Hopfield Lagrange Network Based Method for Economic Emission Dispatch Problem of Fixed-Head Hydro Thermal Systems

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Abstract. *This paper proposes a Hopfield Lagrange Network (HLN) based method (HLNM) for economic emission dispatch of fixed head hydrothermal systems. HLN is a combination of Lagrange function and continuous Hopfield neural network where the Lagrange function is directly used as the energy function for the continuous Hopfield neural network. In the proposed method, HLN is used to find a set of non-dominated solutions and a fuzzy based mechanism is then exploited to determine the best compromise solution among the obtained ones. The proposed method has been tested on four hydrothermal systems and the obtained results in terms of total fuel cost, emission, and computational time have been compared to those other methods in the literature. The result comparisons have indicated that the proposed method is favorable for solving the economic emission dispatch problem of fixed-head hydrothermal systems.*

Keywords

Economic emission dispatch, fixed head, hopfield Lagrange network, hydrothermal systems.

1. Introduction

The short term hydro-thermal scheduling (HTS) problem is to determine the power generation among the available thermal and hydro power plants so that the total fuel cost of thermal units is minimized over a scheduled time of a single day or a week while satisfying both equality and inequality constraints including power balance, available water, and generation limits of both thermal and hydro plants [1]. In practical systems, thermal power generating stations are the sources of carbon dioxide (CO_2), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) causing atmospheric pollution [2]. Therefore, the optimal scheduling of generation in a hydrothermal system involves the allocation of generation among the hydro and thermal plants to simultaneously minimize the fuel cost and emission level of thermal plants satisfying the various constraints on the hydraulic and system network becomes a practical requirement. In the past decades, several conventional methods have been used to solve the HTS problem neglecting environmental aspects such as lambda-gamma iteration method (LGM) [1], an effective conventional method (ECM) based on Lagrange multiplier theory [3], dynamic programming (DP) [4], Lagrange relaxation (LR) method [5], and decomposition and coordination method [6]. Among these methods, Lagrange multiplier theory based method does not find out optimal solution and it must be used together with other optimization techniques [7] whilethe DP and LR methods are more popular ones. However, the computational and dimensional requirements of the DP method increase drastically with large-scale system planning horizon, which is not appropriate for dealing with large-scale problems [8]. On the contrary, the LR method is more efficient and can deal with large-scale problems. However, the solution quality of the LR for optimization problems depends on its duality gap which is a result of the dual problem formulation and might oscillate, leading to divergence for some problems with operation limits and non-convexity of incremental heat rate curves of the generators. Besides, the other methods require simplifications to solve the original model which may yield sub-optimal solutions [2]. Several optimization techniques have been proposed to deal with the economic emission dispatch problems. A particle swarm optimization and gamma based method (γ-PSO) has been suggested in [1] to solve the problem. Similar to LGM [1], the coordination equations are used in the iterative algorithm to obtain optimal solution in the γ-PSO method. Unlike existing PSO [9], each particle in the method is represented with respect to gamma, leading to easier convergence. Two novel search methods have been presented in [10] for dealing with the problem. Those are hybrid algorithm and heuristic searches with genetic algorithm (GA). Both techniques can achieve convergence with a smallermaximum number of generations. However, the computational time of the heuristic searches with GA is slower than the one of the hybrid algorithm. An improved bacterial foraging algorithm (BFA) has been applied to solve the short-term HTS problem considering the environmental aspects given in [11]. A non-dominated sorting genetic algorithm-II (NSGA II) method [12] has been applied to economic environmental dispatch of fixed head hydrothermal scheduling problem with both convex and non-convex fuel cost and emission functions. Another method based on integration of predator-prey optimization and Powell search method (PPO-PS) [13] has been implemented for solving economic emission dispatch for fixed-head hydrothermal systems. The PPO-PS is a powerful method for solving the problem,however, there are many control parameters in this method and an appropriate selection of penalty parameters for a good performance is really a difficult work This paper proposes a Hopfield Lagrange network (HLN) based method (HLNM) for solving the economic emission dispatch of fixed-head hydrothermal systems. The proposedHLN method is a combination of Lagrange function and continuous Hopfield neural network where the Lagrange function is directly used as the energy function for the continuous Hopfield neural network. In addition, the HLN is developed by applying the augmented Hopfield terms;therefore, HLN can tackle oscillation of conventional Hopfield network and get faster convergence as well as obtain higher quality solutions. There is a fact that the proposed HLN is a family of deterministic algorithms, so it also copes with the limited applicability to objective function not to be differentiable. Consequently, the HLN cannot deal with systems where fuel cost and emission functions are represented as nonconvex curves.In the proposed method, HLN is used to find a set of non-dominated solutions and a fuzzy based mechanism is then exploited to determine the best compromise solution among the obtained ones. The proposed method has been tested on four hydrothermal systems and the obtained results in terms of total fuel cost, emission, and computational time have been compared to those other methods in the literature.

