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Research Article

Solving Unit Commitment Problem Employing Proposed Hybrid BBO-discrete Hopfield Neural Network

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Abstract: A novel hybrid approach is developed based on the hybridization of Biogeography Based Optimization and Discrete Hopfield Neural Network. BBO algorithm is employed to tune for the optimal weights of discrete Hopfield Neural Network leading to the minimization of energy function. The proposed hybrid BBO-DHNN is implemented for 10, 20, 40 and 60 units power system under consideration. Based on the simulation results presented, it is clearly noted that the proposed HBDHNN approach results in better solutions for the unit commitment problem considered and this in turn reduces the computational burden to a significant extent. The proposed approaches are developed in MATLAB environment version 7.8.0.347 and executed in a PC with Intel core 2 Duo processor with 2.27 GHz speed and 2 GB RAM with 64 bit operating system.

Keywords: Artificial neural network, biogeography based optimization, discrete hopfield neural network, gravitational search algorithm, unit commitment problem

INTRODUCTION

In general considering the electric power industry sector, key issues lie in the optimal planning and economic operation of the electric power generation systems. Basically, Unit Commitment Problem (UCP) is a major component with regard to the resource management side of the generation part. UCP is an optimization problem to compute the schedule of the generating units within a power system so as to minimize the incurred fuel cost. On performing this UCP optimization process, certain number of constraints like ramp rate limits, unit capacity limit, minimum up time and down time constraints and spinning reserve constraints are to be satisfied. UCP aims to reduce the fuel costs as well the transition cost. Fuel costs involve the production cost and the transition cost includes the start-up and shut- down costs. With respect to the reliability measures considering the generator outages are specified by the spinning reserve constraints.

The hybridization of BBO into the Discrete Hopfield Neural Network results in the formation of Hybrid BBO-Discrete Hopfield NN (HBDHNN). The proposed HBDHNN technique with the features of an evolutionary optimization approach and neural network is used in this study to determine the fuel operating cost so as to minimize it to solve for unit commitment problem. The optimization process of determining the fuel cost for the scheduled horizon is carried with all the equality and inequality constraints being met. This study also considers the minimization with and without ramp rate constraints. The developed HBDHNN technique is employed for 10, 20, 40 and 60 units system to solve UCP.

LITERATURE REVIEW

Here, reviews of some of the works are presented on various methods. Kumar and Palanisamy (2006, 2007a, 2007b) developed a new Dynamic Programming based direct computation Hopfield method for solving short term Unit Commitment (UC) problems of thermal generators. The proposed method determines the weighting factor using formulation calculation rather than trial and error method. Swarup and Simi (2006) presented a new method using artificial neural networks for the solution of the Unit Commitment (UC) and Economic Dispatch (ED) using Hopfield Neural Network (HNN). The method was successfully tested for different cases (3, 5, 6, 10 and 26 generator units), with varying load pattern of different durations (24 h) on Matlab on P-IV machine in windows environment. Rajan and Mohan (2007) presented a new approach for solving short-term Unit Commitment Problem (UCP) using Neural-Based Tabu Search (NBTS) for utility system. Swarup and Valsan (2007) proposed a new method for the solution of the problems of Unit

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Commitment (UC) and Economic Dispatch (ED) using Hopfield Neural Network (HNN). Mori and Ohkawa (2008) proposed a new hybrid meta-heuristic method that makes use of TS-EPSO techniques and evaluates solutions with two layers. Layer 1 determines the on-off state of generators with Tabu Search (TS) while Layer 2 evaluates output of generators with the evolutionary particle swarm optimization (EPSO). Gao *et al*. (2008) presented an algorithm which is based on a Hopfield neural network for determining unit Liu *et al*. (2008) presented a hybrid Artificial Neural Network (ANN) Lagrangian relaxation approach to combinatorial optimization problems in power systems, in particular to unit commitment. Singh and Rajan (2011) proposed a hybrid approach which gives optimal commitment of units to solve the unit commitment problem related to necessary constraints. 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. Jahromi *et al*. (2013) proposed a real-time solution to unit commitment problem by considering different constraints like ramp-up rate, unit operation emissions, next hours load and minimum down time. Shafie-Khah *et al*. (2014) presented a novel hybrid method for solving the Security Constrained Unit Commitment (SCUC) problem which uses an adapted binary programming method and enhanced dual neural network model as optimization tools. Further, a procedure for power flow modeling is developed for including contingency/ security issues, as new contributions to earlier studies.

Considering the above discussed applicability of Hopfield Neural Network, in this research paper hybridizing Discrete Hopfield Neural Network and Biogeography Based optimization, a new approach called HBDHNN (Hybrid BBO-Discrete Hopfield NN) is developed to compute solutions for unit commitment problem minimizing the fuel cost in an effective manner for 10-60 units system.

UNIT COMMITMENT-PROBLEM DEFINITION

Unit commitment problem is considered as a combinatorial optimization problem with multiple constraints to be satisfied.

