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4 authors, including:

Mohamed Kamh
University of Toronto

Almoataz Y. Abdelaziz
Future University in Egypt

S. F. Mekhamer
Ain Shams University, Faculty of Engineering, Egypt, Cairo

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An Augmented Hopfield Neural Network for Optimal Thermal Unit Commitment

A. Y. Abdelaziz*, M. Z. Kamh**, S. F. Mekhamer* & M. A. L. Badr*

Abstract: This paper develops a new solution method of the Thermal Unit Commitment Problem (TUCP) using modified Augmented Hopfield Network (AHN) with enhanced performance. The modifications are mandatory to eliminate the error that conventional AHN structure is reported to suffer from. This error originates from the mapping process, the corner stone in using AHN as an optimization tool. A new solution algorithm is developed by combining the AHN with the proposed modifications. In order to verify the effectiveness of the new algorithm, it is applied and tested to some examples reported in literature and the solution is then compared with that obtained by counterpart Artificial Intelligence (AI) techniques. Unlike other AI techniques, the solution obtained using the modified AHN is more optimal and satisfying all the operating constraints.

Keywords: Hopfield Neural Network (HNN), Power Generation Scheduling, Thermal Unit Commitment Problem (TUCP)

1. NOMENCLATURE

i	Unit's index
j	Interval index
N	Number of units in the system under study
H	Length of simulation horizon
TC	Total generating cost ($)
a_i, b_i, c_i	Cost coefficients of the i^{th} generator
V_{dij}	The status of the i^{th} generator during the j^{th} interval. V_{dij} = 1 for an online state and 0 for an offline state
P_{ij}	Output of the i^{th} generator at the j^{th} interval in Megawatts (MW)
S_i	Start-up cost of the i^{th} unit ($)
L_j	Load demand during the j^{th} interval in MW
$P_{i\text{-}max}$, $P_{i\text{-}min}$	Maximum and minimum generation limits of the i^{th} unit in MW
RUR_i, RDR_i	Maximum allowable ramp up and down rates of the i^{th} generator in MW/hour
mut_i, mdt_i	Minimum up and down times of the i^{th} unit
$T_{on\text{-}ij}$, $T_{off\text{-}ij}$	Number of intervals during which the i^{th} unit has been online or offline successively until the j^{th} hour
SR_j	Spinning reserve requirement during the jth interval in MW
c	Suffix (c) stand for continuous
d	Suffix (d) stand for discrete
$T_{dij \to ckm}$	Interconnection conductance (weight) from the output of the discrete neuron (ij) neuron to the input of the continuous neuron (km)
$W_{ij \to km}$	Interconnection weight form the neuron pair (cij, dij) to the neuron pair (dkm, ckm)
I_{cij}	External input bias to the continuous neuron (ij)
V_{cij}	Output of the continuous neuron (ij). It represents the generation level of the i^{th} unit during the j^{th} interval in MW
U_{dij}	Input to the discrete neuron (ij)
λ	Scaling factor termed as the slope
PM	Power mismatch in MW
ACF	Adaptive correction factor

*Department of Electrical Power and Machines, Faculty of Engineering, Ain Shams University, Cairo, Egypt

**Department of Electrical and Computer Engineering, University of Toronto, Toronto, Canada

2. INTRODUCTION

Customer load demands in electric power systems are periodically changing due to the nature of human activities. In order to cope with these cyclic variations, the dispatcher has to turn on just enough number of generating units to meet the load demand during every interval of the scheduling horizon. Unnecessary units are turned off.

Economic operation of electric power systems has been an interest to researchers for several years. The economic operation determines the optimum schedule of generating units to meet the customer load demands without violating both the unit's and the system's constraints.

Optimal UCP can be stated as "Determine an optimal pattern for the start up and shut down of generators in order to minimize the total operating cost during a period of study called the scheduling horizon without violating any of the operating constraints" [1].

To have a complete solution of UCP, the economic dispatch problem (EDP) must be solved as well. There are two possible ways to do this; the first is to obtain a unit commitment schedule then an economic dispatch is found for this schedule. The other way is to solve both UCP and EDP simultaneously. This makes the problem more difficult to solve. Yet, it is believed that the second method guarantees a more optimal commitment schedule to be found [2].

Many methods have been applied to solve the UCP. They are classified into four main groups; classical optimization methods, heuristic optimization methods, Artificial Intelligence (AI) methods and Hybrid methods.

Classical methods include Dynamic Programming (DP) [3, 4], Lagrangian Relaxation (LR) [5, 6], Network Flow Programming (NFP) [7] and Mixed Integer Programming (MIP) [8]. LR is reported to give good results while DP suffers from the curse of dimensionality. NFP is reported to be faster than both DP and LR. Various decomposition methodologies have been applied to reduce the computation requirement for large-scale systems.

One of the most famous heuristic approaches is the Expert System (ES). An ES based consultant has been developed to solve the UCP [9]. The main shortcoming of ES is that it can not guarantee the global optimality of the solution since it treats the global optimization problem as a sequence of simpler optimization steps.

AI techniques have covered major steps in solving the UCP. AI methods include Simulated Annealing (SA) [10 - 14], Fuzzy Logic (FL) [15], Genetic Algorithms (GA) [14, 16], Particle Swarm Optimization (PSO) [17], Tabu Search (TS) [14, 18] and Hopfield Neural Network (HNN) [1, 2, 19, 20, and 21]. AI techniques are based on mimicking the biological and physical processes. AI techniques can assure the convergence to a very good solution with moderate computational time. Nevertheless, the global optimality of the solution can never be guaranteed since the optimization process of these methods is not based on strict mathematical rules.

