Augmented Lagrange Hopfield Network for Economic Emission Load Dispatch Problem with Quadratic Fuel Cost Function

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Abstract

This paper proposes an augmented Lagrange Hopfield Network (ALHN) based method for solving economic emission dispatch (EELD) problem with quadratic fuel function. The ALHN is the combination of augmented Lagrange function and Hopfield neural network in aim to improve performance in terms of convergence speed and getting global optimization. In addition to minimizing electricity generation fuel cost, emission released into the air from thermal plants is also another main objective needs to be minimized. In order to test the performance of the proposed ALHN two systems including a three unit system with one load case and a six unit system with three load cases are employed. The obtained result by the ALHN compared to that from other methods has revealed that the proposed ALHN is a very promising artificial intelligent algorithm for solving economic emission load dispatch problem.

Keywords: *augmented Lagrange function, Hopfield network, economic emission load dispatch, quadratic fuel cost function, two modifications*

Nomenclature

a_i, b_i, c_i :	Cost coefficients of thermal unit i
d_i, e_i, f_i :	Emission coefficients of thermal unit i
B_{ij}, B_{0i}, B_{00} :	Transmission loss formula coefficients
N :	Number of online generating units
P_D :	Total load demand of the system (MW)
P_L :	Total network loss of the system (MW)
P_i :	Output power of unit i (MW)
P_{imin}, P_{imax} :	Lower and upper generation limits of unit i (MW)
w_1, w_2 :	Weights corresponding to the fuel cost and NOx emission objectives.

1. Introduction

A power system mainly consists of thermal plants to supply electricity to load. There is the fact that the fuel cost of generating electricity from the thermal plant is so expensive, leading the electricity price that customers uses to be high. Besides, the thermal plants are one of the main resources of releasing emission in to the air, causing hotter temperature and climate change for the earth. Therefore, the main objective of the economic emission dispatch problem is to minimize both electricity generation fuel cost and emission [1].

Over decades, many methods have been applied for solving EELD problem such as Improved Hopfield Neural Network Model (IHNN) [2], Tabu Search (TS) [3], fuzzy logic controlled genetic algorithm (FCGA) [4], the Non-dominated Sorting

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Genetic Algorithm - II (NSGA-II) [5], Differential Evolution (DE) [6], biogeography-based optimization (BBO) [7], multi-objective differential evolution (MODE) [8], Hybrid Differential evolution-sequential quadratic programming (DE-SQP) and Hybrid Particle Swarm optimization-sequential quadratic programming (PSO-SQP)[9], parallel synchronous PSO algorithm (PSPSO) [10], Cuckoo Search Algorithm (CSA) [11]. Among the methods, the application of IHNN on the EELD problem is the most limited because it can not deal with complicated problem with nonconvex fuel cost function of thermal units. Besides, the IHNN faces to the local optimization with high number of iteration for convergence. In [6] and [8], the EELD has been successfully solved by DE algorithm based methods. DE has been considered a strong tool for solving optimization problem in engineering fields since it could tackle the disadvantage of IHNN, namely considering nonconvex fuel cost function of thermal units; however, the methods requires a careful section of control parameters. Otherwise, the method can fall within the near optimal solution. The difference between DE in [6] and [8] is that MODE in [8] can determine the best compromise solution which can satisfy both cost and emission minimization requirement without using fuzzy mechanism like DE in [6]. The manner enables MODE to reduce the computing procedure and execution time as well. Two hybrid methods employed in [9], DE-SQP and PSO-SQP, are the combination between two individual methods. The advantage of the methods is that they can take advantage of each individual to enhance the solution approaching the global optimization; however, the methods have to cope with the high number of iterations and longer computational time. BBO has been widely and successfully used for solving the EELD problem and obtained superior results to other methods like NSGA-II and Tabu Search. PSO has become a popular method for over decades in electrical engineering especially power system optimization like load dispatch and optimal power flow. Nevertheless, the method needs more improvement performing on the conventional PSO to achieve higher solution. Compared to other meta-heuristic algorithms, CSA can be considered the most efficient method because it gets 100% convergence rate with higher performance than PSO, DE, *etc.*

In this paper, an Augmented Lagrange Hopfield Network is proposed for solving the EELD problem considering power losses in transmission systems and limits on generation of thermal units. The effectiveness of the proposed ALHN has been tested on two systems and the obtained results have been compared to those from other methods reported in the article.