Fitness function of the unit commitment problem: The main objective of the unit commitment problem is to minimize the sum of fuel cost consumed, the start up and shut down cost of all separate units during the given period of time satisfying the constraints Considering this, the fitness function for the UCP is mathematically represented by equation (1):

$$Fx_i = \sum_{i=1}^{n} \sum_{t=1}^{h} \left[F_{ci} U_{i,t} + C_{SUi} \{U_{i,t}(1-U_{i,t-1})\} + C_{SDi} \{U_{i,t}(1-U_{i,t-1})\} \right] \quad (1)$$

where, $$Fc_i = \alpha_i P^2{}_{g_{i,t}} + \beta_i P_{g_{i,t}} + \lambda_i \quad (2)$$

And,

$$C_{SU_i} = \begin{cases} C_{HSU_i}; & if \quad T^t{}_{off_i} \le T_{down_i} + T_{cold_i} \\ C_{CSU_i}; & if \quad T^t{}_{off_i} > T_{down_i} + T_{cold_i} \end{cases} \quad (3)$$

where,

F_{c_i}	= Fuel cost of the i-th unit (a quadratic function)
n	= Total number of generating units
h	= Total number of hours
$\alpha_i, \beta_i, \lambda_i$	= Fuel cost coefficients of the i-th unit
$P_{g_{i,t}}$	= Power output produced of the i-th generating unit at the specified t-th hour
$C_{SU\,i}$	= Startup cost of the i-th unit
$C_{SD\,i}$	= Shutdown cost of the i-th generating unit
$C_{HSU\,i}$	= Hot start up cost of the i-th unit
$C_{CSU\,i}$	= Cold start up of the i-th unit
$U_{i,t}$	= Status of the i-th generating unit at the specified t-th hour
T_{off_i}	= Continuous off time duration of the i-th unit
T_{down_i}	= Minimum down time of the i-th unit
T_{cold_i}	= Cold start hours of the i-th unit

Constraints for unit commitment problem: Generally, the unit commitment problem is subjected to equality and inequality constraints based on the power system module considered.

Equality constraints for UCP: At each t-th hour, the predicted power demand is equal to the sum of the output powers of the committed generators and is given by:

$$\sum_{i=1}^{n} P_{gi,t} U_{i,t} = P_{demand\_t} \quad (4)$$

where, P_{demand_t} is the power demand at the t-th hour.

Inequality constraints for UCP:

Generating unit's constraints: Each of the committed units must operate within its operating limits as given by:

$$P_{min\_i} \le P_{i,t} \le P_{max\_i} \quad (5)$$

where, P_{min-i}, P_{max-i} are the minimum and maximum operating limits of the i-th generating unit.

Minimum up time constraint: When a unit is started up, the unit should not be shut down before a minimum up-time period being met and mathematically it is expressed for i-th generating unit as given below:

$$T_{ON_i} \geq T_{UP_i} \tag{6}$$

where, T_{ON_i} specifies the ON time duration of the i-th generating unit and T_{UP_i} specifies the min. up time of the i-th generating unit.

Minimum down time constraint: When a unit is started down, that respective unit should not be shut-up before a minimum down-time period being met and it is mathematically expressed for i-th generating unit as given below:

$$T_{OFF_i} \geq T_{DOWN_i} \tag{7}$$

where, T_{OFF_i} represents the off time duration of the i-th generating unit and T_{DOWN_i} represents the minimum down time of the i-th generating unit.

Spinning reserve constraints: The spinning reserve constraints for the UCP is given by:

$$\sum_{i=1}^{n} P_{\max\_i} U_{i,t} \geq P_{demand\_t} + SR_t \tag{8}$$

where, SR_t specifies the maximum reserve at the t-th hour and $P_{demand\text{-}t}$ is the power demand at the t-th hour.

Ramp rate constraints: The ramp rate inequality constraint is given by:

$$\begin{aligned} P_{i,t} - P_{i,t-1} &\leq UR_{limit(i)} \\ P_{i,t-1} - P_{i,t} &\leq DR_{limit(i)} \end{aligned} \tag{9}$$