Hybrid methods combine two or more of the previously mentioned techniques in order to obtain a new technique that outperforms the individual ones. A hybrid of FL, TS, PSO, and Sequential Quadratic Programming (SQP) is used to solve the fuzzy-modeled UCP [22]. A hybrid of priority list and Lagrangian-based AHN is used in [23] to solve ramp-rate constraint unit commitment problem. A hybrid of DP and HNN is used to solve short term TUCP [24]. EDP is solved first using the continuous version of HNN then DP is used to produce the optimum generator schedule. Other hybrid methods were reported in [14] like TS/SA, GA/TS, and GA/SA/TS.

This paper uses the HNN, specifically that version named Augmented Hopfield Network (AHN) [2] after treating its shortcomings. It has been reported that there is a continuous violation of the equality constraints especially the power balance constraint. To solve this problem, the adaptive correction factor algorithm [25] is applied to the AHN to form a new algorithm. The new algorithm is then implemented and tested using two large test systems reported in literature. Comparisons are then made between the solutions obtained by the proposed algorithm and other well known AI techniques. The comparisons reveal the effectiveness of the proposed algorithm. The rest of the paper is organized as follows; Section II introduces the mathematical formulation of the problem. The construction of the classical AHN is introduced in Section III. Section IV introduces the new algorithm after embedding the adaptive correction factor algorithm in the AHN. Section V presents the implementation and results. Finally, comprehensive conclusions of the work are found in section VI.

3. PROBLEM STATEMENT

TUCP is a combinatorial optimization problem that aims to determine an optimal pattern for the start up and shut down of generators in order to minimize the total operating cost during a period of study called the scheduling horizon without violating any of the operating constraints. In this section, the mathematical formulation of the problem is presented.

The TUCP problem can be stated as follows [2]:

Minimize

$$TC = \sum_{j=1}^{H}\sum_{i=1}^{N}\left[\begin{array}{l} a_i (V_{dij} P_{ij})^2 + b_i V_{dij} P_{ij} + \\ c_i V_{dij} + S_i V_{dij} (1 - V_{dij-1}) \end{array}\right] \quad (1)$$

Subjected to the following constraints:

i. Power Balance Constraint:

$$\sum_{i=1}^{N} V_{dij} P_{ij} = L_j \qquad \forall j = 1:H \quad (2)$$

ii. Real Power Generation Limits: These limits define the region within which a unit must be dispatched.

$$\text{if } V_{dij} = 1 \therefore P_{i-min} \le P_{ij} \le P_{i-max} \quad (3)$$

iii. Ramp Up and Down Rates: To avoid undue thermal stresses on the boiler and the combustion equipment, the rate of change of the output power of each dispatchable thermal unit between two successive time intervals must not exceed certain rate during increasing or decreasing the power output of each unit. This can be formed mathematically as follows:

$$\begin{aligned} &\text{if } V_{dij} = V_{dij-1} = 1 \\ &\therefore P_{ij} - P_{ij-1} \le RUR_i \quad \text{(Ramp Up)} \\ &\text{or} \left|P_{ij} - P_{ij-1}\right| \le RDR_i \quad \text{(Ramp Down)} \end{aligned} \tag{4}$$

iv. Minimum Up Time: Once the unit is committed, it must be kept running for certain number of hours, called the minimum up time, before allowing turning it off. This can be formulated as follows:

$$T_{on-ij} \ge mut_i \tag{5}$$

v. Minimum Down Time: Once the unit is turned off, it is not allowed to be brought online again before spending certain number of hours called minimum down time. This can be formulated as follows:

$$T_{off-ij} \ge mdt_i \tag{6}$$

vi. Spinning Reserve Constraint: Spinning reserve refers to the total amount of generation available from all units synchronized (i.e. spinning) on the system minus the present load plus losses being supplied. Spinning reserve is important to maintain system stability in case of loss of one or more of the running units. Spinning reserve requirements of the system may be a percentage of the load or as much as the capacity of the largest unit in the system. The distribution of the spinning reserve among the units is a decision of the national electricity control council of the country.

Mathematically, spinning reserve constraint is modeled as follows:

$$\sum (V_{dij} P_{i-max}) \ge L_j + SR_j \tag{7}$$

4. HOPFIELD NEURAL NETWORK

Hopfield Neural Network (HNN) is a single layer, recurrent, and non-hierarchal neural network. The action of this network is to minimize an energy function [26].

HNN has been extensively used in solving optimization problems in many fields such as traveling salesman problem, analog to digital conversion; satellite scheduling and in the field of power system operation planning [27]. HNN has been used to solve Unit Commitment Problem [2], Economic Dispatch Problem [25], Dynamic Economic Dispatch Problem [28], and many others.

According to the type of variables in the optimization problem, HNN can be classified into three main categories, Continuous HNN (CHN), Discrete HNN (DHN) and Augmented HNN (AHN). The later treats the problems incorporating both continuous and discrete variables, such as TUCP.