2. Problem Formulation

In the EELD problem, the main task is to determine power output of each of the set of available thermal units so that both electricity generation fuel cost and emission released into the air by the thermal plant are minimized while satisfying load balance constraint and limits on generation of each unit. Mathematically, the problem is formulated as follows:

The objective is to minimize cost and emission:

$$\text{Min} \sum_{i=1}^N F_i = \sum_{i=1}^N (w_1 F_{1i}(P_i) + w_2 F_{2i}(P_i)) \quad (1)$$

where:

$$F_{1i}(P_i) = c_i P_i^2 + b_i P_i + a_i \quad (2)$$

$$F_{2i}(P_i) = f_i P_i^2 + e_i P_i + d_i \quad (3)$$

Subject to:

1. Power balance constraints: sum of all thermal units generation is equal to load demand and power losses in transmission line.

$$\sum_{i=1}^N P_i - P_L - P_D = 0 \quad (4)$$

where power losses P_L can be defined as below.

$$P_L = \sum_{i=1}^{N_1} \sum_{j=1}^{N_1} P_i B_{ij} P_j + \sum_{i=1}^N B_{0i} P_i + B_{00} \quad (5)$$

2. Generator operating limits: power output of each unit should be within its upper and lower generation.

$$P_{i \min} \leq P_i \leq P_{i \max} \quad (6)$$

3. Weight constraint: sum of fuel cost and emission weight factors equal one

$$w_1 + w_2 = 1 \quad (7)$$

$$\text{where} \quad 0 \leq w_1, w_2 \leq 1 \quad (8)$$

3. ALHN for EELD Problem

The augmented Lagrange function L of the problem is formulated as follows:

$$L = \left[\begin{array}{l} \sum_{i=1}^N w_1 F_{1i,me}(P_i) + w_2 F_{2i,me}(P_i) + \lambda (P_D + P_L - \sum_{i=1}^N P_i) \\ + \frac{1}{2} \sum_{k=1}^M \beta (P_L + P_D - \sum_{i=1}^N P_i)^2 \end{array} \right] \quad (9)$$

where λ and β are Lagrangian multiplier associated with power balance and penalty factor associated with power balance constraint, respectively.

The energy function E of the problem described in terms of neurons is determined as:

$$E = \sum_{i=1}^N [w_1 F_{1i,me}(V_i) + w_2 F_{2i,me}(V_i)] + \lambda (P_D + P_L - \sum_{i=1}^N V_i) + \frac{1}{2} \beta (P_D + P_L - \sum_{i=1}^N V_i)^2 + \sum_{i=1}^N \int_0^{V_i} g^{-1}(V) dV \quad (10)$$

The energy function E of the problem is rewritten as follows:

$$E = \sum_{i=1}^N (c_i V_i^2 + b_i V_i + a_i) + \lambda (P_D + P_L - \sum_{i=1}^N V_i) + \sum_{i=1}^N \int_0^{V_i} g^{-1}(V) dV \quad (11)$$

Where:

$$a_i = w_1 a_i + w_2 d_i \quad (12)$$

$$b_i = w_1 b_i + w_2 e_i \quad (13)$$

$$c_i = w_1 c_i + w_2 f_i \quad (14)$$

Form energy function (11), the dynamics of the model for updating neuron inputs are defined as follows:

$$\frac{\partial E}{\partial V_i} = \left\{ (b_i + 2c_i V_i) + \left[V_\lambda + \beta \left(P_D + P_L - \sum_{i=1}^N V_i \right) \right] \left(\frac{\partial P_L}{\partial V_i} - 1 \right) + U_i \right\} \quad (15)$$

$$\frac{\partial E}{\partial V_\lambda} = \Delta P = \sum_{i=1}^N P_i - P_L - P_D \quad (16)$$

$$\frac{\partial P_L}{\partial V_i} = 2 \sum_{j=1}^N B_{ij} V_j + B_{i0} \quad (17)$$

The inputs of neurons at iteration n are updated as follows:

$$U_i^{(n)} = U_i^{(n-1)} - \alpha_i \frac{\partial E}{\partial V_i} \quad (18)$$

$$U_\lambda^{(n)} = U_\lambda^{(n-1)} + \alpha_\lambda \frac{\partial E}{\partial V_\lambda} \quad (19)$$

The outputs of continuous neurons are determined as follows:

$$V_i = g(U_i) = \left(\frac{P_{i\max} - P_{i\min}}{2} \right) [1 + \tanh(\sigma U_i)] + P_{i\min} \quad (20)$$

Where σ is slope of sigmoid function that determines the shape of the sigmoid function and is set to 100 for all test systems.