2. Problem Formulation

Consider an electric power system having N1 thermal plants and N2 hydro plants. The problem is to find the active power generation of each plant in the system so as the total generation cost and emission of thermal plants is minimized over an M-schedule period time satisfying power balance, water availability constraint, and generation limits.

2.1. Fuel Cost Objective

The fuel cost function F1 for all thermal units is approximated by a quadratic function as follows [12]:

$$F_1 = \sum_{k=1}^{M} \sum_{i=1}^{N_1} t_k \left\{ a_{fsi} + b_{fsi} P_{sik} + c_{fsi} P_{sik}^2 \right\}, \quad (1)$$

where a_{fsi}, b_{fsi}, cfsiarefuel cost coefficients of thermal plant i; P_{sik} is power output of thermal unit i at subinterval k; t_k is the duration of subinterval k.

2.2. Emission Objective

The atmospheric pollutants such as sulphur oxides (SO_x) and nitrogen oxides (NO_x) caused by fossil-fueled thermal generator can be modeled separately. Each gaseous emission is represented by quadratic function as follows [2]:

$$\mathrm{NO}_{sik} = \alpha_{1si} + \beta_{1si} P_{sik} + \gamma_{1si} P_{sik}^2, \quad (2)$$

$$\mathrm{SO}_{sik} = \alpha_{2si} + \beta_{2si} P_{sik} + \gamma_{2si} P_{sik}^2, \quad (3)$$

$$\mathrm{CO}_{sik} = \alpha_{3si} + \beta_{3si} P_{sik} + \gamma_{3si} P_{sik}^2, \quad (4)$$

and then the total emission can be calculatedas follows [2]:

$$F_2 = w_1 \mathrm{NO}_{sik} + w_2 \mathrm{SO}_{sik} + w_3 \mathrm{CO}_{sik}, \quad (5)$$

where w_1, w_2, and w_3 are positive weighting factors of the individualgaseous emission contribution to the emission objective; α_{1si}, β_{1si}, and γ_{1si} are emission coefficients for NO_x; α_{2si}, β_{2si}, and γ_{2si} are emission coefficients for SO_x; and α_{3si}, β_{3si}, and γ_{3si} are emission coefficients for CO_2.

1) Load Demand Equality Constraint

The total power generation from thermal and hydro plants satisfies the total power demand of the system and transmission losses:

$$\sum_{i=1}^{N_1} P_{sik} + \sum_{j=1}^{N_2} P_{hjk} - P_{LK} - P_{DK} = 0, \quad k = 1, 2, \ldots, M, \quad (6)$$

where the power losses in transmission lines are calculated as follows:

$$P_{LK} = \sum_{i=1}^{N_1+N_2} \sum_{j=1}^{N_1+N_2} P_{ik} B_{ij} P_{jk} + \\ + \sum_{i=1}^{N_1+N_2} B_{0i} P_{ik} + B_{00}, \tag{7}$$

where P_{Dk}, P_{Lk} are load demand, transmission loss during subinterval k, in MW; P_{hjk} is generation output of hydro unit j during subinterval k, in MW; B_{ij}, B_{0i}, and B_{00} are loss formula coefficients of transmission system.

2) Water Availability Constraints

The total water discharge for each hydro plant during the schedule time is fixed:

$$\sum_{k=1}^{M} t_k q_{jk} = W_j, \quad j = 1, 2, \ldots, N_2, \tag{8}$$

where W_j is volume of water available for generation by hydro plant j during the scheduled period, and the water discharge q_{jk} for hydro unit j at subinterval k is determined by:

$$q_{jk} = a_{hj} + b_{hj} P_{hjk} + c_j P_{hjk}^2, \tag{9}$$

where a_{hj}, b_{hj}, c_{hj} are water discharge coefficients of hydro unit j.

3) Generator Operating Limits

The power output of thermal and hydro plants should be limited between their upper and lower boundaries:

$$P_{si\min} \le P_{sik} \le P_{si\max}, \\ i = 1, 2, \ldots, N_1, \; k = 1, 2, \ldots, M. \tag{10}$$

$$P_{hj\min} \le P_{hjk} \le P_{hj\max}, \\ i = 1, 2, \ldots, N_2, \; k = 1, 2, \ldots, M. \tag{11}$$

where $P_{si\max}$, $P_{si\min}$ are maximum and minimum power output of thermal unit i, respectively; and $P_{hj\max}$, $P_{hj\min}$ are maximum and minimum power output of hydro plant j, respectively.