A. Network Dynamics

In AHN, there are two sets of neurons; discrete and continuous sets. These neurons are arranged in pairs, with every discrete neuron having an associate continuous neuron and vice versa [20]. The energy function of AHN is given as [26]:

$$\begin{aligned} E = &-\frac{1}{2}\sum_{i,j}\sum_{k,m} T_{ckm\to cij} V_{cij} V_{ckm} - \sum_{i,j}\sum_{k,m} T_{dkm\to cij} V_{cij} V_{dkm} \\ &-\frac{1}{2}\sum_{i,j}\sum_{k,m} T_{dkm\to dij} V_{dij} V_{dkm} - \sum_{i,j} I_{cij} V_{cij} - \sum_{i,j} I_{dij} V_{dij} \\ &-\frac{1}{2}\sum_{i,j}\sum_{k,m} W_{km\to ij} V_{cij} V_{ckm} V_{dij} V_{dkm} \end{aligned} \tag{8}$$

The relation between inputs (U_{dij}, U_{cij}) and outputs (V_{dij}, V_{cij}) of the neurons are given by [27]:

$$V_{cij} = V_{cij-min} + \frac{1}{2}(V_{cij-max} - V_{cij-min})(1 + \tanh(\lambda U_{cij}) \tag{9}$$

$$V_{dij} = \begin{cases} 1 & \text{if } U_{dij} \ge 0 \\ 0 & \text{if } U_{dij} < 0 \end{cases} \tag{10}$$

$$\begin{aligned} \frac{dU_{cij}}{dt} = &\sum_{k,m} T_{ckm\to cij} V_{ckm} + \sum_{k,m} T_{dkm\to cij} V_{dkm} + I_{cij} \\ &+ \sum_{k,m} W_{km\to ij} V_{dij} V_{dkm} V_{ckm} \end{aligned} \tag{11}$$

$$\begin{aligned} \Delta U_{dij} = &\sum_{k,m} T_{ckm\to dij} V_{ckm} + \sum_{k,m} T_{dkm\to dij} V_{dkm} + I_{dij} \\ &+ \sum_{k,m} W_{km\to ij} V_{cij} V_{dkm} V_{ckm} + \frac{1}{2} T_{dij\to dij}(1 - 2V_{dij}) \\ &+ \frac{1}{2} W_{ij\to ij} V_{cij}^{\,2} (1 - 2V_{dij}) \end{aligned} \tag{12}$$

B. Solving Optimization Problems using AHN

As mentioned earlier, AHN is used to solve optimization problems that have both discrete and continuous variables. Such class of problems is called combinatorial optimization problems.

The generic form of optimization problems take the form of:

Minimize: $f(V_c, V_d)$ (13)

Subjected to: $g(V_c, V_d) = 0$ (14)

& $h(V_c, V_d) \le 0$ (15)

The corner stone in solving optimization problems using AHN is to form the cost function. The cost function is the weighted sum of (14) and the square of (15) [1]. The generic cost function takes the form of:

$$E = A \times f(V_c, V_d) + \sum_{k=1}^{\text{no. of Equality Constraints}} B_k \times \{g_k(V_c, V_d)\}^2 \quad (16)$$

where A and B_k are positive coefficients that determine the relative importance of every term in (16).

The second step is to equate "map" the above cost function with the energy function of AHN (8). This step evaluates the interconnecting weights and biases of the AHN.

Inequality constraints are tackled by dedicated neurons called constraints neurons [1, 26, and 27]. The action of such neurons is to produce large outputs in case of constraint violation. The output of these neurons is scaled and fed back to the variable neurons as an additional input. The sign and value of this input is adjusted to encourage the outputs of the variable neurons to fulfill all inequality constraints. Fig. 1 depicts the interconnection between variable and constraint neurons. Further details of the network structure and applications can be found in [26].

C. Limitations of AHN

As any AI technique, AHN has some limitations and shortcomings as an optimization tool. These limitations are three-fold:

- Due to the nature of cost function (16), the solution obtained using AHN is usually not the minimum of objective function (8). As the number of equality constraints (15) increases, the quality of the solution obtained by AHN deteriorates.
- Selection of AHN parameters; A, B, , and K; greatly affects the quality of the solution.
- Even with fine tuning of the network parameters, equality constraints are still violated. This violation is believed to happen since HNN uses the penalty function method in forming the cost function of the problem to be optimized.

The target of this paper is to treat these limitations in order to fully utilize the advantageous features of AHN as an optimization tool.

5. SOLVING TUCP USING AHN

In order to solve TUCP using AHN, the objective function of the problem (1) is combined with the power balance constraint (2) to form the cost function of AHN. The cost function is then mapped to (8) in order to evaluate the weights and biases of the network. The mapping process yields to the following relations:

$$W_{ij \to ij} = -2B - 2Aa_i \quad (17)$$

$$W_{ij \to kj} = -2B,\ i \neq k \quad (18)$$

$$T_{cij \to dij} = -Ab_i + 2\,BL_j \quad (19)$$

$$T_{dij-1 \to dij} = AS_i \quad (20)$$

$$I_{dij} = -A(S_i + c_i) \quad (21)$$

All other weights and biases in (8) are equal to zero.

Inequality constraints of TUCP include power generation limits, ramp rate limits, minimum up and down times, and spinning reserve constraints. Power generation limits constraint is tackled using (9) by replacing V_{cij}, $V_{cij\text{-}max}$ and $V_{cij\text{-}min}$ by P_{ij}, $P_{i\text{-}max}$ and $P_{i\text{-}min}$ respectively. Other constraints are tackled using the constraint neurons as follows:

A. Spinning Reserve Constraint

The violation of the spinning reserve constraint is interpreted as need of more units to come online. That is why the output of the spinning reserve constraint neuron is fed to the discrete variable neuron of a certain unit to bring it online if the spinning reserve during certain interval without it is not enough [2]. This can be mathematically formulated as:

$$U_{b1-ij} = \sum_{k \neq i} P_{k-max} V_{dkj} - L_j - SR_j \quad (22)$$

$$V_{b1-ij} = \begin{cases} -K_1 U_{b1-ij} & \text{if } U_{b1-ij} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (23)$$

where K_1 is a positive constant.