where,

$UR_{limit(i)}$ = The up-rate limit of the i-th generating unit

$DR_{limit(i)}$ = The down-rate limit of the i-th generating unit

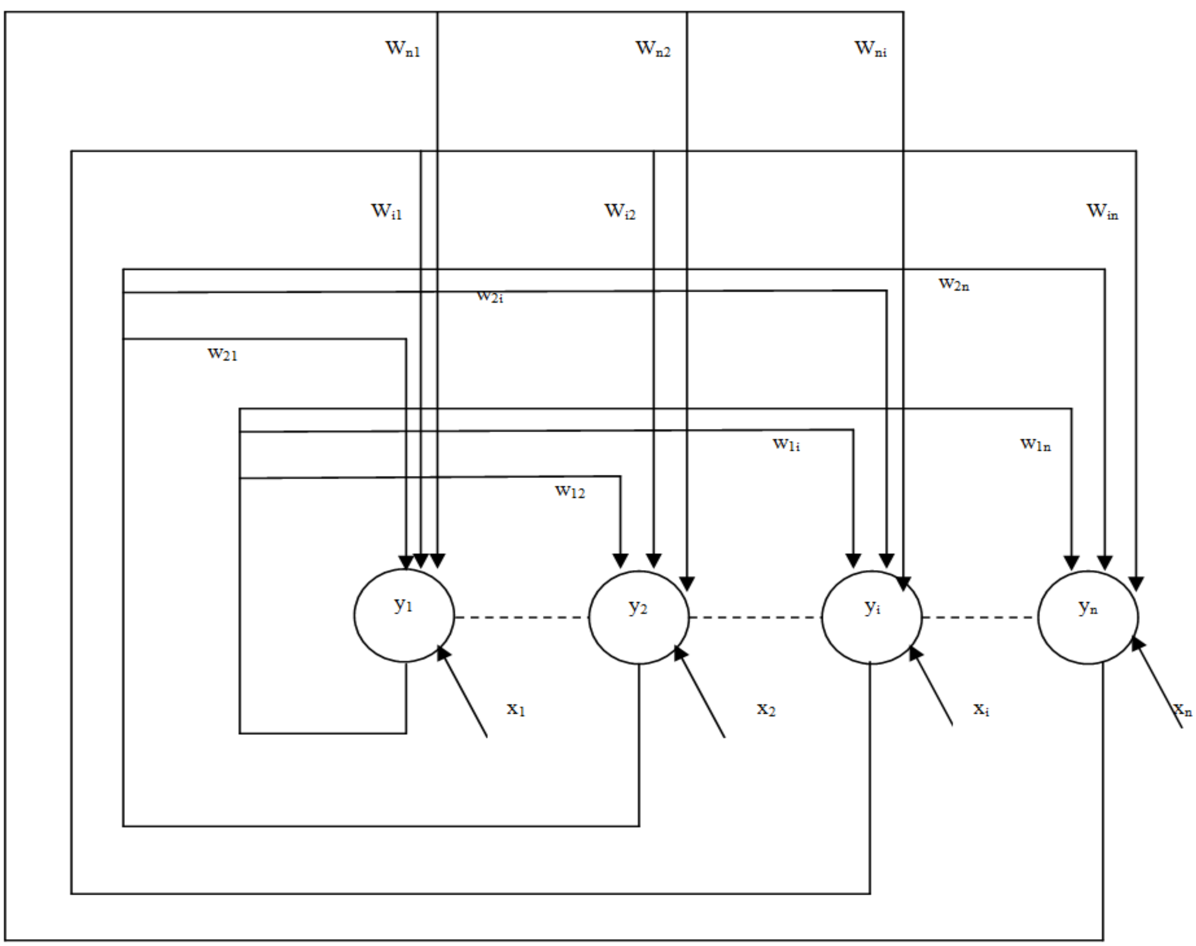


Fig. 1: Architecture of DHNN model

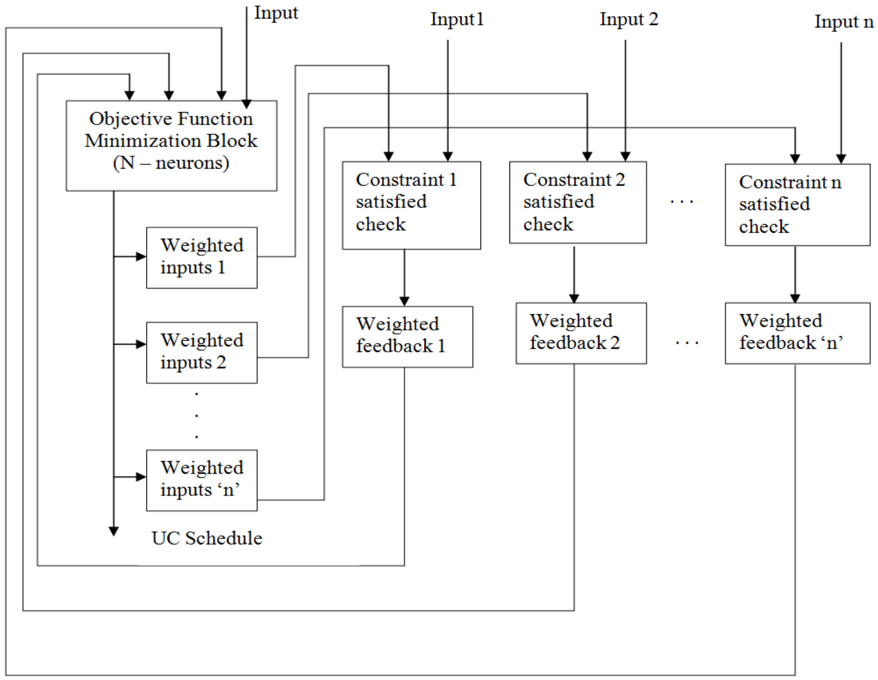


Fig. 2: Proposed architecture for UCP

DISCRETE-HOPFIELD NEURAL NETWORK (DHNN)

DHNN is a recurrent neural network model that executes in an unsupervised learning process. DHNN possess three major parallel processing modules- parallel input channels, parallel output channels and a large number of interconnections between the neural processing elements. The architecture topology of a DHNN is very simple: it has *n* neurons, which are all networked with one another. The Discrete Hopfield neural network is a fully interconnected neural net with each unit connected to every other unit. The net possess symmetric weights with no self connections i.e., all the diagonal elements of the weight matrix of a Hopfield net are zero. The asynchronous discrete time updating of the units in DHNN constructs a function known as energy or Lyapunov function to be computed for the net. This function proves that the net will converge to a stable set of activations. Figure 1 shows the architecture of DHNN model.