3. HLN for the Problem

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

$$L = \sum_{k=1}^{M} \sum_{i=1}^{N_1} t_k \left(a_{si} + b_{si} P_{sik} + c_{si} P_{sik}^2 \right) \\ + \sum_{k=1}^{M} \lambda_k \left(P_{Lk} + P_{Dk} - \sum_{i=1}^{N_1} P_{sik} - \sum_{j=1}^{N_2} P_{hjk} \right) \\ + \sum_{j=1}^{N_2} \gamma_{hj} \sum_{k=1}^{M} \left(t_k q_{jk} - W_j \right). \tag{12}$$

In Eq. (12) λ_k, γ_{hj} are Lagrangian multipliers associated with power balance and water constraint, respectively. Further:

$$a_{si} = \psi a_{fsi} + (1-\psi)(w_1\alpha_{1si} + w_2\alpha_{2si} + w_3\alpha_{3si}), \tag{13}$$

$$b_{si} = \psi b_{fsi} + (1-\psi)(w_1\beta_{1si} + w_2\beta_{2si} + w_3\beta_{3si}), \tag{14}$$

$$c_{si} = \psi c_{fsi} + (1-\psi)(w_1\gamma_{1si} + w_2\gamma_{2si} + w_3\gamma_{3si}), \tag{15}$$

$$0 \le \psi \le 1, \tag{16}$$

where ψ is weighting factor for combination of objectives [14].

The energy function E of the problem is described in terms of neurons is determined in Eq. (17),

$$E = \sum_{k=1}^{M} \sum_{i=1}^{N_1} t_k \left(a_{si} + b_{si} V_{sik} + c_{si} V_{sik}^2 \right) \\ + \sum_{k=1}^{M} V_{\lambda_k} \left(P_{Lk} + P_{Dk} - \sum_{i=1}^{N_1} V_{sik} - \sum_{j=1}^{N_2} V_{hjk} \right) \\ + \sum_{j=1}^{N_2} V_{\gamma_{hj}} \left(\sum_{k=1}^{M} t_k q_{jk} - W_j \right) \\ + \sum_{k=1}^{M} \left(\sum_{i=1}^{N_1} \int_0^{V_{sik}} g^{-1}(V) dV + \sum_{j=1}^{N_2} \int_0^{V_{hjk}} g^{-1}(V) dV \right), \tag{17}$$

where $V_{\lambda k}$ and $V_{\gamma hj}$ are outputs of the multiplier neurons associated with power balance and water constraint, respectively; V_{hjk}, Vsik are output of continuous neuron hjk, sik representing P_{hjk}, P_{sik}, respectively. The dynamics of the model for updating neuron inputs are defined as follows:

$$\frac{dU_{sik}}{dt} = \frac{\partial E}{\partial V_{sik}} = - \begin{Bmatrix} t_k(b_{si} + 2c_{si}V_{sik}) \\ +V_{\lambda k}\left(\frac{\partial P_{Lk}}{\partial V_{sik}} - 1\right) + U_{sik} \end{Bmatrix} \tag{18}$$

$$\frac{dU_{hjk}}{dt} = \frac{\partial E}{\partial V_{hjk}} = - \begin{Bmatrix} V_{\lambda k}\left(\frac{\partial P_{Lk}}{\partial V_{hjk}} - 1\right) \\ +V_{\gamma hj}\left(t_k \frac{\partial q_{jk}}{\partial V_{hjk}}\right) + U_{hjk} \end{Bmatrix} \tag{19}$$

$$\frac{dU_{\lambda k}}{dt} = +\frac{\partial E}{\partial V_{\lambda k}} = P_{Dk} + P_{Lk} - \sum_{i=1}^{N_1} V_{sik} - \sum_{j=1}^{N_2} V_{hjk} \tag{20}$$

$$\frac{dU_{\gamma hj}}{dt} = +\frac{\partial E}{\partial V_{\gamma hj}} = \sum_{k=1}^{M} t_k q_{jk} - W_j. \tag{21}$$

The inputs of neurons at step n are updated:

$$U_{sik}^{(n)} = U_{sik}^{(n-1)} - \alpha_{si} \frac{\partial E}{\partial V_{sik}}, \tag{22}$$

$$U_{hjk}^{(n)} = U_{hjk}^{(n-1)} - \alpha_{hj} \frac{\partial E}{\partial V_{hjk}}, \tag{23}$$

$$U_{\lambda k}^{(n)} = U_{\lambda k}^{(n-1)} + \alpha_{\lambda k} \frac{\partial E}{\partial V_{\lambda k}}, \tag{24}$$

$$U_{\gamma hj}^{(n)} = U_{\gamma hj}^{(n-1)} + \alpha_{\gamma hj} \frac{\partial E}{\partial V_{\gamma hj}}, \tag{25}$$

where $U_{\lambda k}$, $U_{\gamma hj}$ are inputs of the multiplier neurons; U_{sik} and U_{hjk} are inputs of the neurons sik and hjk respectively; $\alpha_{\lambda k}$, $\alpha_{\gamma h}$ are step sizes for updating of multiplier neurons; α_{si}, α_{hj} are step sizes for updating of continuous neurons.