B. Minimum up and down times constraints:

Minimum time constraint neurons are used to tackle these constraints. If the unit was on during the (j – 1)st interval and is shut down during the jth interval (i.e., $Vd_{ij-1} = 1$ and $V_{dij} = 0$), then the minimum up time condition must be checked. The input to the minimum time constraint neuron in this case is given by:

$$U_{b2-ij} = \left(\sum_{k=j-mut_i}^{j-1} V_{dik} \right) - mut_i \quad (24)$$

The output of this neuron is:

$$V_{b2-ij} = \begin{cases} -K_2 U_{b2-ij} & \text{if } U_{b2-ij} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (25)$$

where K_2 is a positive constant.

If the unit was off during the (j – 1)st interval and is brought online during the interval j (i.e., $V_{dij-1} = 0$ and $V_{dij} = 1$), then the minimum down time condition must be checked. The input to the minimum time constraint neuron in this case is given by:

$$U_{b2-ij} = \sum_{k=j-mdt_i}^{j-1} V_{dik} \quad (26)$$

and its output will be:

$$V_{b2-ij} = -K_2 U_{b2-ij} \quad \text{if } U_{b2-ij} > 0 \qquad (27)$$
$$= 0 \quad \text{otherwise}$$

for either cases, the output of the constraint neuron is fed back to the discrete neuron (d_{ij}) to encourage its output (V_{dij}) to be one (zero) in case of violation to the minimum up(down) time constraint.

The interconnection between the spinning reserve and minimum time constraints neuron and the variable neuron is schematically shown in Fig. 2.

C. Ramp Up and Down Rates

Ramp Rate Constraint neurons connect every continuous neuron to the continuous ones representing the same generator in adjacent intervals. Before a continuous neuron is updated, the constraint neurons linking it to the neurons representing adjacent intervals must first be updated.

To activate this neuron for the i^{th} generator during the j^{th} interval, it must be online for the two successive intervals $j-1$ and j (i.e., $V_{dij-1} = V_{dij} = 1$). The second step is to check whether it is a case of ramping up or down. If ramping up happens (i.e., $P_{dij-1} < P_{dij}$) then the input to the ramp rate constraint neuron is given by:

$$U_{b3-ij} = P_{ij} - P_{ij-1} - RUR_i \qquad (28)$$

where the suffix b refers to constraint neuron.

This constraint has two outputs, V_{b3-ij} and $V_{b3-ij-1}$, given by:

$$V_{b3-ij} = V_{b3-ij-1} = 0 \quad \text{if } U_{b3-ij} \le 0 \qquad (29)$$
$$V_{b3-ij} = -V_{b3-ij-1} = -K_3 U_{b3-ij} \quad \text{if } U_{b3-ij} > 0$$

where K_3 is a positive constant.

The sign of Eq. (23) is reversed in case of ramping down.

In both cases, V_{b3-ij} and $V_{b3-ij-1}$ are fed back to the continuous neurons (cij, and cij-1) respectively in order to decrease (increase) its output, P_{ij}, in the case of violation to that ramp up (down) constraint. In this way both neurons, (cij) and (cij-1), are equally encouraged to adjust their outputs in order to fulfill the ramp rate constraint. The connection of the ramp rate constraint neuron to the variable neurons is shown schematically in Fig. 3.

6. PROPOSED MODIFICATIONS TO AHN

As mentioned earlier, the solution obtained using AHN always suffers from violation to some constraints, especially the power balance constraint. This problem could be minimized by fine tuning of the network parameters [25]. Nevertheless, it was found that even by doing this, equality constraints are always violated producing a noticeable quantity of power mismatch.

This problem has been partially solved by adding the resulted power mismatch to the load as if it were a "load offset" before applying it to the network [2, 20]. The shortcomings of such approach are bi-fold:

- The load offset is not constant for all cases.
- The network dynamics must be run twice. In the first time, the amount of the power mismatch (load offset) is determined. In the second time, the correct solution is generated after adding the constant offset to the load. This is a time consuming approach.

In previous work, the authors proposed an algorithm called "Adaptive Correction Factor (ACF) Algorithm" that can be applied to the solution of AHN after running it once in order to eliminate the power mismatch. The proposed algorithm was tested successfully to solve EDP and found to be faster than and as accurate as classical optimization methods (e.g. Newton-Raphson) [25]. The proposed algorithm was tested in solving dynamic economic dispatch problem (DEDP) and found to be faster and more accurate than conventional HNN [28].

In this paper, the algorithm is modified to treat the combinatorial optimization problems such as TUCP. The complete algorithm is explained as follows:

Step <1>: Let Schedule1 be the solution obtained by running the AHN dynamics.

Step <2>: Starting from the first interval of the scheduling horizon, calculate the power mismatch (PM) in Schedule1 using:

$$PM_j = L_j - \text{Schedule1}_j \qquad j = 1{:}H \qquad (30)$$

Step <3>: If the power mismatch is less than an arbitrary accepted tolerance ε, go to step <6>. Else, calculate the correction factor (CF) using:

$$CF_j = 1 + \frac{PM_j}{L_j} \qquad (31)$$

Let Schedule2 be:

$$\text{Schedule2}_j = CF_j \times \text{Schedule1}_j \qquad (32)$$

Step <4>: Check that the online units in Schedule2 do not violate their maximum and minimum generating levels. If violation happens then saturate their outputs to the violated limit.

