exploitation. The majority of the suggested enhancements were concentrated on three areas: improving global search capabilities, preventing premature convergence, and cutting computing time. Some scholars suggested using real-coded values rather than binary bit sequences to cut down on processing time [18–20]. This method eliminates the computing time required for encoding and decoding, but it severely restricts the variety of mutations.

There are two standard methods that are often employed: one is to create a new random value to replace the current one, and the other is to add one more component, typically selected at random, to the current one. In the sense that the new value is unrelated to the old one, none of them maintains the notion of natural mutation. Many efforts have been made to increase population variety in order to improve global search capabilities [18–19].

Reproduction

Reproduction is the first genetic algorithm operator. A mating pool is created by the reproduction genetic algorithm operator, which chooses the best individuals of a population. Another name for the operator is the selection operator. The proportionate reproduction operator, which selects a string into the mating pool with a probability proportionate to its fitness, is the most often used reproduction operator. Stochastic sampling with replacement (SSR) is the fundamental roulette wheel selection technique. Individuals are chosen in accordance with the segment size and selection probability, which stay constant throughout the selection process. By enlarging a person's segment if they are chosen, stochastic sampling with partial replacement (SSPR) expands on SSR. The segment's size is decreased by one each time a person is chosen. The segment size is set to zero if it becomes negative. There are two separate stages in remainder sampling techniques. The people are chosen deterministically based on the integer portion of their anticipated trials during the integral phase. The remaining people are then chosen at random from a fractional portion of each person's predicted values. The roulette wheel selection method known as stochastic remainder is used. The first genetic operator is this one. In accordance with their fitness levels, copies of the strings are cloned into a different string known as the "mating pool." This suggests that as the search goes on, strings with higher fitness values will be more likely to contribute further strings. The roulette wheel approach [21] is used for replication in this study. This approach allocates a place on the roulette wheel to each member of the population based on their relative fitness. The likelihood of being chosen as the next generation's parents is highest for those with the biggest chunk on the wheel.
[22]

Crossover

The primary genetic operator is crossover, which is the exchange of chromosomal segments across individuals. A crossover probability (PC) controls the frequency of crossover, which is not done on every pair of people. The arithmetic crossover operator is used in this article. This operator's fundamental idea is taken from convex set theory. The following is the definition of simple arithmetic operators using the combination of two vectors (chromosomes):

$s' = \lambda s + (1-\lambda) t$

$t' = (1-\lambda) s + \lambda t$

Where λ is uniformly distributed random variable between 0 and 1.

Mutation

The strings undergo mutation upon crossing. The algorithm is kept from being stuck in a local minimum via mutation. Both the random disruption of genetic information and the recovery of lost genetic materials are functions of mutation. Mutation is meant to aid in the investigation of the whole search space, while crossover is meant to take use of the existing solution to identify better ones. In order to preserve genetic variety in the population, mutation is thought of as a background operator. It modifies some of the population's building pieces at random to introduce new genetic structures. Mutation preserves population diversity and aids in escaping the trap of local minima [20].. Letus suppose $C = (C_1, \ldots C_i, \ldots C_n)$ is a parent chromosome $C_i = [a_i, b_i]$ is a gene to be mutated and a_i and b_i are the lower and upper ranges for gene C_i. A new gene in the offspring chromosomes, C_i may arise from the application of two different mutation operators respectively. The present paper uses uniform mutation operator. This operator is single point random mutation, in which a single gene C_i is randomly chosen number from range

$[a_i, b_i]$ to replace C_i and to form new chromosome C'. It is controlled by mutation probability (M_C).Mutation is done using following equation:

$$C_{new,j} = C_{min,j} + rand(C_{max,j} - C_{min})$$

where,

$C_{min,j}$ and $C_{max,j}$ are the maximum and minimum value of j^{th} variable.

RVGA ALGORITHM FOR FIXED HEAD SHORT TERM HYDRO THERMAL SCHEDULING

The flow diagram in Figure 4 also applies to the 'RVGA search algorithm' introduced here.

1. Create the initial population of thermal power and hydropower generations by treating the last steam generator's thermal power production as a slack thermal generator in each time slot and the hydropower generation in the previous time period as a slack hydro generator.
2. To determine water release and hydropower in the slack time slot, use the water availability equation (7); to determine dependent thermal generation for the slack thermal unit, use the load balance equation in each time slot.
3. Determine the fitness value for every chromosome in the hydro population. Select the hydro population using a roulette wheel.

