A HYBRID APPROACH BASED ON ANN AND PSO FOR PROFICIENT SOLVING OF UNIT COMMITMENT PROBLEM

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Abstract: *This paper presents a new hybrid approach to solve the short-term unit commitment problem using Artificial Neural Network (ANN) and Particle Swarm Optimization (PSO). The objective of this paper is to find the generation scheduling such that the total operating cost can be minimized, when subjected to a variety of constraints. This also means that it is desirable to find the optimal generating unit commitment in the power system for the next H hours. PSO, which happens to be a Global Optimization technique for solving Unit Commitment Problem, operates on a system, which is designed to encode each unit's operating schedule with regard to its minimum up/down time. In this, the unit commitment schedule is coded as a string of symbols. An initial population of parent solutions is generated at random. Here, each schedule is formed by committing all the units according to their initial status ("flat start"). Here the parents are obtained from a pre-defined set of solution's i.e. each and every solution is adjusted to meet the requirements. Then, a random decommitment is carried out with respect to the unit's minimum down times. The network is trained by a numerous possible combinations of demand and their corresponding optimal generation schedule, which can be determined by the PSO algorithm. For the purpose of training, BP algorithm, one of the most widely used training algorithms is utilized for our approach. After the process of training, given any demands of a time horizon, the network effectively gives a schedule of unit's commitment which will satisfy the demands of all the periods with minimum total cost. A thermal Power System in India demonstrates the effectiveness of the proposed approach; extensive studies have also been performed for different power systems consist of 10, 26, 34 generating units. Numerical results are shown comparing the cost solutions and computation time obtained by using the IPSO and other conventional methods like Dynamic Programming (DP), Legrangian Relaxation (LR) in reaching proper unit commitment.*

Key words: *Artificial Neural Network; Particle Swarm Optimization; Unit Commitment*

1. Introduction

In power stations, the investment is pretty costlier and the resources in operating them are considerably becoming sparse of which focus turns on to optimizing the operating cost of the power station. In today's world, it becomes an utmost necessity to meet the demand as well as optimize the generation. Unit commitment in power systems refers to the optimization problem for determining the on/off states of generating units that minimize the operating cost for a given time horizon. The solution of the unit commitment problem is a complex optimization problem. The exact solution of the UCP can be obtained by a complete enumeration of all feasible combinations of generating units, which could be very huge number. The unit commitment has commonly been formulated as a nonlinear, large scale, mixed-integer combinational optimization problem.

Research endeavors, therefore, have been focused on; efficient, near-optimal UC algorithms, which can be applied to large-scale, power systems and have reasonable storage and computation time requirements. A survey of existing literature [1-37] on the problem reveals that various numerical optimization techniques have been employed to approach the complicated unit commitment problem. More specifically, these are the Dynamic Programming method (DP), the Mixed Integer Programming method (MIP), the Lagrangian relaxation method (LR), the Branch and Bound method (BB), the Expert system (ES), the Fuzzy Theorem method (FT), the Hop Field method (H), the Tabu Search method (TS), the Genetic Algorithm (GA), the Artificial Neural Network (ANN), the integration of Genetic Algorithm, Tabu search, Simulated Annealing (GTS), the TS and Decomposition method (TSD), the extended neighborhood search algorithm (ENSA), the Evolutionary Programming (EP), the Particle Swarm Optimization (PSO) and so on. The major limitations of the numerical techniques are the problem dimensions, large computational time and complexity in programming.

The DP method [1-2], [13] is flexible but the disadvantage is the "curse of dimensionality", which results it may leads to more mathematical complexity and increase in computation time if the constraints are taken in to consideration. The MIP methods [3-4] for solving the unit commitment problems fail when the number of units increases because they require a large memory and suffer from great computational delay. This new approach significantly improves the performances of MILP-based heuristics to the problem, either in terms of required running time, or in terms of quality of the obtained solutions [5].

The proposed MILP model allows to accurately represent most of the hydroelectric system characteristics, and turns out to be computationally solvable for a planning horizon of one week, proving the high efficiency of modern MILP software tools, both in terms of solution accuracy and computing time [6]. The LR approach [7-10] to solve the short-term UC Problems was found that it provides faster solution but it will fail to obtain solution feasibility and solution quality problems and becomes complex if the number of units increased. The proposed methods [11] are effective for large-scale UCP's without the ramp-rate limit constraints, as compared with the existing methods. A successive sub problem solving method is developed and applied to solve unit commitment problems with identical units. The commitments of the identical units can be differentiated and the homogenous oscillations are avoided or greatly alleviated [12]. The proposed LR is efficiently and effectively implemented to solve the UC problem. The proposed LR total production costs over the scheduled time horizon are less than conventional methods especially for the larger number of generating units [13]. Based on forecasted data, profit-based UC is solved by considering power and reserve generation simultaneously. The optimization problems were solved using a hybrid method between LR and EP. [14]

The BB method [15] employs a linear function to represent fuel cost and start-up cost and obtains a lower and upper bounds. The difficulty of this method is the exponential growth in the execution time for systems of a practical size. An ES algorithm [16], [19] rectifies the complexity in calculations and saving in computation time. But it will face the problem if the new schedule is differing from schedule in database. In the FT method [17], [19] using fuzzy set solves the forecasted load schedules error but it will also suffer from complexity. The H neural network technique [18] considers more constraints but it may suffer from numerical convergence due to its training process. TS [20-21] is a powerful, general-purpose stochastic optimization technique, which can theoretically converge asymptotically to a global optimum solution with probability one. But it will take much time to reach the near-global minimum.