Step <5>: Repeat steps <2> through <4> for the entire scheduling horizon. After that update the schedule as follows:

$$\text{Schedule1}_j = \text{Schedule2}_j \qquad (33)$$

Re-calculate the power mismatch using Eq. (30).Then go to step <3>.

Step <6>: Print out the final schedule.

7. IMPLEMENTATION AND RESULTS

Software package implementing the proposed AHN algorithm, to solve the TUCP, is developed using MATLAB®. AHN parameters are tuned as follows:

- $A = 1.6$, $B = 2$ and ; $\lambda = 10^{-3}$; as recommended by the authors in [25].
- $K_1 = K_2 = K_3 = 0.1$ as reported in [2].

In order to prove the validity and effectiveness of the algorithm, two reported test systems are solved using the proposed algorithm. The results are compared with some other AI techniques. In order to incorporate all constraints and to judge the speed of the algorithm, the second test system is modified and solved again using the proposed algorithm. Detailed discussion of results is given below.

A. Test System # 1

The system consists of ten thermal units scheduled over 24 hours. The system is adopted in [14] and its data is given in the appendix in Tables I and II. The ramp rate constraint is not considered in this example. Complete solution of the example is given in Table III. Note that obtained schedule forces units 1 and 5 to remain offline for the entire horizon.

Total operating cost obtained by the modified AHN is compared with that obtained by some other reported Artificial Intelligence (AI) techniques [20]. The results of comparison are depicted in Fig. 4. Negative (positive) sign means that the cost obtained by AHN is less (more) than other methods. Two important notes are concluded:

- Modified AHN is more efficient than Simulated Annealing (SA). Not only does the AHN produce cheaper cost but also it violates none of the constraints On the contrary, the solution obtained by SA suffered from power deficit of 2 MW during the 4th hour and a surplus of 3 MW during the 23rd hour.
- While the cheapest reported solution was obtained by Genetic Algorithm, only 0.73 % cheaper than the AHN solution, the solution of GA suffered from a deficit of 2 MW in the total generation during the 4th hour. Table III shows that the solution of AHN satisfies all of the constraints.
- For the other methods, EDP has been treated as a separate problem that was tackled by quadratic programming. AHN can simultaneously solve EDP and UCP. This is a very important advantage in AHN since the computational time is expected to be reduced by using one algorithm for both problems instead of two.

B. Test System # 2:

Twenty-six thermal units are to be scheduled over 24 hours. Detailed data of the system are extracted from [11]. Note that neither the spinning reserve nor the ramp rate constraints were considered in this example. Fig. 5 shows the percentage reduction in the total operating cost obtained by AHN compared with other reported AI techniques for test system # 2. Using the proposed algorithm, the total operating cost is $657858. It is shown from Fig. 5 that the solution of AHN is 0.35 % to 0.73 % cheaper than other solutions.

As in the first case study, the solution obtained using AHN does not violate any of the constraints. Nevertheless, other techniques violated some of the constraints during some intervals.

These violations are listed below:

- SA and the hybrid of GA/SA/TS, violated the minimum up time constraint of the 11th unit.
- The solution obtained by SA violated the minimum down constraint of the 12th unit.
- The solution generated by GA violated the maximum generation level of the 20th unit during the 8th hour.

C. Test System # 3:

To prove the validity and efficiency of the proposed algorithm, the second test system is modified to incorporate both spinning reserve and ramp rate constraints. The spinning reserve requirement is set to 10% of the hourly load demand while the ramp rate limits of each unit are set to 20% of its corresponding maximum output power as recommended in [12]. Using the proposed algorithm, the detailed schedule of test system #3 is given in Table 4. Table 5 gives the hourly and total costs of test system # 3. Using the proposed algorithm, the total operating cost is $661722. It is concluded that the fulfillment of the spinning reserve and the ramp rate requirements causes an increase in the total cost than in the case of test system # 2.

The obtained results show that all the constraints are fulfilled. The algorithm with the proposed enhancements is efficient. The computational time is about 30 seconds using Intel Centrino® 1.83 GHz processor. This is quite a reasonable time since the application is offline.

8. CONCLUSION

This paper presents a new and efficient algorithm to solve thermal unit commitment problem (TUCP) using modified Augmented Hopfield Network (AHN). After that, the structure of AHN is introduced together with the reported drawbacks of the conventional structure. The proposed modifications are introduced and the proposed algorithm is fully explained. In order to prove the superiority of the algorithm over other AI techniques, three different reported test systems of different sizes are solved using the enhanced AHN. The solution is compared to other well known AI techniques. The proposed algorithm is found to be more efficient than other AI techniques. Not only does the enhanced AHN fulfill all the constraints but also it produces the cheapest solution when compared with the other aforementioned AI techniques.

It is proven that the modified AHN outperforms other AI techniques regarding the solution quality. This is due to the ability of AHN to solve both EDP and TUCP simultaneously. Other AI techniques require a separate algorithm for solving EDP.

While this paper discusses the comparison of the proposed AHN method with other AI methods only, to be useful, the proposed method should also be compared with the methods that are actually used by industry, such as Lagrangian relaxation and mixed integer linear programming. Also, network related constraints should be included in the unit commitment schedules. The authors believe that the unit commitment problem now should consider all constraints that can be handled by other methods. This will be considered in the future work.