In DHNN architecture model, the processing elements are modeled as amplifiers and these possess sigmoidal monotonic input-output relations. The proposed architecture shown in Fig. 2 consists of 'n' number of X input neurons and Y output neurons. It should be noted that apart from receiving a signal from input, the y_1 neurons receives signal from its other output neurons also. This is the case for the all other output neurons as well. Hence, there exists a feedback output value being returned at each output neuron. An energy function or Lyapunov function is defined for these symmetrically connected neurons which are very specific for a particular connection. The ultimate action of DHNN is to minimize this energy function.

In DHNN, to compute weight matrix and store the set of input patterns, the formula employed is:

$$w_{ij} = \sum_{p} (2S_i(p)-1)(2s_j(p)-1) \text{ for } i \neq j \text{ and } W_{ii} = 0 \tag{10}$$

where, $s(p) = s_1(p),..........s_i(p),.......s_n(p))$ are the binary input patterns. When the input patterns are bipolar, the weight matrix is calculated using:

$$w_{ij} = \sum_{p} s_i(p) s_j(p) \text{ for } i \neq j \text{ and } W_{ii} = 0 \tag{11}$$

The DHNN will converge to a stable limit point with respect to an energy function of the system. In this case, the energy function is a function that is bounded below and is a non-increasing function of the state of the system. The energy function for the discrete Hopfield network is given by:

$$E = -0.5 \sum_{i \neq j} \sum_{j} y_i \, y_j \, w_{ij} - \sum x_i \, y_i + \sum_{i} \theta_i y_i \tag{12}$$

The change in energy is due to a change in the state of the neuron and is given by ΔE. It is noted that the activation of the net changes by ΔYi. This can be calculated using the following equation:

$$\Delta E = -\left[\sum_{j} y_j \, w_{ij} + x_i - \theta_i \right] \Delta y_i \tag{13}$$

Table 1: Pseudo code for proposed hybrid BBO-discrete hopfield NN algorithm

Start
Randomly initialize the population.
Evaluate the fitness function and sort the population from best to worst.
Initialize the probability of species count for each of the Habitat
Do the following when the stopping criteria is not met
Save the best habitats in a temporary array (Elitism)
For each habitat, map the Habitat Suitability Index (HSI) to number of species S, λ and μ
Select the immigration island based on μ
Perform migration of randomly selected SIVs based on the selected island in previous step.
Invoke Discrete Hopfield neural Network:
Employ the optimized weights tuned using BBO.
When the activations of the net are not converged, perform the following steps
Set initial activations of the net equal to the external input vector x, $y_i = x_i$ (i = 1,…n)
For each of the output unit Y_i,
Calculate the net input of the neural network employing equation (14):

$$y_{-ini\,j} = x_i + \sum_j y_i \, w_{ji} \tag{14}$$

Determine the activations of the output signal:

$$y_{ij} = \begin{cases} 1 & if \quad y_{-ini\,j} > \theta_i; \\ y_{ij} & if \quad y_{-ini\,j} = \theta_i; \\ 0 & if \quad y_{-ini\,j} < \theta_i; \end{cases} \tag{15}$$

Broadcast the value of yi to all other units. Compute the Energy function of the system:

$$E = -0.5 \sum_{i \neq j} \sum_j y_{ij} w_{ij} - \sum x_i \, y_{ij} + \sum_i \theta_i y_{ij} \tag{16}$$

Return the energy function output.
Test for convergence
Else Refine the habitats and sort the population
Check for feasible solution and the presence of a similar habitat

Stop

where, ΔY_i is the change in the output of neuron i, θ_i is the threshold value, w_{ij} is the interconnected weights, x_i are the input signals transmitted, y-th neurons correspond to the output neurons from which the signals are received. The main aim is to minimize the energy function of the DHNN model.

Biogeography based optimization: The concept of how species migrate from one island to another, how new species arise and how species become extinct is defined by biogeography process. Basically, a habitat is any Island (area) wherein it is geographically isolated from other Islands. Habitats with a high HSI (High Suitability Index) tend to possess more number of species; on the other hand those with a low HSI possess small number of species. Also, High HSI habitats possess low species immigration rate as they are saturated with species and also these possess high emigration rate. Low HSI habitats has high species immigration rate due to their sparse populations. In BBO, emigration does not mean that emigrating island loses a feature. The worst solution is assumed to possess worst features; and thus it possesses a very low emigration rate and a low chance of sharing its features. The solution with best features possesses the highest probability to share them (Simon, 2008).

Proposed hybrid BBO-Discrete Hopfield Neural Network (HBDHNN) model: Table 1 presents the pseudo code for the proposed hybrid BBO-Discrete Hopfield Neural Network algorithm. The proposed HBDHNN model is devised wherein the advantages of BBO is brought into NN model to minimize the cost of the energy function. BBO acts to tune the weights of the discrete Hopfield neural network. Populations are randomly generated for the BBO process and based on their Habitat Suitability Index, the populations move through the solution space to achieve optimal tuned weights. The immigration and emigration rate plays a key role in the movement of the species through the habitat. Without BBO, random weights will be considered for the training process of Discrete Hopfield NN and more computational time will be taken for convergence. As a result, incorporating tuned weights from BBO leads to faster convergence of the network by minimizing the energy function. As BBO and Discrete Hopfield network are hybridized together, this process overcomes the occurrence of local and global optima and as well the premature convergence of the network. Applicability of the proposed BBO-discrete Hopfield NN for solving unit commitment problem is presented in the forthcoming section.