Perform crossover operation on the hydro population by keeping the 96^{th} time slot as dependent. Total number of chromosomes on which crossover is done depend upon the crossover probability P_c. Once the Chromosomes are determined crossover is done using following equation

$$P_{H\,i,j} = P_{H\,i,j} + rand(P_{H\,i+1,j} - P_{H\,i,j})\, P_{H\,i+1,j} = P_{H\,i,j} + rand(P_{H\,i+1,j} - P_{H\,i,j})$$

Perform mutation operation on hydro population by keeping the 96^{th} time slot as dependent. The variables which have to be mutated depend upon the probability of mutation (PM). Mutation is done using the equation

$$P_{H\,i,j} = P_{H\,min,j} + rand(P_{H\,max,j} - P_{H\,min,j})$$

Check whether the termination criterion is satisfied. If yes terminate the program and display the result. Else go to step3.

6 .Flow chart for RVGA

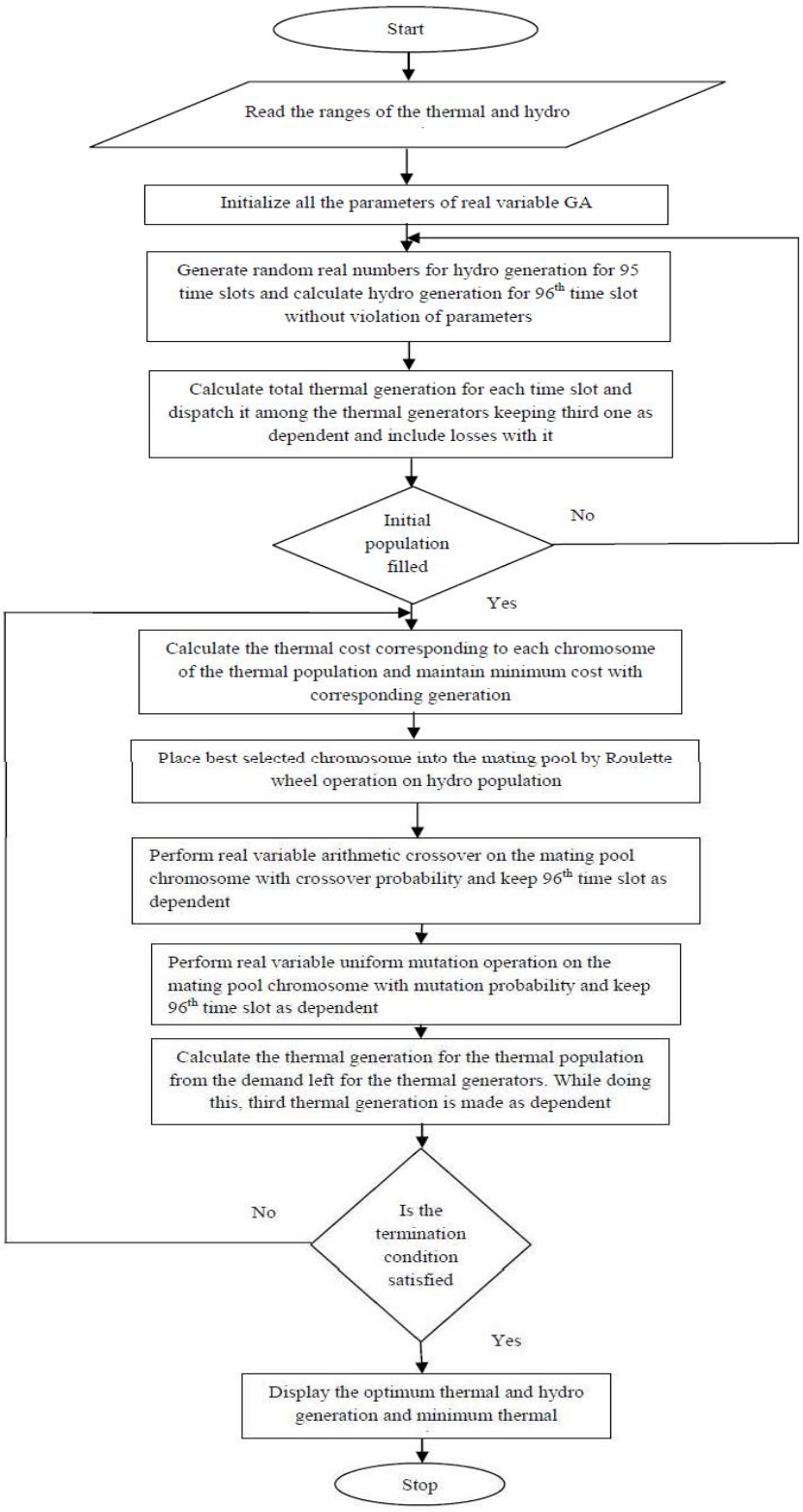


Figure 4.Flowchart for RVGA

Test system

Short-term hydro thermal scheduling typically deals with one-day to one-week intervals of operation [1-2 and 15]. Short-term hydro thermal scheduling (STHTS), which involves day-ahead scheduling for 24 hours at intervals of 15 minutes, is the subject of this article [22–23]. Figure 5 displays the total load demand during a 24-hour period for a 96-time interval. Three thermal units that were taken from [24 and 15] and a Sewa hydroelectric plant make up the test system.A PC (Pentium-IV, 512MB, 3.0GHz) was used to run the real variable genetic algorithm, which was built in MATLAB 7.9. Thirty such runs, each with a distinct random beginning solution, were carried out in both test scenarios. Curve fitting was used to estimate the hydroelectric system's polynomial cost coefficients using experimental data from the Sewa hydroelectric project site. The equivalent
hydro system obtained with $R^2 = 0.9995$ and SSE=0.4615 is presented in section 2.1. The equivalent hydro system