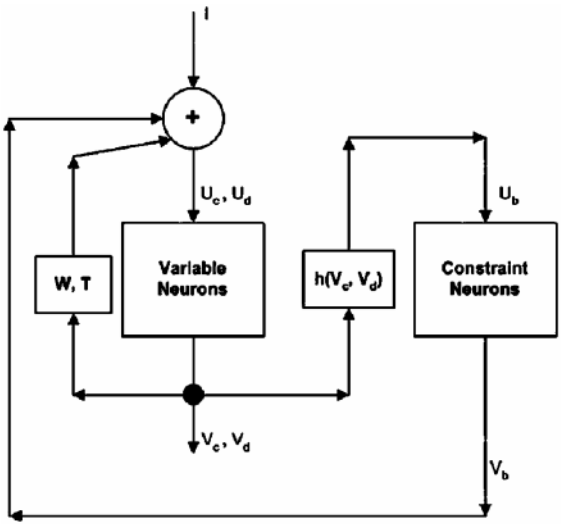

Fig. 1: Schematic Diagram of the Connection between Variable and Constraint Neurons

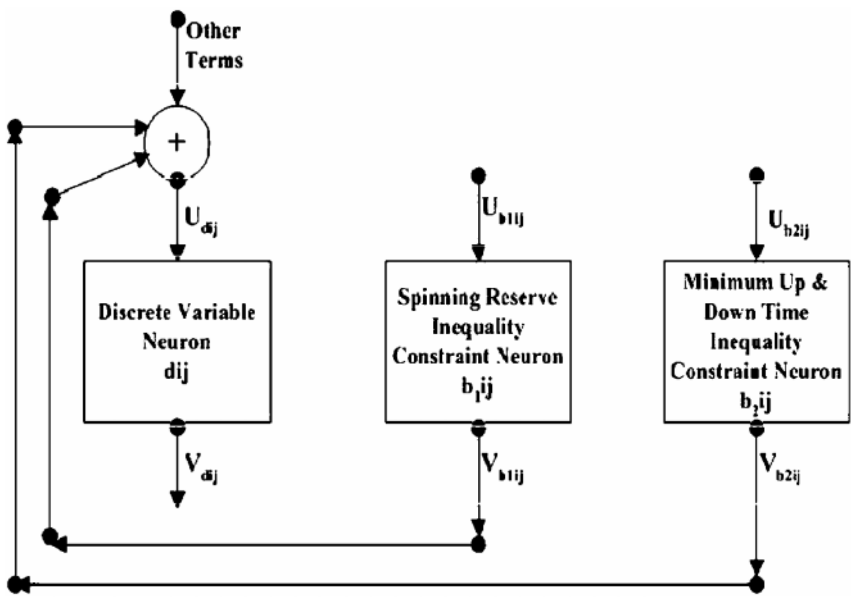

Fig. 2: Schematic Diagram of Connecting the Spinning Reserve and Minimum Time Constraints Neurons to Variable Neurons

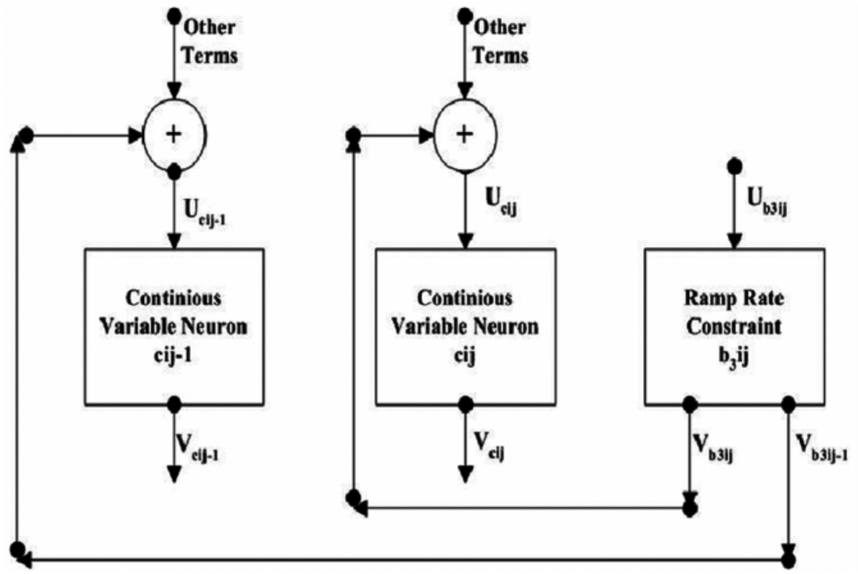

Fig. 3: Schematic Diagram of Connecting the Ramp Rate Constraint Neurons to Variable Neurons

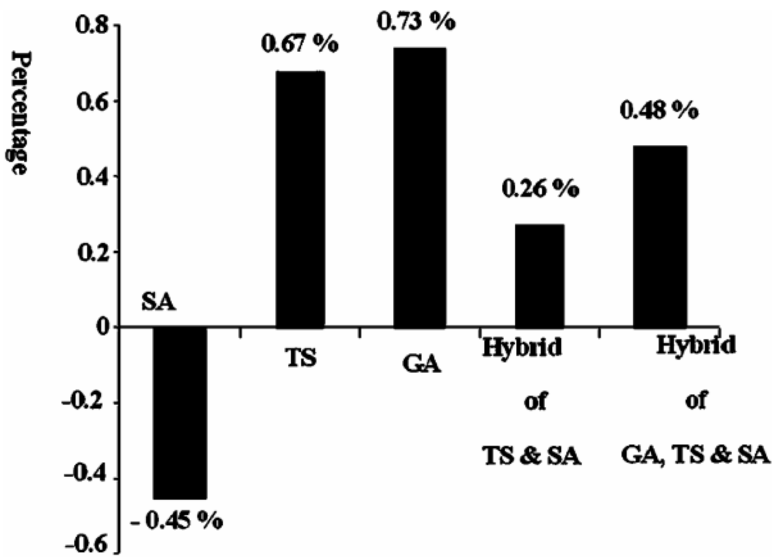

Fig. 4: Percentage Difference Between the Total Operating Cost Obtained by AHN and Other Reported AI Techniques for Test System # 1