GA [19], [22-23] is a general-purpose stochastic and parallel search method based on the mechanics of natural selection and natural genetics. It is a search method to have potential of obtaining near-global minimum. And it has the capability to obtain the accurate results within short time and the constraints are included easily. The total objective is the sum of objectives and constraints, which are the fuel cost, start up cost, spinning reserve and minimum up-down time violation. The power balance constraint (equality relation) is satisfied prior to genetic operation. This ensures a feasible solution during every stage of the GA simulation. The spinning reserve is treated as an objective with minimization in the total objective function [25]. This algorithm [26] provides a modeling framework less restrictive than previous approaches such as dynamic programming or Lagrangian relaxation. The algorithm competes advantageously in terms of generating solutions with other approaches. Computing time requirements to address problems of realistic size are moderate. The use of integer coding and the use of new genetic operators differentiate the new GA from previous, binary GA implementations [27]. Developed algorithms provide optimal unit commitment and also optimal MW values for energy, spinning reserve and non-spin. Presented algorithm and analysis could be beneficial to GENCO with big number of generators to maximize the profit and bid in competitive electricity market [28].

The ANN [18] has the advantages of giving good solution quality and rapid convergence. And this method can accommodate more complicated unit-wise constraints and are claimed for numerical convergence and solution quality problems. The solution processing in each method is very unique. The integration of the ANN STLF [29] program into a SCADA/EMS system results in two major benefits. First, the level of accuracy of forecasting performance is improved. Second, the improvement in forecasting accuracy improves the quality of UC scheduling and results in a large amount of cost savings per year.

The EP [30-31] has the advantages of good convergent property and a significant speedup over traditional GA's and can obtain high quality solutions. The "Curse of dimensionality" is surmounted, and the computational burden is almost linear with the problem scale. CCA [32] has a good convergent property and a significant speedup over traditional GAs and can obtain high quality solutions.

The GTS [24] shows the reasonable combination of local and global search. It adopts the acceptance probability of SA to improve the convergence of the simple GA, and the tabu search is introduced to find more accurate solutions. The TSD [33] has considered the time varying start-up costs as well as the non-linearity in the hydrothermal systems. It can be used as post processor for existing generation scheduling methods or in cases where rescheduling of units is required due to change in the system status. And the application of the modified Benders decomposition method is to solve with constraints that are difficult to formulate. In order to obtain the better results, the experience of the operators in applying some system specific conditions has been included in the Tabu Search method. The proposed approach by this paper can be used in conjunction with the other optimization method to pursue a more comprehensive feasible solution if the initial solutions obtained by other optimization methods fail to satisfy some specific constraints. In ENSA [34], the constrained models for fuel limits, emission limits and generation capacity limits are discussed and used for typical models. The method can make use of an algorithm that satisfies the objective of the sub problem. Most suitably, and starts from an initial solution even though the solution may be feasible. The higher integral economic effect is pursued, and the feasibility of the algorithm is maintained. The proposed method may be used for rescheduling purposes where the experience of human experts will be combined with the analytical method of optimal scheduling. The algorithm can also be used in other complicated mixed integer programming problems, such as integrated resource planning.

The feasibility of the candidate solutions is checked so that physical constraints are not violated in the final solution. The CBM determination and allocation is performed simultaneously in the proposed optimization process [35]. The simulation results obviously display a satisfactory performance by IPSO, with respect to both the quality of its evolved solutions and the computational requirements [36]. The flexibility in the demand constraint both in terms of possibility of buying and selling in the market gives better indication of the likely future scenarios so that better bidding strategy can be made. The numerical results on the generation company with 3 units demonstrate the quick speed convergence and higher accuracy of proposed approach [37].

From the surveyed research works it can be understood that solving the UCP gains high significance in the domain of power systems. Solving the UCP by a single optimization algorithm is ineffective and time consuming. Hence, we are proposing a UCP solving approach based on PSO and ANN which provides an effective scheduling with minimum cost. The proposed approach solves the UCP with less time consumption rather than the approaches solely based on a single optimization algorithm.

2. Problem Formulation

The main aim is to find the generation scheduling so that the total operating cost can be reduced when it is exposed to a variety of constraints [38]. The overall objective function of the UCP is given below,

$$F_T = \sum_{t=1}^{T} \sum_{i=1}^{N} \left(F_{it}(P_{it}) U_{it} + S_{it} V_{it} \right) \frac{\text{Rs}}{\text{h}} \tag{1}$$

Where

U_{it} ~ unit i status at hour t=1(if unit is ON)=0(if unit is OFF)

V_{it} ~ unit i start up / shut down status at hour t =1 if the unit is started at hour t and 0 otherwise.

F_T ~ total operating cost over the schedule horizon (Rs/Hr)

S_{it} ~ start up cost of unit i at hour t (Rs)

For thermal and nuclear units, the most important component of the total operating cost is the power production cost of the committed units. The quadratic form for this is given as

$$F_{it}(P_{it}) = A_i P^2{}_{it} + B_i P_{it} + C_i \frac{Rs}{h} \tag{2}$$

Where

A_i, B_i, C_i ~ the cost function parameters of unit i (Rs./MW^{2}hr, Rs./MWhr, Rs/hr)

$F_{it}(P_{it})$ ~ production cost of unit i at a time t (Rs/hr)

P_{it} ~ output power from unit i at time t (MW)

The startup value depends upon the downtime of the unit. When the unit i is started from the cold state then the downtime of the unit can vary from a maximum value. If the unit 'i' have been turned off recently, then the downtime of the unit varies to a much smaller value. During the downtime periods, the startup cost calculation depends upon the treatment method for the thermal unit. The startup cost S_{it} is a function of the downtime of unit i and it is given as

$$S_{it} = So_i\left[1 - D_i \exp\left(\frac{-Toff_i}{Tdown_i}\right)\right] + E_i Rs \qquad (3)$$

Where
So_i ~ unit i cold start – up cost (Rs)

D_i, E_i ~ start – up cost coefficients for unit i

2.1 Constraints

Depending on the nature of the power system under study, the UCP is subject to many constraints, the main being the load balance constraints and the spinning reserve constraints. The other constraints include the thermal constraints, fuel constraints, security constraints etc. [38]

2.1.1 Load Balance Constraints

The real power generated must be sufficient enough to meet the load demand and must satisfy the following factors given in (4).

$$\sum_{i=1}^{N} P_{it} U_{it} = PD_t \qquad (4)$$

Where
PD_t ~ system peak demand at hour t (MW)
N ~ number of available generating units
U(0,1) ~ the uniform distribution with parameters 0 and 1
UD(a,b) ~ the discrete uniform distribution with parameters a and b

2.1.2 Spinning Reserve Constraints

The spinning reserve is the total amount of real power generation available from all synchronized units minus the present load plus the losses. It must be sufficient enough to meet the loss of the most heavily loaded unit in the system. This has to satisfy the equation given in (5).

$$\sum_{i=1}^{N} P\max_i U_{it} >= (PD_t + R_t); 1 \le t \le T \qquad (5)$$

Where
$P\max_i$ ~ Maximum generation limit of unit i
R_t ~ spinning reserve at time t (MW)
T ~ scheduled time horizon (24 hrs.)