Solving UCP using proposed hybrid BBO-discrete hopfield neural network: It is been noted that the unit commitment problem cannot be handled effectively in an accurate manner within the framework of traditional Hopfield Neural Network. As Discrete Hopfield NN (DHNN) operates with '1' and '0' status, it is employed to solve unit commitment problem. The unit commitment schedule consists of only ones and zeros, based on whether the unit is ON or OFF. The output y_{ij}, presents the status of the i-th generator in j-th period, which takes values 1 or 0. As a result, this UCP is mapped to solve by carrying out discrete Hopfield NN. In this case, the power demand and spinning reserve is specified and the transmission losses are neglected. The steps adopted to solve UCP using proposed HBDHNN technique are as follows:

Step 1: Initialize BBO parameters and required probability of species for each Habitat.
Step 2: For each habitat, map the Habitat Suitability Index (HSI) to number of species S, λ and μ.
Step 3: Perform migration of randomly selected SIVs, return the solution value.
Step 4: In DHNN architecture, to solve UCP, it is classified into two blocks-objective function block and the constraint block. Variable neurons represent the objective function neurons and they receive weighted feedback from the constraint neurons. Each of the constrained blocks handles one constraint of the problem.
Step 5: The input to the constrained neurons is the weighted output of the variable-neurons and the current values. With these neuronal outputs, the constraint satisfaction is verified.
Step 6: Based on the weights, a feedback is sent to the variable neurons. This acts the new input to the variable neuron and the output is updated.
Step 7: Repeat the process until all the feedback from constraint block becomes to zero. This means that all the constraints are satisfied (this proves any number of constraint can be handled).
Step 8: Return the minimized value of the cost for the UCP.
Step 9: Stop.

The proposed Hybrid BBO-DHNN approach is employed for 10, 20, 40 and 60 unit systems over a scheduling period of 24 h and is simulated to obtain the solutions for the UCP. It considers all the equality and inequality constraints. Figure 2 shows the architecture for the proposed Hybrid BBO-DHNN for solving UCP with respect to considered units.

IMPLEMENTATION AND RESULTS

The proposed Hybrid BBO-Discrete Hopfield NN algorithm in this study is used to determine solution to unit commitment problem and thereby to reduce the fuel operating cost of the considered systems. The developed biogeography based search algorithm explores the search space in an effective manner to optimize the weight values of DHNN and in turn minimize the fuel operating cost with the given equality and inequality constraints satisifed (including ramp rate constraints). For implementing the proposed Hybrid BBO-DHNN approach to solve UCP, the population size for the algorithm is considered to be 50 and the maximum number of generation is set as 1000. The simulation is carried out in MATLAB environment version 7.8.0.347 to solve different unit commitment problems 10, 20, 40 and 60 units on a Intel core 2 Duo Processor of 2.27GHz with 2 GB RAM personal computer. The proposed Hybrid BBO-DHNN technique operates under two set of conditions; with and without ramp rate constraints. Table 2 presents the parametric values of the proposed HBDHNN technique.

UCP without ramp rate constraints: The proposed hybridized BBO based Discrete Hopfield Neural Network is applied for UCP considering the specified equality and inequality constraints-demand constraint, unit capacity constraint, spinning reserve constraint and up/ down constraint omitting the ramp rate constraint and also considering the ramp rate with penalty factor added to it.

Small scale UCP: To implement the proposed BBO-DHNN, a 10 unit system is considered under the small scale UCP. The information related to the fuel cost data with the generation constraints of 10 units system and the load data for 24 h scheduled horizon in this case are similar to that as presented in Table 3 and 4 of (Zhao *et al*., 2006). During the process of simulation, the reserve required is set to 10% of the power demand. The developed Hybrid BBO-DHNN approach is applied for computing solutions to UCP considering all the constraints excluding the ramp rate constraint in this

Table 2: Parametric values of the proposed hybrid BBO-discrete HNN technique

Parameters of proposed HBDHNN approach	Values of the parameters
Habitat size	50
Habitat modification probability	1
Immigration probability bounds per gene	(0,1)
Step size for numerical integration	1
Maximum immigration	1
Migration rate for each island	1
Mutation probability	0.005
Maximum iteration	1000

Table 3: Fuel cost data of 10 units system with generation constraints

Unit No.	P_{min} (MW)	P_{max} (MW)	Min up time (h)	Min down time (h)	Hot start cost ($)	Cold start cost ($)	Cold start time (h)	Initial states (h)	Cost coefficients α($)	β($/ MWh)	λ($/ MWh^2)
1	150	455	8	8	4500	9000	5	8	1000	16.19	0.00048
2	150	455	8	8	5000	10000	5	8	970	17.26	0.00031
3	20	130	5	5	550	1100	4	-5	700	16.60	0.00200
4	20	130	5	5	560	1120	4	-5	680	16.50	0.00211
5	25	162	6	6	900	1800	4	-6	450	19.79	0.00398
6	20	80	3	3	170	340	2	-3	370	22.26	0.00712
7	25	85	3	3	260	520	2	-3	480	27.74	0.00079
8	10	55	1	1	30	60	0	-1	660	25.92	0.00413
9	10	55	1	1	30	60	0	-1	665	27.27	0.00222
10	10	55	1	1	30	60	0	-1	670	27.79	0.00173