The outputs of continuous neurons and multiplier neurons:

$$V_{sik} = g(U_{sik}) = (P_{si\max} - P_{si\min})\left(\frac{1+\tanh(\sigma U_{sik})}{2}\right) + P_{si\min}, \quad (26)$$

$$V_{hjk} = g(U_{hjk}) = (P_{hj\max} - P_{hj\min})\left(\frac{1+\tanh(\sigma U_{hjk})}{2}\right) + P_{hj\min}, \quad (27)$$

where σ is slope of the sigmoid functionwhich determines the shape of the sigmoid function. The outputs of multiplier neurons are determined using a transfer function:

$$V_{\lambda k} = U_{\lambda k}, \quad (28)$$

$$V_{\gamma hj} = U_{\gamma hj}, \quad (29)$$

3.1. Initialization

The initial outputs of continuous neurons are set at their middle limits and the multiplier neurons are set as follows:

$$V_{\lambda k}^{(0)} = \frac{1}{N_1}\sum_{i=1}^{N_1} t_k\left(b_{si} + 2c_{si}V_{sik}^{(0)}\right) / \left(1 - \frac{\partial P_{Lk}}{\partial V_{sik}}\right), \quad (30)$$

$$V_{\gamma hj}^{(0)} = \frac{1}{M}\sum_{k=1}^{M} V_{\lambda k}^{(0)}\left(1 - \frac{\partial P_{Lk}}{\partial V_{hjk}}\right) / \left(t_k\frac{\partial q_{jk}}{\partial V_{hjk}}\right). \quad (31)$$

3.2. Stopping Criteria

The algorithm will be terminated when either the 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

The economic emission dispatch of hydrothermal system is a very complex problem due to many variables and objectives. Moreover, three cases of dispatch for each system consisting of economic dispatch, emission dispatch and economic emission dispatch are carried out. For economic dispatch, only fuel cost is minimized while emission is neglected and for emission dispatch, only emission is minimized whereas the fuel cost is neglected. On the contrary, for economic emission dispatch, both fuel cost and emission are considered and the compromise solution for the economic emission dispatch must satisfy both fuel cost and emission objectives. However, the determination of the compromise is not simple since there is a conflict between the two objectives for an optimal solution. In fact, if a solution tends to have good fuel cost, its emission will become worse and vice versa. Consequently, the Fuzzy-Based Mechanism is carried out to determine the best compromise. In the technique, two weight factors associate with fuel objective and emission objective are employed to determine a set of non-dominated solutions and then the cardinal priority of each non-dominated solution is calculated. As a result, solution with the highest value of cardinal priority is chosen as a compromise solution. On the other hand, the set of non-dominated solutions has a significant impact on the determination of the compromise solution. If the number of non-dominated solutions is low, a good compromise can be skipped and if a large number of non-dominated solutions is calculated, the task for obtaining the solution is time consuming. Therefore, the determination of the best compromise is not simple and must be carefully carried out. In this paper, the best compromise solution for the problem is determined using the fuzzy satisfying method [14]. The fuzzy goal is represented in linear membership function as follows [14]:

$$\mu(F_j) = \begin{cases} 1 & \text{if} \quad F_j \le F_{j\min}, \\ \dfrac{F_{j\max} - F_j}{F_{j\max} - F_{j\min}} & \text{if} \quad F_{j\min} < F_j < F_{j\max}, \\ 0 & \text{if} \quad F_j \ge F_{j\max}, \end{cases} \quad (32)$$

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 [15]:

$$\mu_D^k = \sum_{i=1}^{N_{obj}} \mu(F_i^k) / \sum_{k=1}^{N_p}\sum_{i=1}^{N_{obj}} \mu(F_i^k), \quad (33)$$

where μ_D^k is the cardinal priority of $k-th$ non-dominated solution, $\mu(F_j)$ 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 [16]:

$$\text{Max}\left\{\mu_D^k : k = 1, 2, \ldots, N_p\right\}. \quad (34)$$

5. Numerical Results

The proposed method has been tested on four systems where the first system has one thermal and one hydro power plant, the second one consists of one thermal and two hydropower plants, the third and last ones

Tab. 1: Result comparison for the economic dispatch for the first three systems ($\psi = 1, w_1 = w_2 = w_3 = 0$).

System	Method	Fuel cost ($)	Emission (kg)			CPU time (s)
			NO_x	SO_2	CO_2	
1	LGM [2]	96 024.42	14 829.94	44 111.89	247 838.53	-
	EPSO [2]	96 024.61	14 830.00	44 111.98	247 839.50	-
	γ-PSO [2]	96 024.40	14 829.93	44 111.88	247 838.43	-
	HLN	96 024.37	14 834.48	44 112.91	247 696.31	0.92
2	LGM [2]	848.241	575.402	4 986.16	2 951.46	-
	EPSO [2]	848.204	575.513	4 986.00	2 952.00	-
	γ-PSO [2]	847.908	575.477	4 985.74	2 951.65	-
	HLN	848.349	575.261	4 986.42	2 950.19	0.4
3	LGM [2]	53 053.79	28 199.21	74 867.81	454 063.64	-
	EPSO [2]	53 053.79	28 199.21	74 867.80	454 063.56	-
	γ-PSO [2]	53 053.79	28 199.21	74 867.80	454 063.63	-
	HLN	53 051.61	28 556.53	74 954.09	458 621.31	0.32

Tab. 2: Result comparison for the emission dispatch for the first three problems ($\psi = 0, w_1 = w_2 = w_3 = 1/3$).