obtained is $q(P) = 0.065844P^2 - 675.36P + 5122.8$ m^3/ hr. The lower and upper limits of hydro units for
$H \quad H \quad H$
Sewa hydro electric power plant are 12MW and 126MW respectively. The characteristic functions of three thermal plants [24 and 15] considering valve point loading are defined as follows

$C = 0.01P_{T1}^2 + 0.1P_{T1} + 100 + |200 \times \sin(0.0315 \times (50 - P_{T1}))|$

$C = 0.02P_{T2}^2 + 0.1P_{T2} + 120 + |170 \times \sin(0.0420 \times (40 - P_{T2}))|$

$C = 0.01P_{T3}^2 + 0.1P_{T3} + 150 + |215 \times \sin(0.0630 \times (30 - P_{T3}))|$

The boundary condition of the problem is defined by the upper and lower limits of the generation capacity of the four plants that are given by:

$50MW \le P_{T1}(t) \le 200MW$

$40MW \le P_{T2}(t) \le 170MW$

$30MW \le P_{T3}(t) \le 215MW$

$12MW \le P_{H1}(t) \le 126MW$

The system electrical losses are associated with the hydro plant and three steam plants are expressed as follows:

$$B = \begin{bmatrix} 0.00004 & 0 & 0 & 0 \\ 0 & 0.0005 & 0 & 0 \\ 0 & 0 & 0.00025 & 0 \\ 0 & 0 & 0 & 0.0005 \end{bmatrix} \text{MW}^{-1}$$

During the schedule time, the hydro plant's water reservoir may only take down 1555200 m3. Figures 5 and 6 show the outcomes of the interval-wise reservoir hydro discharge and optimum power production schedule, respectively.

One of the GA parameters, probability of crossover (PC), is maintained at 0.5 in table 1, while the other GA parameter, probability of mutation (PM), is changed between 0.05 and 0.09. The program is executed thirty times for every PM value, and the average, maximum, and least cost values are shown. Additionally, the execution time mean is recorded. The GA parameters are determined from this ideal value. The iteration count is set at 100. According to the figures obtained using the given technique, the thermal cost is 39285 rupees per hour.