The output of the multiplier neuron is determined by a transfer function as follows:

$$V_\lambda = g(U_\lambda) = U_\lambda \quad (21)$$

Stopping Criteria: The algorithm of ALHN will be terminated when either maximum error $Err_{\max}$ is lower than a predefined threshold ε or maximum number of iterations $N_{\max}$ is reached.

4. Best Compromise Solution by Fuzzy-Based Mechanism

One of the methods to find the best compromise solution from Pareto-optimal front is fuzzy satisfying method [12]. The fuzzy goal is represented in linear membership function as follows [12]:

$$\mu(F_j) = \begin{cases} 1 & \text{if } F_j \leq F_{j\min} \\ \frac{F_{j\max} - F_j}{F_{j\max} - F_{j\min}} & \text{if } F_{j\min} < F_j < F_{j\max} \\ 0 & \text{if } F_j \geq F_{j\max} \end{cases} \quad (22)$$

Where F_j is the value of objective j ; $F_{j\max}$ and $F_{j\min}$ are maximum and minimum values of objective j , respectively.

For each k non-dominated solution, the membership function is normalized as follows [13]:

$$\mu_D^k = \sum_{i=1}^{N_{obj}} \mu(F_i^k) \bigg/ \sum_{k=1}^{N_p} \sum_{i=1}^{N_{obj}} \mu(F_i^k) \quad (23)$$

where μ_D^k is the cardinal priority of k th non-dominated solution, $\mu(F_i^k)$ is membership function of objective j , N_{obj} is number of objective functions, and N_p is number of Pareto-optimal solutions.

The solution that attains the maximum membership μ_D^k in the fuzzy set is chosen as the 'best' solution based on cardinal priority ranking:

$$\text{Max } \{\mu_D^k; k = 1, 2, \dots, N_p\} \quad (24)$$

5. Results and Discussions

The algorithm of AHLN is run on an Intel 1.8 GHz PC with 4 GB of Ram. The ALHN is tested on two systems. The first and second systems have three and six thermal units, respectively. For termination criteria, the maximum tolerance ε is set to 10^{-4} for all dispatches.

5.1. Test System I

In the section, a system with three thermal units and transmission losses is considered. The data for the system is taken from [5].

The economic dispatch and environmental dispatch are respectively carried out by setting w_1 and w_2 in equation (8) to 1 and 0, and 0 and 1. The result for economic dispatch and emission dispatch obtained by ALHN are respectively reported in Tables 1 and 2 along with that from other methods. The cost, emission and computational time comparison have revealed that the ALHN can get either approximate or higher solution and faster convergence speed than Tabu Search [3], NSGA-II [5] and CSA [11].

For determining the best compromise solution, i.e. solution of economic emission dispatch, w_1 and w_2 in equation (8) are set to from 0 to 1 with unequal step depending on the obtained solution. The set of solutions for the cases is depicted in Figure 1. Fuzzy-Based Mechanism is then used to determine the best compromise and result is given in Table 3. Clearly, ALHN can get better cost and faster execution time than NSGA-II [5] and CSA [11] while the three methods obtain the same emission.