System	Method	Fuel cost ($)	Emission (kg)				CPU time (s)
			NO_x	SO_2	CO_2	NO_x+SO_2+CO_2	
1	LGM [2]	96488.08	14376.32	44202.36	242406.08	300984.76	-
	EPSO [2]	96488.38	14376.41	44202.51	242407.42	300986.33	-
	γ-PSO [2]	96488.08	14376.32	44202.36	242406.08	300984.76	-
	HLN	96809.80	14267.87	44312.40	241263.61	299843.87	0.49
2	LGM [2]	851.98	571.99	4993.75	2922.82	8488.56	-
	EPSO [2]	853.15	571.73	4995.19	2922.14	8489.06	-
	γ-PSO [2]	851.98	571.99	4993.75	2922.82	8488.56	-
	HLN	851.91	572.00	4993.66	2922.81	8488.47	1.8
3	LGM [2]	54359.64	21739.27	74131.82	373122.57	468993.66	-
	EPSO [2]	54359.66	21739.27	74131.82	373122.57	468993.66	-
	γ-PSO [2]	54359.53	21739.19	74131.68	373121.27	468992.14	-
	HLN	55392.75	19986.58	73824.88	350972.26	444783.71	0.12

have two thermal and two hydropower plants. The data for the thermal and hydro plants in the first three systems are from [3] whereas emission data are from [16]. The data for the last one are from [12]. The proposed method is coded in Matlab 7.2 programming language and run on an Intel 1.8 GHz with 4GB of RAM PC.

5.1. The First Three Systems

The objectives of the test systems in this section include one fuel cost and three emissions of NO_x, SO_2 and CO_2 scheduled in 24 subintervals with one hour for each. For each system, three cases of dispatches are considered including economic dispatch ($\psi = 1, w_1 = w_2 = w_3 = 0$), emission dispatch ($\psi = 0, w_1 = w_2 = w_3 = 1/3$), and economic emission dispatch ($\psi = 0.5, w_1 = w_2 = w_3 = 1/3$). The obtained results from the proposed method for three dispatch cases including economic dispatch, emission dispatch, and economic emission dispatch for the three test systems are compared to those from other methods including LGM, EPSO, and γ-PSO in [2] as given in Tab. 1, Tab. 2, and Tab. 3. For the economic dispatch, the proposed HLN can obtain better total costs than the others except for the System 2 where the cost is slightly higher than for the others. For the emission dispatch, the proposed HLN can obtain less total emission than the others for all test systems. In the economic emission dispatch, there is a trade-off between total cost and emission objectives and the obtained solutions from the methods are non-dominated as in Tab. 3. The total computational time for each system for the three cases is given in Tab. 4. The study in [2] has not reported computer processor and we fail to compare the processor. However, as indicated in Tab. 4 in the paper, HLN is very fast compared to LGM [2], EPSO [2], γ-PSO [2] since HLN has gotten optimal solutions with 1.51 seconds for System 1, 3 seconds for System 2 and 0.740 second for System 3 whereas that time from LGM is 10 seconds higher, from EPSO is about 100 seconds and from γ-PSO is about 40 seconds. Clearly, these methods are time consuming and it is very slow for convergence as compared to HLN. Convergence characteristics obtained by HLN in terms of maximum error and number of iterations for economic dispatch of System 1, System 2 and System 3 are depicted in Fig. 1, Fig. 2 and Fig. 3. Clearly, HLN has obtained the optimal solution with the lowest number of iterations at System 3, 2594 iterations and with the highest number of iterations at System 1, 6263 iterations. Consequently, the convergence time for economic dispatch of the System 1 is the longest meanwhile this time for System 3 is the fastest and they are respectively 0.92 and 0.32 as reported in Tab. 1. The optimized control variables for test System 1 is given in table Tab. A in Appendix section.

Tab. 3: Result comparison for the economic emission dispatch of the first three system ($\psi = 0.5, w_1 = w_2 = w_3 = 1/3$).

System	Method	Fuel cost ($)	Emission (kg)				CPU time (s)
			NO_x	SO_2	CO_2	$NO_x+SO_2+CO_2$	
1	LGM [2]	96421.702	14384.101	44176.312	242456.004	300984.76	-
	EPSO [2]	96421.725	14384.108	44176.324	242456.109	300986.33	-
	γ-PSO [2]	96421.46	14384.03	44176.195	242454.92	300984.762	-
	HLN	96465.712	14328.17	44181.95	241776.424	300286.544	0.1
2	LGM [2]	851.208	572.235	4992.707	2923.986	8488.928	-
	EPSO [2]	851.079	572.264	4992.547	2923.061	8487.872	-
	γ-PSO [2]	852.388	571.97	4994.167	2923.301	8489.438	-
	HLN	850.065	572.723	4991.026	2927.027	8490.776	0.8
3	LGM [2]	54337.014	21745.127	74144.989	373165.02	469025.136	-
	EPSO [2]	54337.027	21745.138	74115.007	373165.186	469025.331	-
	γ-PSO [2]	54336.888	21745.021	74114.821	373163.42	469023.262	-
	HLN	55158.62	20031.652	73731.958	351363.758	445127.368	0.3