Table 1

=.5	neration cost (Rs/hr)			an CPU time (Sec)	ndard deviation
M	in	ax	verage		
05	393	165	39824	313.1875	320.0229158
06	713	165	947.17	372.1076738	163.5572275
07	285	983	39775	439.9290127	244.4735841
08	581	018	9821.6	466.64	190.6863918
09	309	102	39883	367.0245689	204.9910567

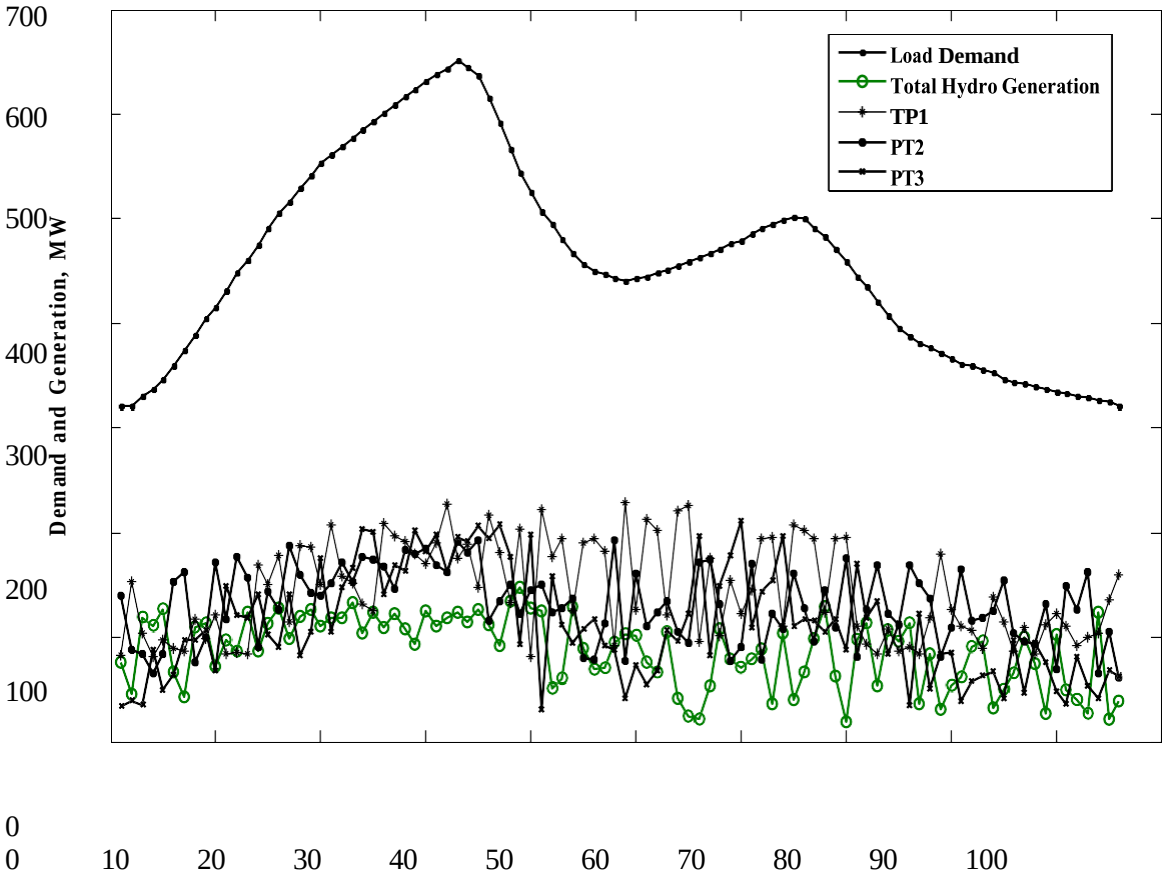
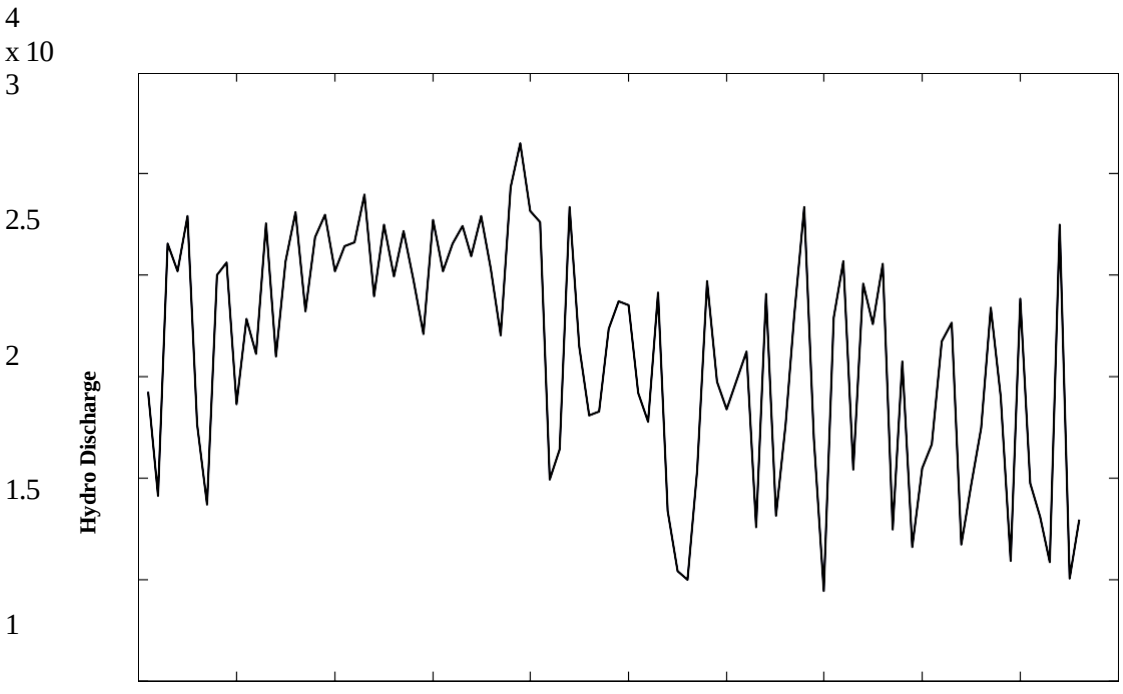