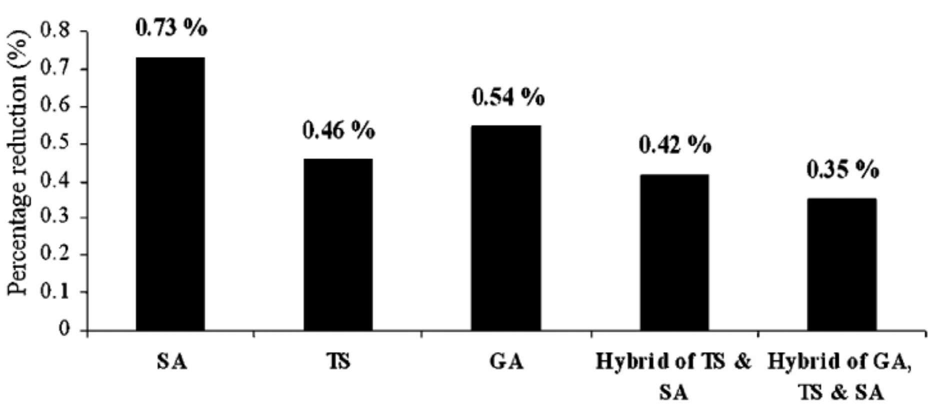

Fig. 5: Percentage Reduction in the Total Operating Cost Obtained by AHN Compared with Other Reported AI Techniques for Test System # 2

Table 1
Hourly Load and Spinning Reserve Demands of
Test System #1

Hour (j)	Load L_j(MW)	Spinning Reserve SR_j (MW)	Hour (j)	Load L_j(MW)	Spinning Reserve SR_j (MW)
1	1025	85	13	3275	240
2	1000	85	14	2950	210
3	900	65	15	2700	200
4	850	55	16	2550	195
5	1025	85	17	2725	200
6	1400	110	18	3200	220
7	1970	165	19	3300	250
8	2400	190	20	2900	210
9	2850	210	21	2125	170
10	3150	230	22	1650	130
11	3300	250	23	1300	100
12	3400	275	24	1150	90

Table 2
Data of Generating Units of Test System # 1

Unit (i)	a_i $/MW^2. hour (x$10^{-5}$)	b_i $/MW. hour	c_i $/hour	S_i $/start	$P_{i\text{-min}}$ GW(x100)	$P_{i\text{-max}}$	mut_i hours	mdt_i hours
1	113	9.023	820	2050	3	10	5	4
2	160	7.654	400	1460	1.3	40	3	2
3	147	8.752	600	2100	1.65	6	2	4
4	150	8.431	420	1480	1.30	4.2	1	3
5	234	9.223	540	2100	2.25	7	4	5
6	515	7.054	175	1360	0.5	2	2	2
7	131	9.121	600	2300	2.50	7.5	3	4
8	171	7.762	400	1370	1.10	3.75	1	3
9	128	8.162	725	2200	2.75	8.5	4	3
10	452	8.149	200	1180	0.75	2.5	2	1

Table 3
Schedule and Hourly Operating Costs of Test System #1*

Hour (j)	Unit (i) 2	3	4	6	7	8	9	10	$\sum_{i=1}^{N} P_{ij}$	Start-Up cost ($)	Fuel Cost ($)	Total Cost ($)
1	400	0	0	185.26	0	351.37	0	88.369	1025	0	9670.1	9670.1
2	400	0	0	179.91	0	335.58	0	84.505	1000	0	9446.7	9446.7
3	357.57	0	0	167.95	0	296.63	0	77.848	900	0	8561.1	8561.1
4	332.17	0	0	162.25	0	279.11	0	76.467	850	0	8123.3	8123.3
5	315.25	0	216.73	142.82	0	270.87	0	79.337	1025	1480	10080	11560
6	289.56	0	199.4	144.78	0	271.46	407.19	87.615	1400	2200	14058	16258
7	344.59	329.52	280.8	172.3	0	323.06	404.57	115.16	1970	2100	19841	21941
8	400	287.68	414.35	200	0	375	562.92	160.05	2400	0	23816	23816
9	346.46	380.35	363.79	173.23	433.08	324.81	645.68	182.58	2850	2300	28887	31187

Table 3. contd...

Table 3. contd...