2.1.3 Thermal Constraints

The temperature and pressure of the thermal units vary very gradually and the units must be synchronized before they are brought online. A time period of even 1 hour is considered as the minimum down time of the units. There are certain factors, which govern the thermal constraints, like minimum up time, minimum down time and crew constraints.

Minimum up time:

If the units have already been shut down, there will be a minimum time before they can be restarted and the constraint is given in (6).

$$Ton_i \ge Tup_i \qquad (6)$$

Where
Ton_i ~ duration for which unit i is continuously ON (Hr)
Tup_i ~ unit i minimum up time (Hr)

Minimum down time:

If all the units are running already, they cannot be shut down simultaneously and the constraint is given in (7).

$$Toff_i \ge Tdown_i \qquad (7)$$

Where
$T\,down_i$ ~ unit i minimum down time (Hr)
$T\,off_i$ ~ duration for which unit i is continuously OFF (Hr)

2.1.4 Must Run Units

Generally in a power system, some of the units are given a must run status in order to provide voltage support for the network.

2.1.5 Ramping Constraints

If the ramping constraints are included, the quality of the solution will be improved but the inclusion of ramp-rate limits can significantly enlarge the state space of production simulation and thus increase its computational requirements. And it results in significantly more states to be evolved and more strategies to be saved. Hence the CPU time will be increased.

When ramp-rate limits are ignored, the number of generators consecutive online/offline hours at hour t, provides adequate state description for making its commitment decision at hour (t+1). When ramp-rate limits are modeled, the state description becomes inadequate. An additional status, generators energy generation capacity at hour t is also required for making its commitment decision at hour (t+1). These additional descriptions add one more dimension to the state space, and thus significantly increase the computational requirements. Therefore, we have not included in this algorithm.

3. Hybrid Algorithm to Solve UCP using PSO and ANN

The proposed hybrid intelligence technique for UCP utilizes PSO Algorithm and ANN. By means of PSO, we determine the units and their generation schedule for a particular demand with minimum cost. In this manner, with the assistance of PSO we determine the same for different possible demands and then train the ANN. The training algorithm, hereby, we utilize the BP algorithm, trains the neural network by an optimal schedule which satisfies the demand of current period based on the demand of previous period. Thus, we are dividing the problem into two stages; one is for determining the minimum cost for a particular demand and another is for determining the minimum cost for unit commitment during all the periods. But the demand varies during all the periods. Hence, different possible demands are need to be generated which can be performed by the BP algorithm, training algorithm for ANN.

3.1 Generating Training set for ANN

To generate training set of ANN, it is essential to generate different possible combinations of the demand to determine the optimal generation schedule throughout the T periods. Succinctly, the training set for ANN is comprised of different demands and the corresponding least cost generation schedule. Let the power demand vector be

$$P_d = [P_{d1} \;\; P_{d2} \;\; P_{d3} \;\cdots\; P_{dm}] \tag{8}$$

It is assumed that the demand vector in the above mentioned equation exhibits arithmetic progression and so the vector element can be determined by

$$P_{d_{i+1}} = P_{d_1} + (i \times d)\,; \quad i = 1,2,3,\ldots,m \tag{9}$$

where,

d is the difference between successive members, $P_{d_{i+1}} - P_{d_i}$. Then the set representation of the different possible pairs of vector elements chosen from the demand vector is as follows

$$D_t = \begin{Bmatrix} (P_{d_1},P_{d_2}), & (P_{d_1},P_{d_3}), & \cdots & (P_{d_1},P_{d_m}) \\ (P_{d_2},P_{d_1}), & (P_{d_2},P_{d_3}), & \cdots & (P_{d_2},P_{d_m}) \\ (P_{d_3},P_{d_1}), & (P_{d_3},P_{d_2}), & \cdots & (P_{d_3},P_{d_m}) \\ \vdots & & & \\ (P_{d_m},P_{d_1}), & (P_{d_m},P_{d_2}), & \cdots & (P_{d_m},P_{d_{m-1}}) \end{Bmatrix} \tag{10}$$

In equation (10), D_t is the demand training set given as the input set for ANN. In the given set, the element (P_{d_1}, P_{d_2}) represents that P_{d_1} is the demand of previous period and P_{d_2} is the demand of current period. This is under consideration because the start-up cost given in equation (3) also considers the generation schedule of all the previous periods and so it is necessary to determine the optimal generation schedule based on the generation schedule of the previous period. Hence, different combinations of a pair of periods are generated as in equation (10) and for each combination, an optimal generation schedule is need to be determined using PSO. The schedule is calculated not only for the combination of demand but also for the demand in the vector which is given in the equation (8). For all those different possible demands, PSO is applied and optimal generation schedule is determined.

3.2. Determining optimal generation schedule by PSO

As mentioned earlier, in order to find an optimal solution to an objective function (fitness function) in a search space, PSO method is used which belongs to the group of direct search methods. PSO is used to determine the optimal generation schedule for a particular demand. The steps of the algorithms which is used for our approach is demonstrated in the Figure 1.