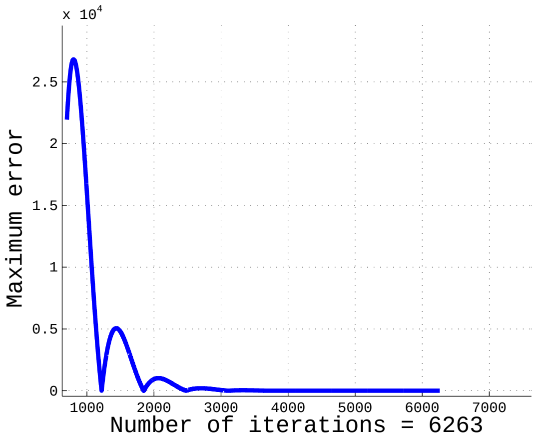

Fig. 1: Convergence characteristic obtained by HLN for economic dispatch of System 1.

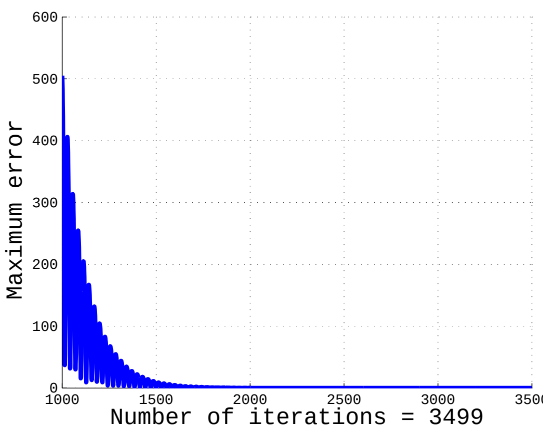

Fig. 2: Convergence characteristic obtained by HLN for economic dispatch of System 2.

5.2. The Fourth System

The test system in this case includes one total cost function and one emission function scheduled in three subintervals with eight hours for each [12]. The proposed HLN method is applied for obtaining the optimal solutions for the economic, emission and economic emission dispatches.

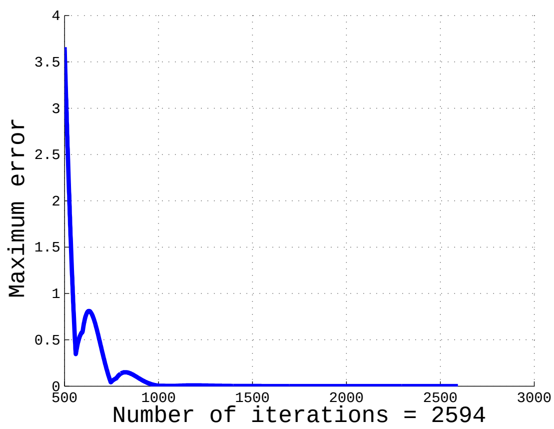

Fig. 3: Convergence characteristic obtained by HLN for economic dispatch of System 3.

Tab. 4: Computational time comparison for the first three systems.

Method	System 1	System 2	System 3
LGM [2]	14.83	11.46	12.26
EPSO [2]	95.36	83.73	105.0
γ-PSO [2]	43.44	39.27	49.01
HLN	1.51	3	0.740

The values of w_1, w_2 and w_3 in Eq. (13), Eq. (14), Eq. (15) are fixed at 1, 0 and 0, respectively. The value of ψ in Eq. (16) is set to one and zero for the economic and emission dispatches, respectively. For the case of economic emission dispatch, we have determined 11 non-dominated solutions to form Pareto optimal front with the change of weight factor ψ from 0 to 1. The best compromise solution from the obtained 11 non-dominated solutions is determined by the fuzzy based mechanism in Section 4. The obtained results in terms of fuel cost, emission and computational time for the three cases from the proposed method are compared to those from PSO, PSO with penalty method (PSO-PM), predator-prey optimization (PPO), PPO with penalty

Tab. 5: Result comparison for the three cases of dispatch of the fourth system.

Method	Economic dispatch		Emission dispatch		Compromise dispatch		
	Cost ($)	CPU (s)	Emis. (lb)	CPU (s)	Cost ($)	Emis. (lb)	CPU (s)
PSO-PM [13]	65741	18.25	585.67	18	65821	620.78	18.98
PSO [13]	65241	18.32	579.56	18.31	65731	618.78	19.31
PPO-PM [13]	64873	16.14	572.71	15.93	65426	612.34	16.53
PPO [13]	64718	15.99	569.73	15.18	65104	601.16	16.34
PPO-PS-PM[13]	64689	15.98	568.78	15.92	65089	600.24	16.15
PPO-PS [13]	64614	15.89	564.92	15.45	65058	594.18	16.74
HLN	64576	0.3	579.12	0.68	64807	617.64	0.74