Table 4: Load data for 24 h

Hours	Load (MW)	Hours	Load (MW)
1	700	13	1400
2	750	14	1300
3	850	15	1200
4	950	16	1050
5	1000	17	1000
6	1100	18	1100
7	1150	19	1200
8	1200	20	1400
9	1300	21	1300
10	1400	22	1100
11	1450	23	900
12	1500	24	800

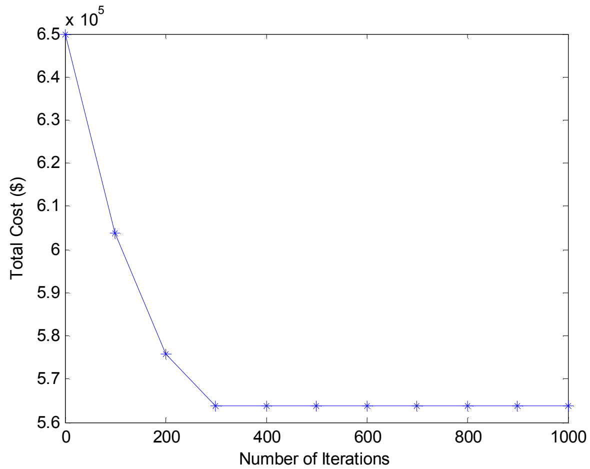
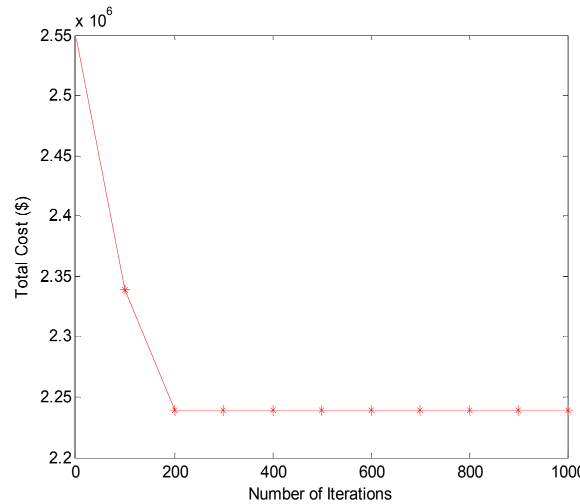


Fig. 3: Convergence plot of proposed hybrid BBO – DHNN for 10 units system



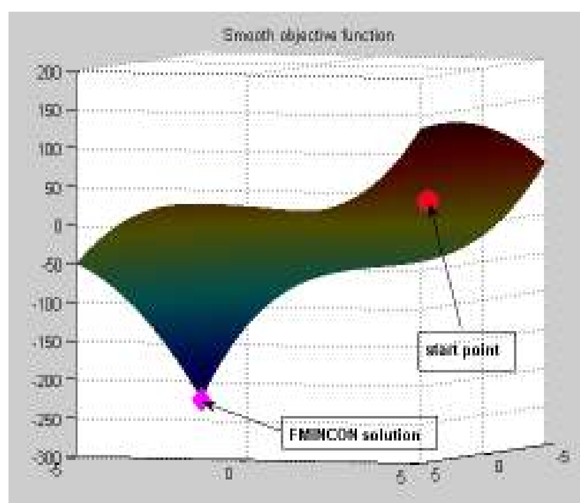


Fig. 4: Convergence plot of proposed hybrid BBO – DHNN for 40 units system

section. The unit commitment schedule and cost in 24 h schedule horizon employing the proposed BBO-Discrete Hopfield NN approach is tabulated in Table 5. The evolutionary training process is carried out for 50 independent trials and the statistical results computed are reported in Table 6. It is noted from the statistical analysis that the best cost, worst cost and average cost computed employing the proposed BBO-Discrete Hopfield NN is noted to be minimal in comparison with that of the earlier methods. Table 6 depicts the average computational time taken for the entire simulation is minimal in comparison with that of the other methods. Figure 3 to 6 shows the convergence plot obtained during the simulation of hybrid BBO-DHNN approach. It is well noted that convergence results in reducing the fuel cost of the system incurred.

Large scale UCP: The proposed hybrid BBO-Discrete Hopfield NN technique, a neural network architecture model is implemented for solving large-scale UCP of 20, 40 and 60 units system. In large-scale UCPs, the first 10 units are duplicated and the power demand is