As depicted in Figure 1, for a power demand of P_d, initially, a population of random individuals is taken. The random individuals include random particles and their velocities. Hereby, a logical algorithm is utilized to generate the initial random solutions of particles which can be discussed as follows,

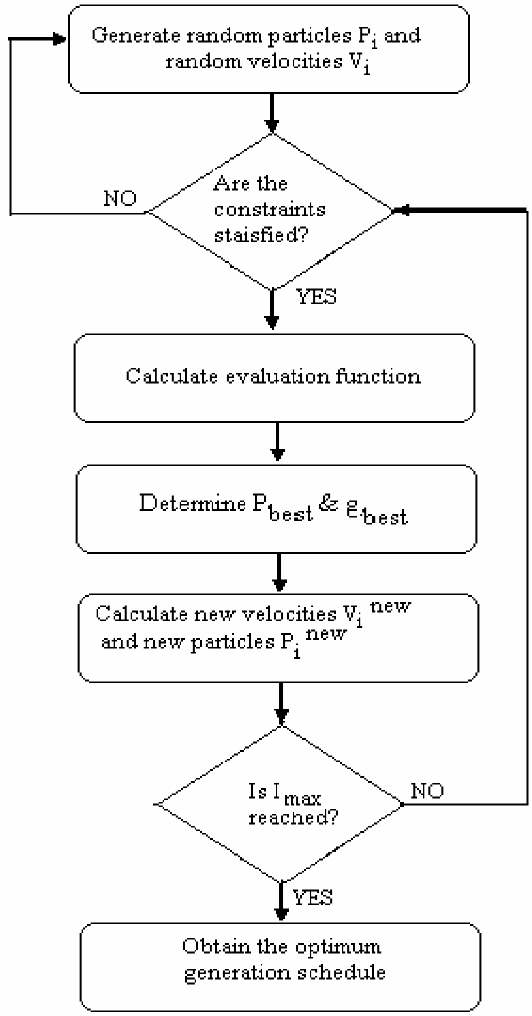

Figure 1: Steps involved in PSO to determine the optimal generation schedule

1. Generate an arbitrary integer r which satisfies the condition $r \le n$.
2. For the r^{th} unit, generate a random integer indicating the power generated by the unit which should essentially satisfy the condition

$$P_{g_r}^{(\min)} \le P_{g_r} \le P_{g_r}^{(\max)}$$

3. The remaining power to be generated i.e. $P_d - P_{g_r}$ is subjected for the following decision,

$$P_d = \begin{cases} P_d - P_{g_r} & ;\ if\ \ P_d - P_{g_r} < P_{th} \\ \dfrac{P_d - P_{g_r}}{2} & ;\ else \end{cases} \qquad (11)$$

4. Allot P_d to the next unit to generate (now, let the next unit as r) whose maximum limit of power generation is greater than the remaining free units. The allotment of P_d to the unit is based on the following condition

$$P_{g_r} = \begin{cases} P_d & ;if\ \ P_{g_r}^{(\min)} \le P_d \le P_{g_r}^{(\max)} \\ P_{g_r}^{(\min)} & ;if\ \ P_d < P_{g_r}^{(\min)} \\ P_{g_r}^{(\max)} & ;if\ \ P_d > P_{g_r}^{(\max)} \end{cases} \qquad (12)$$

5. Determine $P_d - P_{g_r}$. If $P_d - P_{g_r} < 0$, go to step 1; If $P_d - P_{g_r} > 0$, go to step 3; If $P_d - P_{g_r} = 0$, then terminate the criteria.

By the above mentioned algorithm, a vector is obtained which represents the amount of power to be generated by each unit. Hence, some different possible vectors are generated by repeating the algorithm and it can be given as

$$P_i = \left[P_{g_1}^{(i)}, P_{g_2}^{(i)}, \cdots, P_{g_n}^{(i)} \right] \qquad (13)$$

Equation (13) represents the initial particles that are satisfying the constraints given in equation (4) and (5) are generated as random initial solutions for the PSO algorithm. In parallel, random velocities are also generated for the corresponding particles as follows

$$v_i = \left[v_1^{(i)}, v_2^{(i)}, \cdots, v_n^{(i)} \right] \qquad (14)$$

In equation (14), the velocities for each particle element are randomly generated within the maximum and minimum limit and so the each element of the velocity vector v_i satisfies $v_{\min} \le v_i\ (j) \le v_{\max}$. After determining the initial particles and their corresponding velocities, the particles are evaluated by the evaluation function which is given by

$$\min \sum_{i=1}^{n} (F_{it}(P_{it})U_{it} + S_{it}V_{it}) \frac{R_s}{h} \qquad (15)$$

Based on the evaluation function given in equation (15), p_{best} and g_{best} for the initial particles are determined. Then new velocities are determined as

$$v_i^{new}(j) = w * v_i^{cnt}(j) + c_1 * a_1 * [p_{best_i}(j) - P_i^{cnt}(j)] + c_2 * a_2 * [g_{best}(j) - P_i^{cnt}(j)] \tag{16}$$

where, $1 \le i \le l$, $1 \le j \le n$, $v_i^{cnt}(j)$ stands for current velocity of the particle, $v_i^{new}(j)$ stands for new velocity of a particular parameter of a particle, a_1 and a_2 are arbitrary numbers in the interval $[0,1]$, c_1 and c_2 are acceleration constants (often chosen as 2.0) and w is the inertia weight that is given as

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{I_{\max}} \times I \tag{17}$$

where, $w_{\max}$ and $w_{\min}$ are the maximum and minimum inertia weight factors respectively which are chosen randomly in the interval $[0,1]$, I is the current number of iteration and $I_{\max}$ is the maximum number of iterations. The velocity of such newly attained particle should be within the limits. Before proceeding further, this would be checked and corrected.

$$v_i^{new}(j) = \begin{cases} v_{\max}(j) & ;\ v_i^{new}(j) > v_{\max}(j) \\ v_{\min}(j) & ;\ v_i^{new}(j) < v_{\min}(j) \end{cases} \tag{18}$$