method (PPO-PM), PPO-PS with penalty method (PPO-PS-PM), and PPO-PS in [13] as given in Tab. 5. As observed from the table, the proposed method can obtain better cost than other methods for the two cases of economic and combined economic emission dispatch. However, HLN gets lower emission than PSO-PM and PSO only and higher emission than rest of methods for emission dispatch and economic emission dispatch. Furthermore, as seen in Tab. 5 HLN has been run under one second for each dispatch case while it has taken from 15 to 20 seconds for other methods. Obviously, HLN is much faster than these methods although no computer has been reported for the methods in [13] and computer processor comparison has not been performed. Figure 4 shows the convergence characteristic obtained by HLN for economic dispatch of the system. Obviously, the applied HLN method can obtain the optimal solution for the case with fewer number ofiterations than that for three systems above and therefore the execution time for the system is shorter than that for the three systems.

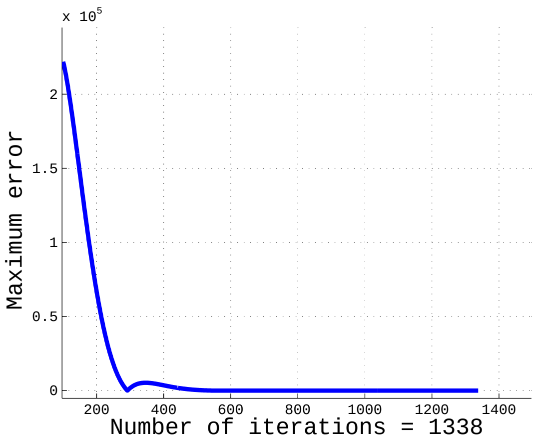

Fig. 4: Convergence characteristic obtained by HLN for economic dispatch of System 4.

6. Conclusions

In this paper, a Hopfield Lagrange network based method has been efficiently implemented for solving the economic emission short-term hydrothermal scheduling problem. The proposed method is a combination of Lagrange function and continuous Hopfield neural network for solving optimal single-objective dispatch problem and a fuzzy based mechanism for obtaining the best compromise solution among several non-dominated solutions. The Hopfield Lagrange network is an improvement of the continuous Hopfield neural network by using the Lagrange function as its energy function. The advantages of the Hopfield Lagrange network are that it is simple, fast, and efficient for solving optimization problems. The proposed method has been tested on four systems with different number of objectives and the obtained results have been compared to those from other methods in the literature. The result comparisons have indicated that the proposed method can obtain better solution than many other methods with shortercomputational time. Therefore, the proposed method can be very favored for solving economic emission dispatch of short-term fixed-head hydrothermal problems.

References

[1] WOOD, A. J. and B. F. WOLLENBERG. *Power Generation, Operation and Control*. 3rd ed. New York: John Wiley & Sons, 1996. ISBN 0-471-58699-4.

[2] SASIKALA, J. and M. RAMASWAMY. PSO Based Economic Emission Dispatch for Fixed Head Hydrothermal Systems. *Electrical Engineering*. 2012, vol. 94, iss. 4, pp. 233–239. ISSN 1432-0487. DOI: 10.1007/s00202-012-0234-x.

[3] RASHID, A. H. A. and K. M. NOR. An Efficient Method for Optimal Scheduling of Fixed Head Hydro and Thermal Plants. *IEEE Transactions on Power Systems*. 1991, vol. 6, iss. 2, pp. 632–636. ISSN 0885-8950. DOI: 10.1007/0.1109/59.76706.

[4] YANG, J. and N. CHEN. Short Term Hydrothermal Coordination Using Multi-Pass Dynamic Programming. *IEEE Transactions on Power Systems*. 1989, vol. 4, iss. 3, pp. 1050–1056. ISSN 0885-8950. DOI: 10.1109/59.32598.

[5] SALAM, M. S., K. M. NOR and A. R., HAMDAN. Hydrothermal Scheduling Based Lagrangian Relaxation Approach to Hydrothermal Coordination. *IEEE Transactions on Power Systems*. 1998, vol. 13, iss. 1, pp. 226–235. ISSN 0885-8950. DOI: 10.1109/59.651640.

[6] LI, C., A. J. SVOBODA, C. L. TSENG, R. B. JOHNSON and E. HSU. Hydro Unit Commitment in Hydro-Thermal Optimization. *IEEE Transactions on Power Systems*. 1997, vol. 12, iss. 2, pp. 764–769. ISSN 0885-8950. DOI: 10.1109/59.589675.

[7] BENHAMIDA, F. and R. BELHACHEM. Dynamic Constrained Economic/Emission Dispatch Scheduling Using Neural Network. *Advances in Electrical and Electronic Engineering*. 2013, vol. 11, no. 1, pp. 1–9. ISSN 1804-3119. DOI: 10.15598/aeee.v11i1.745.

[8] DIEU, V. N. and W. ONGSAKUL. Hopfield Lagrange for Short-Term Hydrothermal Scheduling. In: *IEEE Russia Power Tech*. St. Petersburg: IEEE, 2005, pp. 1–7. ISBN 978-5-93208-034-4. DOI: 10.1109/PTC.2005.4524597.