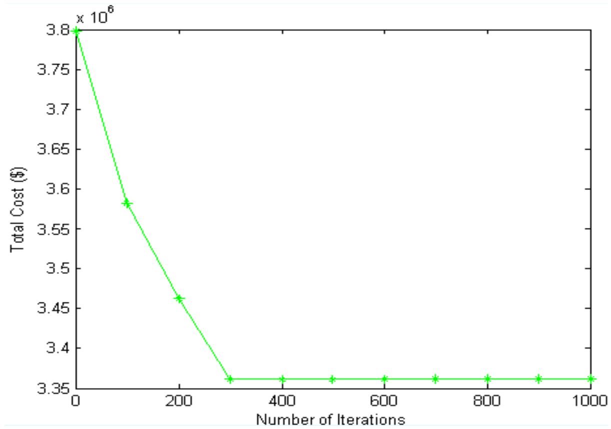


Fig. 5: Convergence plot of proposed hybrid BBO – DHNN for 60 units system

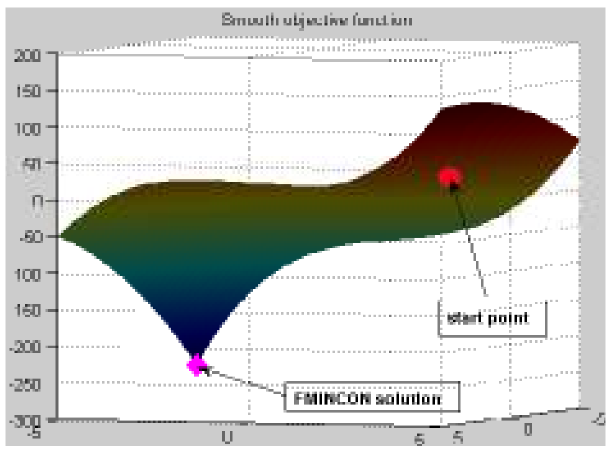


Fig. 6: Objective function of DHNN

Table 5: Unit commitment schedule and cost in 24 h of 10 units system without ramp constraint using hybrid BBO-DHNN approach

	Generation schedule												
Hours	1	2	3	4	5	6	7	8	9	10	Running cost ($)	Start up cost ($)	Spinning reserve (MW)
1	455	245	0	0	0	0	0	0	0	0	13678.4598	0	210
2	455	297	0	0	0	0	0	0	0	0	14550.2390	0	162
3	455	372	0	0	25	0	0	0	0	0	16804.1089	900	228
4	455	455	0	0	45	0	0	0	0	0	18592.1976	0	122
5	455	445	0	130	24	0	0	0	0	0	20016.2937	560	210
6	455	362	130	130	24	0	0	0	0	0	22382.1033	1100	232
7	455	424	129	130	25	0	0	0	0	0	23259.8670	0	180
8	455	455	130	129	35	0	0	0	0	0	24148.0025	0	132
9	455	455	130	129	85	24	24	0	0	0	27244.9876	860	198
10	455	455	130	130	160	30	25	10	0	0	30052.1256	60	150
11	455	455	130	130	160	72	24	10	10	0	31912.4513	60	158
12	455	455	130	130	160	80	25	40	10	10	33887.6337	60	162
13	455	445	130	130	160	30	25	10	0	0	30052.3675	0	152
14	455	445	129	130	84	20	25	0	0	0	27249.0327	0	198
15	455	445	130	129	30	0	0	0	0	0	24148.6579	0	130
16	455	312	130	130	24	0	0	0	0	0	21510.6788	0	282
17	455	262	130	130	25	0	0	0	0	0	20636.4784	0	330
18	455	365	129	130	25	0	0	0	0	0	22385.0234	0	230
19	455	455	130	129	24	0	0	0	0	0	24145.9965	0	131
20	455	455	130	130	162	32	25	10	0	0	30054.2187	490	150
21	455	455	130	130	87	32	25	0	0	0	27250.0065	0	196
22	455	445	0	0	145	20	24	0	0	0	22733.3217	0	132
23	455	445	0	0	0	24	0	0	0	0	17641.0097	0	92
24	455	345	0	0	0	0	0	0	0	0	15423.8767	0	110

Total running cost ($) = 559759.1385
Total start up cost ($) = 4090
Total operating cost ($) = Total running cost + Total start up cost = 563849.1385

multiplied by 2, 4 and 6 respectively for carrying out simulation. Hybrid BBO-Discrete Hopfield NN carries out the search process for minimizing the running cost and in turn the operating cost by carrying out weight optimization of Hopfield NN. This overcomes the occurrence of local and global optima over the search space and increases the convergence of the neural network.

The proposed technique is implemented and the simulated statistical results are tabulated in Table 5 to 7.

Computed solution to UCP with ramp rate constraints: The developed BBO based discrete Hopfield Neural Network approach is simulated for 10, 20, 40 and 60 units system with the ramp rate constraint included and the results are presented in this section. The ramp rate constraint is considered for implementation of the proposed hybrid BBO-DHNN with the penalty function included and the proposed technique attempts to satisfy the specified equality and inequality constraints.

Small scale UCP: The proposed algorithm is implemented for 24 h scheduling horizon with ramp rate constraints along with penalty function added for 10-60 units system. The fuel running cost, optimal dispatch of committed generating units, start-up cost and spinning reserve for 24 h horizon simulated are tabulated in Table 8. The computational efficiency of the proposed approach is validated with the simulation

Table 6: Simulation results employing different algorithms for 10 units and 20 units system with hybrid BBO–DHNN approach

	10 Units system				20 Units system			
Algorithms	Best cost ($)	Worst cost ($)	Average cost ($)	Time taken (s)	Best cost ($)	Worst cost ($)	Average cost ($)	Time taken (s)
Gravitational search Algorithm (Roy 2013)	563938	564241	564008	2.89	1123216	1123758	1123427	13.72
Proposed hybrid BBO – Discrete DHNN approach	563849	563882	563867	1.03	1122942	1123364	1123098	2.64

Table 7: Simulation results employing different algorithms for 40 units and 60 units system using hybrid BBO–DHNN approach