10	400	436.26	420	200	352.9	375	752.79	213.04	3150	0	31702	31702
11	400	479.89	420	200	390.81	375	806.43	227.88	3300	0	33221	33221
12	400	509.46	420	200	416.58	375	841.46	237.5	3400	0	34243	34243
13	400	472.64	420	200	384.49	375	797.5	225.38	3275	0	32966	32966
14	400	379.16	420	200	302.23	375	680.59	193.02	2950	0	29706	29706
15	400	299.53	420	200	264.25	375	577.2	164.02	2700	0	27262	27262
16	400	259.84	375.37	200	264.28	375	525.9	149.61	2550	0	25824	25824
17	400	307.91	420	200	265.63	375	589.05	167.41	2725	0	27504	27504
18	400	451	420	200	365.69	375	770.37	217.94	3200	0	32206	32206
19	400	479.89	420	200	390.81	375	806.43	227.88	3300	0	33221	33221
20	358.59	342.9	376.52	179.3	364.42	336.18	734.79	207.3	2900	0	29334	29334
21	331.25	0	331.32	165.62	414.06	310.55	445.52	126.67	2125	0	21470	21470
22	321.81	0	221.25	160.91	0	301.7	513.6	130.74	1650	0	16326	16326
23	400	0	0	193.39	0	375	331.61	0	1300	0	12573	12573
24	379.42	0	0	173.58	0	316.23	280.78	0	1150	0	11232	11232
* Units 1 and 5 are forced to shut down in order to achieve the most economic schedule.									Total Cost	8080	531273	539353

Table 4

Schedule of Test System #3 for Units 10 Through 18

(The entry of the j^{th} row and the i^{th} column is the output of the i^{th} generator during the j^{th} hour, P_{ij}, in MW)-Units 1 through 9 are off during the entire schedule.

Hour (j)	Unit (i) 10	11	12	13	14	15	16	17	18
1	0	0	76	73.999	0	0	0	155	155
2	0	0	70.808	59.191	0	0	0	155	155
3	0	0	55.608	43.991	0	0	0	147.92	147.88
4	0	0	40.408	28.791	0	0	0	150.65	150.6
5	0	0	51.159	28.84	0	0	0	155	155
6	75.6	75.6	60.264	37.335	0	0	0	154.18	154.18
7	76	76	75.464	52.535	0	0	100	155	155
8	75.601	75.601	75.601	65.816	0	99.475	99.475	154.19	154.19
9	76	76	76	76	100	100	100	155	155
10	76	76	76	76	100	100	100	155	155
11	76	76	76	76	100	100	100	155	155
12	75.982	75.982	75.982	75.982	99.976	99.976	99.976	154.96	154.96
13	76	76	76	76	100	100	100	155	155
14	76	76	76	76	100	100	99.077	155	155
15	75.891	75.891	75.891	75.891	99.506	99.45	79.077	154.78	154.78
16	73.304	73.244	73.187	73.127	79.515	79.459	59.077	153.44	153.44
17	75.314	75.314	75.314	75.314	99.036	98.812	58.448	153.6	153.6
18	75.752	75.752	75.752	75.752	99.674	99.674	78.448	154.49	154.49
19	76	76	76	76	100	100	98.448	155	155
20	76	76	76	76	100	100	100	155	155
21	76	76	76	76	100	97.416	97.3	155	155
22	71.776	71.75	71.725	69.86	100	77.603	77.487	155	155
23	56.576	56.55	56.525	54.66	0	57.603	57.487	151.4	151.4
24	41.376	41.35	41.325	39.46	0	37.603	37.487	139.97	139.87

Table 4 (Continued) - Schedule of Test System #3 for Units 19 Through 26

Hour (j)	Unit (i)							
	19	20	21	22	23	24	25	26
1	155	155	0	0	0	350	350	350
2	155	155	0	0	0	350	350	350
3	147.82	147.77	0	0	0	333.39	347.81	347.81
4	150.57	150.53	0	0	0	332.19	348.13	348.13
5	155	155	0	0	0	350	350	350
6	154.18	154.18	0	0	0	348.16	348.16	348.16
7	155	155	0	0	0	350	350	350
8	154.19	154.19	155.41	91.791	0	348.16	348.16	348.16
9	155	155	194.81	131.19	0	350	350	350
10	155	155	197	129	0	350	350	350
11	155	155	197	149	0	350	350	350
12	154.96	154.96	196.95	109.6	0	349.92	349.92	349.92
13	155	155	197	119	0	350	350	350
14	155	155	191.53	105.39	0	350	350	350
15	154.78	154.78	152.13	98.668	0	349.5	349.5	349.5
16	153.44	153.44	112.73	73.151	0	346.48	346.48	346.48
17	153.6	153.6	104.91	72.606	0	346.84	346.84	346.84
18	154.49	154.49	144.31	90.34	0	348.86	348.86	348.86
19	155	155	183.71	123.84	0	350	350	350
20	155	155	197	149	0	350	350	350
21	155	155	194.68	136.6	0	350	350	350
22	155	155	155.659	114.14	0	350	350	350
23	151.4	151.4	116.259	74.74	0	330.23	341.88	341.88
24	139.74	139.62	76.859	73.458	0	263.59	344.15	344.15

Table 5
Hourly Costs of Test System #3

Hour (j)	Start-Up cost ($)	Fuel Cost ($)	Total Cost ($)
1	0	17627	17627
2	0	17359	17359
3	0	16441	16441
4	0	16142	16142
5	0	16690	16690
6	160	19029	19189
7	100	21561	21661
8	700	29879	30579
9	100	33959	34059
10	0	33959	33959
11	0	34421	34421
12	0	33504	33504
13	0	33728	33728
14	0	33271	33271
15	0	31801	31801
16	0	28953	28953
17	0	29578	29578

Table 5. contd...

Table 5. contd...

18	0	31390	31390
19	0	33506	33506
20	0	34421	34421
21	0	33985	33985
22	0	31597	31597
23	0	25766	25766
24	0	22095	22095
Total	1060	660662	661722

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