Depend upon the newly obtained velocity vector, the particles are updated and obtained as new particles as follows

$$P_i^{new}(j) = P_i^{new}(j) + v_i^{new}(j) \tag{19}$$

Then the parameter of each particle is checked whether it is ahead the lower and upper bound limits. The minimum and maximum generation limit of each unit is referred by the lower and upper bound values respectively. If the new particle infringes the minimum and maximum generation limit, then a decision making process is performed as follows

$$P_i^{new}(j) = \begin{cases} P_{g_i}^{(\max)} & ;\ if \quad P_{g_i}^{new}(j) > P_{g_i}^{(\max)} \\ P_{g_i}^{(\min)} & ;\ if \quad P_{g_i}^{new}(j) < P_{g_i}^{(\min)} \end{cases} \tag{20}$$

The newly obtained particles are evaluated as mentioned earlier and so p_{best} for the new particles are determined. With the concern of p_{best} and the g_{best}, new g_{best} is determined. Again by generating new particles, the same process is repeated until the process reaches the maximum iteration $I_{\max}$. Once the iteration reaches the $I_{\max}$, the process is terminated and so that a generation schedule of all the units with minimum cost is obtained which will meet the demand at the particular period. In the similar fashion, the optimum generating schedule for all the possible demand set is determined. So, a complete training set which includes the various possible demands and the corresponding optimum generation schedule is generated.

3.3. Training the ANN by Back propagation (BP) algorithm

Two different networks N_1 and N_2 are used for our proposed approach; one is for receiving the optimal generation schedule for a particular demand where the schedule does not depends upon the previous period demand. Another network is for receiving the optimal generation schedule which depends on the previous period demand. Hence, the first network is configured with a single input unit and n hidden and output units. The second network is configured with 2 input units and n hidden and output units. The two different configurations of the network used for our approach is depicted in the Figure 2.

The BP algorithm, the most widely used algorithm is used to train the two networks. In order to train the neural network, a pair of load profiles and their corresponding commitment schedules satisfying all the constraints are used. The commitments of units are used as the target outputs to train the network. The training steps are given as follows:

Step 1: Initialize the input weights of all the neurons, except the neurons in the input layer, by arbitrarily choosing an integer from the interval $(0,1)$. The weights of the input neurons keep a constant value 1.

Step 2: Apply a training sample x_1 and (x_1, x_2) to the network N_1 and N_2 respectively.

Step 3: Determine the output at the output layers of the network as

$$y_j = \frac{1}{1+\exp(-x_j)} \quad (21)$$

where, y_j is the output of j^{th} neuron which follows sigmoid function and x_j is the total weighted input which can be calculated as

$$x_j = \sum_{i=1}^{n} y_i w_{ij} \quad (22)$$

Step 4: Determine error by considering the actual output of the network and the desired output by

$$e_j = y_j(1-y_j)(y_j - d_j) \quad (23)$$

$$e_j = y_j(1-y_j)\sum_{i=1}^{n} w_j(y_j - d_j) \quad (24)$$

The error calculation for output layer and hidden layer is given in equation (23) and (24) respectively and d_j represents the desired output.

Step 5: Adjust the weights of all the neurons using the calculated e_j as follows

$$\Delta w_{ij} = e_j . \eta . x_j \quad (25)$$

where, Δw_{ij} is the change of weight and η is the rate of learning, usually, 0.2 and 0.15 for output and hidden layers respectively. The modification of weights starts from the output layer, hidden layer and then input layer.

Repeat the process iteratively until either the error reaches a tolerable value $(e_j < 0.1)$ or the iteration reaches maximum limit. Once the training process is completed, the network is ready to provide the optimal generation schedule for any demand. By giving the demand for T periods as the input to the network, the network provides an optimal commitment of units which has minimum cost. By applying the obtained outputs of the network in the equation (26), the overall objective function given in the equation (1) can be determined.

$$F_t = \sum_{t=1}^{T} c_t \quad (26)$$

In equation (26), c_t is the minimum cost of the units commitment obtained from ANN. So, given a demand set for T periods, the proposed hybrid approach offers the optimal units commitment which satisfies the demand of the T periods with minimum cost. Eventually, the commitments of units in an optimal manner are obtained so as to fulfill the demand at the particular period by satisfying the mentioned constraints.

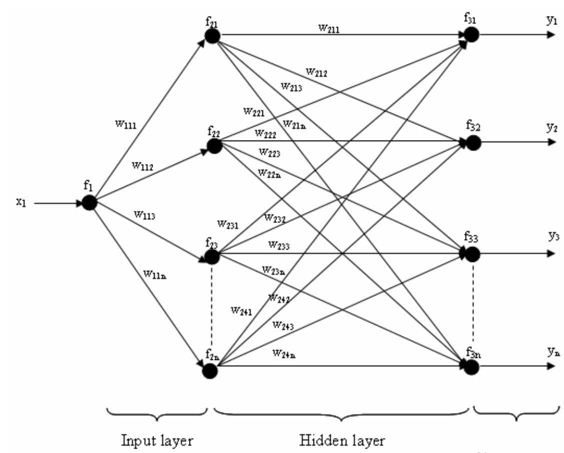

Figure 2(a): Single input- n outputs Neural Network to obtain an optimal generation schedule given a demand

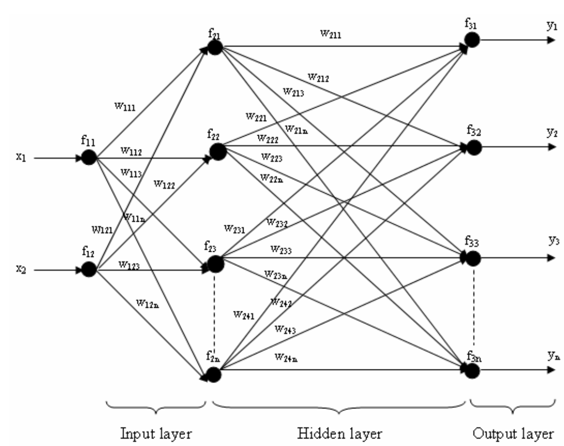

Figure 2 (b): Two inputs- n outputs Neural Network to obtain an optimal generation schedule given a demand of current and previous periods

4. Results and Discussion

The proposed hybrid intelligence technique for UCP which is based on the PSO-ANN has been implemented in the working platform of MATLAB (version 7.8). We have considered an Indian thermal power system with seven unit's utility system for a time span of 24 hours for evaluating the performance of the proposed technique. The operation data for the system is given in the Table I. The daily load data of 10, 26, 34 unit systems are shown in Table II. The schedule for the demand of each hour is obtained from the ANN which has been already trained by BP.