Table 1. Result Comparison for the Economic Load Dispatch for System 1

Unit	Tabu Search [3]	NSGA-II [5]	BBO [7]	CSA[11]	ALHN
P1 (MW)	435.69	435.885	435.195	435.1984	435.2582
P2 (MW)	298.828	299.989	299.972	299.9700	299.9009
P3 (MW)	131.28	129.951	130.662	130.6606	130.6679
Cost (\$/h)	8344.60	8344.60	8344.59	8344.59	8344.5927
Emission (kg/h)	0.09863	0.0986	0.09869	0.09869	0.09869
Cpu (s)	-	-	-	0.09	0.01

Table 2. Result Comparison for the Emission Dispatch for System 1

Unit	Tabu Search [3]	NSGA-II [5]	BBO [7]	CSA[11]	ALHN
P1 (MW)	502.914	505.81	508.576	508.5804	508.4998
P2 (MW)	254.294	252.951	250.446	250.4425	250.5012
P3 (MW)	108.592	106.023	105.724	105.7229	105.7456
Cost (\$/h)	8371.14	8363.63	8365.11	8365.11	8365.06
Emission (kg/h)	0.0958	0.09593	0.09592	0.09592	0.09592
Cpu (s)	-	-	-	0.07	0.015

Table 3. Result Comparison for the Economic Emission Dispatch for System 1

Unit	NSGA-II [5]	CSA [11]	ALHN
P1 (MW)	470.957	470.9502	470.8516
P2 (MW)	280.663	280.7243	280.7948
P3 (MW)	113.675	113.6211	113.6507
Cost (\$/h)	8349.72	8349.722	8349.6957
Emission (kg/h)	0.09654	0.09654	0.09654
Cpu (s)	-	0.09	0.014

Figure 1. Pareto-optimal Front for Fuel Cost and Emission for System I

5.2. Test System II

In the section, a system with six thermal units and without transmission losses is considered. The load demand is 1800 MW. The data of the system including fuel cost function and emission function are taken from [4]. Similar to system 1, three cases of dispatch are performed and the obtained results are indicated in Tables 4, 5 and 6. As observed from table 4, ALHN and CSA have the same cost and whereas FCGAs [4] and CGAs [4] obtain the highest cost. ALHN is the fastest one among the four reported methods. For emission dispatch and economic emission dispatch, ALHN and CSA get the same cost and emission; however, the ALHN is still faster than CSA.

Table 4. Result Comparison for the Economic Dispatch for System 2

Method	CGAs [4]	FCGAs [4]	CSA [11]	ALHN
P ₁ (MW)	222.42	250.49	248.0009	248.01
P ₂ (MW)	190.73	215.43	217.7156	217.72
P ₃ (MW)	95.36	109.92	75.1775	75.191
P ₄ (MW)	555.63	572.84	588.0389	588.03
P ₅ (MW)	367.92	325.66	335.5298	335.52
P ₆ (MW)	367.92	325.66	335.5372	335.537
Cost (\$/h)	16589.05	16585.85	16579.33	16579.33
Cpu (s)	19.66	10.44	0.062	0.01

Table 5. Result Comparison for the Economic Dispatch for System 2

Method	CSA [11]	ALHN
P ₁ (MW)	283.4604	305.5824
P ₂ (MW)	259.3104	305.5923
P ₃ (MW)	126.2102	200
P ₄ (MW)	412.8611	251.4163
P ₅ (MW)	359.0789	368.7037
P ₆ (MW)	359.0789	368.7052
Emission(Kg/h)	2511.9957	2511.9957
Cpu (s)	0.03	0.008

Table 6. Result Comparison for the Economic Emission Dispatch for System 2

Method	CSA [11]	ALHN
P ₁ (MW)	283.4604	283.4531
P ₂ (MW)	259.3104	259.3118
P ₃ (MW)	126.2102	126.2125
P ₄ (MW)	412.8611	412.8607
P ₅ (MW)	359.0789	359.0891
P ₆ (MW)	359.0789	359.0727
Cost (\$/h)	16641.901	16641.904
Emission(Kg/h)	2790.9434	2790.9343
Cpu (s)	0.034	0.009

6. Conclusion

In this paper, a Augmented Lagrange Hopfield Network has been proposed for solving economic emission load dispatch. The ALHN is the combination of augmented Lagrange function and Hopfield neural network in aim to improve performance in terms of convergence speed and getting global optimization. In fact, the proposed ALHN has been tested on two systems with several dispatch including economic dispatch, emission dispatch and economic emission dispatch. The result comparisons are carried out among the ALHN and several methods have shown that ALHN can get either approximate or better solution and faster execution time than all methods reported in the paper. The statement can give the conclusion that the proposed ALHN is very effectiveness and robustness for solving EELD problem.

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