Figure 5. Hourly hydro and thermal generation scheduling for a day



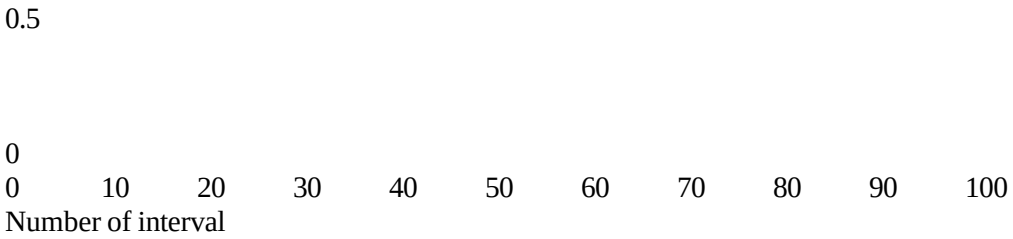


Figure 6. Hydro plant discharges ($10^4 m^3$ / hr)

CONCLUSION

This paper presents, tests, and applies a real variable genetic algorithm (RVGA) iteration method for short-term hydro-thermal scheduling for fixed head hydro-thermal problems under significant operating constraints on a test system of one hydro and three thermal plants to search the hydro and thermal generations during the entire scheduling period. RVGA is used as a random search method, but the goal function—that is, the operational cost function—directs the search. The development of quick computing capabilities has made it possible to determine the "best" option using advanced techniques for increased accuracy. RVGA may provide many optimum solutions to a problem by either picking a sample of the best answers from the final generation or by repeating trials with varied beginning populations. It is very sensitive to the initial feasible values. Even when the objective function is non-convex, discontinuous, and non-differentiable, the RVGA search strategy still performs well. RVGA eliminates the encoding and decoding stages as well as the challenge of figuring out the maximum length of binary sequences by using actual value to represent people or chromosomes. Additionally, an experimental data set from the Sewa hydroelectric power plant is used to construct a model for the hydro system. The investigation shows that the quadratic fit model is the most effective model for water discharge rate vs power (MW). An enhanced solution may also come from further adjusting the RVGA control parameters, such as population size, crossover, and mutation rates. One of the primary disadvantages of the RVGA approach is the absence of a strong theoretical foundation for the setting of the GA parameters, which are determined after extensive testing. The results showed that the suggested approach is very successful in achieving an ideal generation schedule. This study demonstrates the possibility of employing the suggested RVGA approach to find a more nearly optimum solution to the HT scheduling issue.

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