TABLE I
OPERATION DATA OF SEVEN UNITS UTILITY SYSTEM

Unit	Running Cost			Start-up cost			P_{min} (MW)	P_{max} (MW)
	A_i (Rs/MWh^2)	B_i (Rs/MWh)	C_i (Rs)	So_i (Rs)	D_i (Rs)	E_i (Rs)		
1	0.255	70	750	4250	29.5	10	15	60
2	0.198	75	1250	5050	29.5	10	20	80
3	0.198	70	2000	5700	28.5	10	30	100
4	0.191	70	1600	4700	32.5	9	25	120
5	0.106	75	1450	5650	32	9	50	150
6	0.0675	65	4950	14100	37.5	4.5	50	150
7	0.074	60	4100	11350	32	5.5	75	200

TABLE II
DAILY GENERATION OF 10,26,34 UNIT SYSTEM

Hour	Load		
	10 Unit	26 Unit	34 Unit
1	103	1820	1025
2	100	1800	1000
3	90	1720	900
4	85	1700	850
5	103	1750	1025
6	140	1910	1400
7	197	2050	1970
8	240	2400	2400
9	285	2600	2850
10	315	2600	3150
11	330	2620	3300
12	340	2580	3400
13	328	2590	3275
14	295	2570	2950
15	270	2500	2700
16	255	2350	2550
17	272	2390	2725
18	320	2480	3200
19	330	2580	3300
20	290	2620	2900
21	213	2600	2125
22	165	2480	1650
23	130	2150	1300
24	115	1900	1150

The demand for 24 hour time horizon is just simulated and it is not the actual demand which is practically satisfying by the units. An optimal generation schedule for each period and the total operating cost for the whole 24 periods are obtained from the ANN. The PSO contributes in the generation of training set for ANN by determining the optimal generation schedule for a particular demand. The performance of PSO for a particular demand is depicted in the Figure 3.

TABLE III
OPTIMAL GENERATION SCHEDULE FOR UTILITY SYSTEM SATISFYING 24 HOUR DEMAND ALONG WITH ITS TOTAL OPERATING COST

Time	1	2	3	4	5	6	7	8	9	10	11	12
Power Demand (MW)	400	410	420	410	430	420	430	440	430	440	450	480
Unit												
1	84.5	94.0	89.5	81.5	90.0	90.5	90.0	100	90.0	100	110	48.5
2	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0
5	144.5	150	150	128.5	150	139.5	150	150	150	150	150	111.5
6	0	0	0	0	0	0	0	0	0	0	0	150
7	171	144	180.5	200	190	190	190	190	190	190	190	170

Time	13	14	15	16	17	18	19	20	21	22	23	24	Total Operating Cost (p.u)
Power Demand (MW)	490	480	500	490	500	440	470	440	450	420	440	420	
Unit													
1	94.5	41.5	101.75	52.5	74.75	110	130	100	110	89.0	113	91.5	0.9763
2	0	0	0	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	0	0	0	
5	150	150	150	150	150	150	150	150	150	150	137	138.5	
6	115.5	118.5	117.25	117.5	108.25	0	0	0	0	0	0	0	
7	128	170	131	170	147	200	190	190	190	181	190	190	

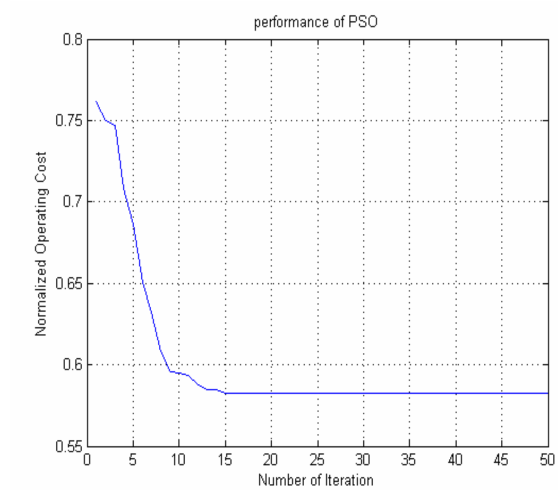

Figure 3: The normalized cost for an optimal generation schedule versus the number of iterations of the PSO operation

In practical use, ANN's provides many advantages to the decision makers. They do not require any modeling or programming for matching inputs to outputs. Moreover, they are able to run with missing or with the larger data. It is also easier, cheaper and quicker to make the system learn from complex data set by training. In consideration of these kinds of advantages, ANN's are used in a wide range of applications in engineering and management practices. Given a demand, the PSO generates an optimal unit commitment with minimum cost. In Figure 3, the improvement of PSO is illustrated in terms of offering the commitment of units with minimum cost. The affixed graph is obtained for solving the power demand of 400 Mw by the seven unit's utility system. In every number of iteration, the cost of the schedule offering by the PSO gets reduced. After a certain number of iterations, the cost remains constant for all the remaining iterations, which means that there no more generation schedule is available with cost which lesser than the previous cost. For the evaluation of performance, we have solved the UCP by PSO only and thus we have compared the computational time taken by the proposed hybrid approach and by the PSO solely to solve the problem.