[9] KINCL, Z. and Z. KOLKA. Test Frequency Selection Using Particle Swarm Optimization. *Advances in Electrical and Electronic Engineering*. 2013, vol. 11, no. 6, pp. 507–513. ISSN 1804-3119. DOI: 10.15598/aeee.v11i6.912.

[10] GEORGE, A., M. C. REDDY and A. Y. SIVARAMAKRISHNAN. Multi-Objective, Short-Term Hydro Thermal Scheduling Based on Two Novel Search Techniques. *International Journal of Engineering Science and Technology*. 2010, vol. 2, no. 11, pp. 7021–7034. ISSN 0975-5462.

[11] FARHAT, I. A. and M. E. EL-HAWARY. Multi-Objective Short-Term Hydro-Thermal Scheduling Using Bacterial Foraging Algorithm. In: *Electrical Power and Energy Conference*. Winnipeg: IEEE, 2011, pp. 176–181. ISBN 978-1-4577-0405-5. DOI: 10.1109/EPEC.2011.6070190.

[12] BASU, M. Economic Environmental Dispatch of Fixed Head Hydrothermal Power Systems Using Nondominated Sorting Genetic Algorithm-II. *Applied Soft Computing*. 2011, vol. 11, no. 3, pp. 3046–3055. ISSN 1568-4946. DOI: 10.1016/j.asoc.2010.12.005.

[13] NARANG, N., J. S. DHILLON and D. P. KOTHARI. Multiobjective fixed head hydrothermal scheduling using integrated predator-prey optimization and Powell search method. *Energy*. 2012, vol. 47, iss. 1, pp. 237–252. ISSN 0360-5442. DOI: 10.1016/j.energy.2012.09.004.

[14] SAKAWA, M., H. YANO and T. YUMINE. An Interactive Fuzzy Satisfying Method for Multi-Objective Linear Programming Problems and Its Applications. *IEEE Transactions on Systems Man and Cybernetics*. 1987, vol. 17, no. 4, pp. 654–661. ISSN 0018-9472. DOI: 10.1109/TSMC.1987.289356.

[15] TAPIA, C. G. and B. A. MURTAGH. Interactive Fuzzy Programming with Preference Criteria in Multi-Objective Decision Making. *Computers & Operations Research*. 1991, vol. 18, no. 3, pp. 307–316. ISSN 0305-0548. DOI: 10.1016/0305-0548(91)90032-M.

[16] DHILLON, J. S., S. C. PARTI and D. P. KOTHARI. Fuzzy Decision-Making in Stochastic Multiobjective Short-Term Hydrothermal Scheduling. *Generation, Transmission and Distribution*. 2002, vol. 149, iss. 2, pp. 191–200. ISSN 1350-2360. DOI: 10.1049/ip-gtd:20020176.

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Appendix

Tab. A: Control variables for System 1 with four objective function.

Subinterval	Economic dispatch		Emission dispatch		Economic emission dispatch	
	V_{sk} (MW)	V_{hk} (MW)	V_{sk} (MW)	V_{hk} (MW)	V_{sk} (MW)	V_{hk} (MW)
1	231.8904	235.1858	273.9742	191.3175	262.9423	202.7468
2	203.7237	232.3999	255.0545	178.9122	241.6737	192.7512
3	194.3511	231.4743	248.7678	174.7781	234.6012	189.4216
4	186.8589	230.735	243.7456	171.4712	228.9492	186.7587
5	180.3075	230.0889	239.3563	168.578	224.0081	184.4292
6	199.0364	231.9369	251.91	176.8451	238.1364	191.0863
7	262.0162	238.1735	294.2544	204.5551	285.7133	213.4201
8	372.883	249.2464	369.2893	252.9993	369.7242	252.5449
9	431.1394	255.1173	408.9719	278.2835	414.0031	273.0073
10	440.7196	256.0864	415.5146	282.4302	421.2937	276.3661
11	459.9057	258.0303	428.6318	290.7249	435.9021	283.0872
12	469.5116	259.0052	435.2064	294.873	443.2198	286.4496
13	350.0483	246.9553	353.7829	243.0565	352.3935	244.5063
14	373.8355	249.3421	369.9367	253.4137	370.4474	252.88
15	384.3185	250.3959	377.0649	257.9718	378.4086	256.5668
16	419.6542	253.9568	401.1346	273.3081	405.2662	268.9784
17	484.8987	260.569	445.7479	301.5109	454.9472	291.8319
18	503.1996	262.4327	458.3018	309.395	468.9038	298.2275
19	464.7076	258.5175	431.9177	292.7989	439.5598	284.7682
20	443.5954	256.3775	417.4794	283.6742	423.4827	277.3739
21	397.6752	251.7403	386.1555	263.774	388.5566	261.2612
22	354.8016	247.4318	357.0085	245.1277	355.9999	246.1804
23	312.0972	243.1598	328.071	226.4914	323.6217	231.1235
24	277.1106	239.6738	304.4332	211.1759	297.1317	218.7611