	40 Units system				60 Units system			
Algorithms	Best cost ($)	Worst cost ($)	Average cost ($)	Time taken (s)	Best cost ($)	Worst cost ($)	Average cost ($)	Time taken (s)
GSA (Roy 2013)	2242741	2243586	2243145	74.66	3362447	3365013	3363322	103.41
Proposed hybrid BBO – DHNN approach	2239465	2242987	2242685	19.87	3362012	3363318	3362824	47.98

Table 8: Unit commitment schedule and cost in 24 hours of 10 units system with ramp rate constraint using BBO–DHNN approach

	Generation schedule											
Hours	1	2	3	4	5	6	7	8	9	10	Running cost ($)	Start up cost ($)	Spinning reserve (MW)
1	455	245	0	0	0	0	0	0	0	0	13680.0376	0	210
2	454	310	0	0	0	0	0	0	0	0	14550.5592	0	162
3	455	370	0	0	24	0	0	0	0	0	16806.9987	900	224
4	455	445	0	0	40	0	0	0	0	0	18592.9127	0	121
5	455	422	0	100	25	0	0	0	0	0	20017.0937	560	210
6	455	390	130	130	25	0	0	0	0	0	22382.8721	1100	230
7	455	412	130	130	25	0	0	0	0	0	23261.0056	0	184
8	455	455	129	130	30	0	0	0	0	0	24148.5199	0	135
9	454	455	130	129	84	20	30	0	0	0	27246.2934	860	197
10	455	455	130	129	162	30	25	10	0	0	30053.4478	60	150
11	455	455	129	130	162	74	25	10	10	0	31913.6057	60	155
12	455	455	130	130	162	80	25	40	10	10	33887.8897	60	164
13	455	455	130	130	162	33	25	10	0	0	30052.7025	0	152
14	455	445	130	129	84	20	25	0	0	0	27249.9987	0	198
15	455	445	129	129	25	20	0	0	0	0	24149.1132	0	130
16	455	312	130	129	25	0	0	0	0	0	21511.9213	0	282
17	455	264	129	130	25	0	0	0	0	0	20636.7098	0	332
18	455	360	129	130	30	0	0	0	0	0	22385.6634	0	236
19	455	455	130	129	24	0	0	0	0	0	24146.0052	0	134
20	455	455	130	130	130	60	30	10	0	0	30054.5564	490	150
21	455	455	130	100	145	20	25	0	0	0	27250.3125	0	210
22	455	445	0	0	100	60	30	0	0	0	22733.8097	0	138
23	455	445	0	0	0	0	0	0	0	0	17641.6678	0	92
24	455	345	0	0	0	0	0	0	0	0	15424.0921	0	112

Total running cost ($) = 559777.7887
Total start up cost ($) = 4090
Total operating cost ($) = 563867.7887

Table 9: Best cost computed with different algoirthms for 10, 20, 40 and 60 untis system with ramp constraint using BBO-DHNN approach

Algorithms	Total operating cost ($)			
	10 - Unit	20 - Unit	40 - Unit	60 - Unit
QM (Viana and Pedroso, 2013)	570396	1135452	Unsuccessful	Unsuccessful
ILA (Viana and Pedroso, 2013)	570396	1135452	2267535.7	3398614.4
SDPSP (Mhanna and Jabr, 2012)	564482	1124498	2244709	3364736
GSA (Roy, 2013)	564384	1124475	2244652	3364643
Proposed hybrid BBO – DHNN approach	563868	1123653	2241696	3362987

results obtained for the proposed technique are compared with Quadratic Model (QM) (Viana and Pedroso 2013), Iterative Linear Algorithm (ILA) (Viana and Pedroso 2013), Semi Definite Programming Relaxation and Selective Pruning (SDPSP) (Mhanna and Jabr, 2012) and Gravitational Search Algorithm (GSA) (Roy, 2013). It is inferred from Table 9 that the fuel cost of proposed BBO-DHNN approach is minimized in comparison with that of QM, ILA, SDPSP and GSA which clearly indicates that the proposed hybrid BBO-DHNN technique is computationally efficient than that of the other methods proposed in the literature.

Large scale UCP: The ramp up and down rate are taken from Mhanna and Jabr (2012) and the generator data are taken from Zhao *et al*. (2006). Simulation results of 20, 40 and 60 units with respect to the fuel cost of the proposed method are compared with that of the other earlier techniques and as tabulated in Table 9.

CONCLUSION

In this study, a novel hybrid approach is developed based on the hybridization of Biogeography Based Optimization and Discrete Hopfield Neural Network. BBO algorithm is employed to tune for the optimal weights of discrete Hopfield Neural Network leading to the minimization of energy function. The proposed hybrid BBO-DHNN is implemented for 10, 20, 40 and 60 units power system under consideration. Based on the simulation results, it is clearly noted that the proposed HBDHNN approach results in better solutions for the unit commitment problem considered and this in turn reduces the computational burden to a significant extent. The hybridization of BBO into DHNN simulates the optimization process towards faster local and global search and results in better optimal solutions. Further, the statistical results computed using the proposed hybrid BBO-DHNN approach prove their effectiveness for the considered small-scale and large-scale unit systems. The computational time obtained depicts that the proposed method yields minimal computational time than that of the earlier methods.

Conflict of interest: It is to state that the authors declare that there is no conflict of interest for publishing this study in this journal.

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