The simulated demand set, corresponding generation schedule, the minimum operating cost and the computational time for the utility system is given in the Table III. The status of unit i at time t and the start-up / shut - down status obtained are the necessary solutions and are obtained for DP, LR, PSO, PSO-ANN methods. Table IV shows the comparison of cost and CPU time for utility and IEEE systems. In comparison with the results produced by the referenced techniques (DP, LR, ANN, PSO), the PSO-ANN method obviously displays a satisfactory performance.

TABLE IV
COMPARISONS OF COST AND CPU TIME FOR UTILITY & IEEE SYSTEMS

System	Methods	Total Cost (p.u.)	CPU Time (Sec)
7 – Unit Utility System	DP	1.00000	605
	LR	0.96481	578
	ANN	0.93760	535
	PSO	0.92690	519
	PSO-ANN	0.92410	514
10 – Unit IEEE System	DP	1.00000	325
	LR	0.94123	279
	ANN	0.91263	236
	PSO	0.90905	218
	PSO-ANN	0.90700	211
26 – Unit IEEE System	DP	1.00000	509
	LR	0.95968	495
	ANN	0.92788	452
	PSO	0.91273	440
	PSO-ANN	0.90802	431
34 – Unit IEEE System	DP	1.00000	1452
	LR	0.99910	1368
	ANN	0.96489	1321
	PSO	0.95790	1320
	PSO-ANN	0.95185	1307

5. Conclusion

The proposed approach PSO-ANN has performed well in solving the UCP by recognizing the optimal generation schedule. The approach has been tested for the seven unit's utility system with the consideration of load balance and spinning reserve constraints, which are the most significant constraints. Prior to test the system, we have trained the network by different possible combinations of the demand set and its corresponding optimal schedule using the BP algorithm.

For the test demand set which consists of demand for 24 periods, the hybrid approach effectively yields optimal generation schedule for the periods. In comparison with the results produced by the referenced techniques (DP, LR, ANN, PSO), the PSO-ANN method obviously displays a satisfactory performance. There is no obvious limitation on the size of the problem that must be addressed, for its data structure is such that the search space is reduced to a minimum; No relaxation of constraints is required; instead, populations of feasible solutions are produced at each generation and throughout the process.

References

[1] WL.Snyder, HD.Powell, and C.Rayburn, "Dynamic Programming approach to Unit Commitment", IEEE Trans. Power Systems, Vol.3, No.2, pp. 339-350, 1987.

[2] Y.Y.Hsu., Su, C.C.Liang, C.C.Lin.C.J. and C.T.Huang., "Dynamic Security Constrained Multi-Area Unit Commitment", IEEE Trans. Power Systems, Vol.6, pp.1049-1055, 1991.

[3] Samer Takriti and John R.Birge, "Using Integer Programming to Refine Lagrangian – Based Unit Commitment Solutions", IEEE Trans. Power Systems, Vol.15, No.1, pp.151-156, 2000.

[4] M.R.Mohan, K.Kuppusamy, M.Abdullah Khan, "Optimal Short-term Hydro-Thermal Scheduling using Decomposition Approach and Linear Programming Method", International Journal of Electrical Power and Energy Systems, Vol. 14, No.1, pp.39-44, 1992.

[5] Antonio Frangioni, Claudio Gentile, and Fabrizio Lacalandra Tighter, "Approximated MILP Formulations for Unit Commitment Problems", IEEE Transactions on Power Systems, Vol. 24, No. 1, February 2009, pp. 105-113.

[6] Alberto Borghetti, Claudia D'Ambrosio, Andrea Lodi, and Silvano Martello, "An MILP Approach for Short-Term Hydro Scheduling and Unit Commitment with Head-Dependent Reservoir", IEEE Transactions on Power Systems, Vol. 23, No. 3, August 2008, pp. 1115-1124.

[7] J.M.Ngundam, F.Kenfack, T.T.Tatietse, "Optimal Scheduling Of Large – Scale Hydrothermal Power Systems Using The Lagrangian Relaxation Technique", International Journal of Electrical Power & Energy Systems, Vol. 22, No.1, pp.237-245, 2002.

[8] A.G.Bakirtzis, C.E.Zoumas, "Lambda of Lagrangian relaxation solution to unit commitment problem", IEE Proc. Generation, Transmission and Distribution, Vol.147, No.2, pp.131-136, 2000.

[9] Chuan-ping Chang, Chih-wen Liu, Chun-chang Liu, "Unit Commitment by Legrangian Relaxation and Genetic Algorithms", IEEE Trans. Power Systems, Vol.15, No.2, pp.707-714, 2000.

[10] R.Nieva., A.Inda., and I.Guillen, "Lagrangian Reduction Of Search Range For Large Scale Unit Commitment", IEEE Trans. Power Systems, Vol.2, pp.465-473, 1987.

[11] Takeshi Seki, Nobuo Yamashita, and Kaoru Kawamoto, "New Local Search Methods for Improving the Lagrangian-Relaxation-Based Unit Commitment Solution", IEEE Transactions On Power Systems, Vol. 25, No. 1, February 2010, pp. 272-283.

[12] Qiaozhu Zhai, Xiaohong Guan, and Jian Cui, "Unit Commitment with Identical Units: Successive Sub problem Solving Method Based on Lagrangian Relaxation", IEEE Transactions On Power Systems, Vol. 17, No. 4, November 2002, pp. 1250-1257.

[13] F. Benhamida, "A Hybrid Lagrangian Relaxation – Dynamic Programming Solution to the Unit Commitment Problem", Journal of Electrical Engineering, Vol. 9, No. 4, 2009, pp. 31-40.

[14] Pathom Attaviriyanupap, Hiroyuki Kita, Eiichi Tanaka, and Jun Hasegawa, "A Hybrid LR–EP for Solving New Profit-Based UC Problem Under Competitive Environment", IEEE Transactions On Power Systems, Vol. 18, No. 1, February 2003, pp. 229-237.

[15] A.I.Cohen and M.Yoshimura, "A Branch and Bound Algorithm for Unit Commitment", IEEE Trans. Power and Apparatus, Vol. 102, No.2, pp.444-451, 1983.

[16] Z.Ouyang, SM.Shahidehpour, "Short term Unit Commitment Expert System", International Journal of Electrical Power System Research, Vol. 20, pp.1-13, 1990.

[17] C.C.Su, Y.Y.Hsu, "Fuzzy Dynamic Programming: an application to Unit Commitment", IEEE Trans. Power Systems, Vol.6, No.3, pp.1231-1237, 1991.

[18] H.Sasaki, M.Watanabe, J.Kubokawa, N.Yorino, “A solution method of Unit Commitment by artificial neural networks”, IEEE Trans. Power Systems, Vol.7, No.3, pp.974-981, 1992.
[19] N.P.Padhy, “Unit Commitment using Hybrid Models: A Comparative Study for Dynamic Programming, Expert Systems, Fuzzy System and Genetic Algorithms”, International Journal of Electrical Power & Energy Systems, Vol.23, No.1, pp.827-836, 2000.
[20] A.H.Mantawy, Youssef L. Abdel-Magid, Shokri Z.Selim, “A Unit Commitment By Tabu Search”, IEE Proc. Generation, Transmission and Distribution, Vol. 145, No. 1, pp.56-64, 1998.
[21] Whei-Min Lin, Fu-Sheng Cheng, Ming-Tong Tsay, “An Improved Tabu Search for Economic Dispatch With Multiple Minima”, IEEE Trans. Power Systems, Vol.17, No.1, pp.108-112, 2002.
[22] Yong-Gang Wu, Chun-Ying Ho, Ding-Yi Wang, “A Diploid Genetic Approach to Short-Term Scheduling of Hydro-Thermal System”, IEEE Trans. Power Systems, Vol.15, No.4, pp.1268-1274, 2000.
[23] Ying-Yi Hong, Chih-Yuan Li, “Genetic Algorithm Based Economic Dispatch for Cogeneration Units Considering Multiplant Multibuyer Wheeling”, IEEE Trans. Power Systems, Vol.17, No.1, pp.134-140, 2002.
[24] A.H.Mantawy, Youssef L. Abdel-Magid, Shokri Z.Selim, “Integrating Genetic Algorithm, Tabu Search And Simulated Annealing For The Unit Commitment Problem”, IEEE Tans. Power Systems, Vol.14, No.3, pp.829-836, 1999.
[25] K. S. Swarup and S. Yamashiro, “Unit Commitment Solution Methodology Using Genetic Algorithm” IEEE Transactions on Power Systems, Vol. 17, No. 1, February 2002, pp. 87-91.
[26] José Manuel Arroyo, and Antonio J. Conejo, “A Parallel Repair Genetic Algorithm to Solve the Unit Commitment Problem”, IEEE Transactions On Power Systems, Vol. 17, No. 4, November 2002, pp. 1216-1224.
[27] Ioannis G. Damousis, Anastasios G. Bakirtzis, and Petros S. Dokopoulos, “A Solution to the Unit-Commitment Problem Using Integer-Coded Genetic Algorithm”, IEEE Transactions On Power Systems, Vol. 19, No. 2, May 2004, pp. 1165-1172.
[28] E.Mariappane, K.Thyagarajah, “A Genetic Algorithm Approach to Price-Based Unit Commitment”, Journal of Electrical Engineering, Vol. 9, No. 4, 2009, pp. 41-46.
[29] Titti Saksornchai, Wei-Jen Lee, Kittipong Methaprayoon, James R. Liao, and Richard J. Ross, “Improve the Unit Commitment Scheduling by Using the Neural-Network-Based Short-Term Load Forecasting”, IEEE Transactions On Industry Applications, Vol. 41, No. 1, January/February 2005, pp. 169-179.
[30] K.A.Juste, H.Kita, E.Tanaka, J.Hasegawa, “An Evolutionary Programming Solution to the Unit Commitment Problem”, IEEE Trans. Power Systems, Vol.14, No.4, pp.1452-1459, 1999.
[31] H.T.Yang, P.C.Yang and C.L.Huang, “Evolutionary Programming Based Economic Dispatch for Units with Non-smooth Fuel Cost Functions”, IEEE Trans. Power Systems, Vol.11, No.1, pp.112-117,
[32] Haoyong Chen and Xifan Wang,” Cooperative Co evolutionary Algorithm for Unit Commitment”, IEEE Transactions On Power Systems, Vol. 17, No. 1, February 2002, pp. 128-133.
[33] X.Bai, M.Shahidehpour, “Hydro-Thermal Scheduling by Tabu Search and Decomposition Method”, IEEE Trans. Power Systems, Vol.11, No.2, pp.968-975, 1996.
[34] X.Bai, M.Shahidehpour, “Extended Neighbourhood Search Algorithm for Constrained Unit Commitment”, Electrical Power and Energy Systems, Vol.19, No.5, pp.349-356, 1997.
[35] Maryam Ramezani, Mahmood-Reza Haghifam, Chanan Singh, Hossein Seifi, and Mohsen Parsa Moghaddam, “Determination of Capacity Benefit Margin in Multi area Power Systems Using Particle Swarm Optimization”, IEEE Transactions On Power Systems, Vol. 24, No. 2, May 2009, pp. 631-641.
[36] B. Zhao, C.X. Guo , B.R. Bai, Y.J. Cao, “An improved particle swarm optimization algorithm for unit commitment”, Electrical Power and Energy Systems, Vol. 28, 2006, pp. 482–490.
[37] S.Chitra Selvi R.P.Kumudini Devi, C.Christober Asir Rajan, “A Hybrid Approaches for the Profit Based Unit Commitment Problem in the Deregulated Markets”, Journal of Electrical Engineering, Vol. 9, No. 3, 2009, pp. 35-41.
[38] A.J.Wood And B.F.Woolenberg, Power Generation and control 2nd Edn., New York: John Wiley and Sons., 1996.