Economic Emission Load Dispatch with Multiple Fuel Options Using Hopfield Lagrange Network

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Abstract

In this paper, a Hopfield Lagrange network (HLN) is proposed for solving economic emission load dispatch (EELD) problem with multiple fuel options (MFO). Economic load dispatch (ELD) problem with MFO has been solved for recent years. However, it is more realistic to add CO2 emission to objective of ELD problem because generating units not only use fuels but also release emissions to the air. Consequently, ELD problem becomes EELD problem. 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. By using equivalent cost function and HLN, the paper proposed an effective method to solve EELD problem with MFO. The proposed method is tested on one test system consisting of ten generating units with various load demands and compared to other methods. In addition, the best compromise from the set of obtained solutions is found and compared to this from lamda-iteration (LI) method. The result comparisons have indicated that the proposed method is a highly effective method.

Keywords: *Hopfield Lagrange network, economic emission load dispatch, multiple fuel options*

Nomenclature

a_{ik}, b_{ik}, c_{ik}:	Cost coefficients for fuel cost function k of unit i
B_{ij}, B_{0i}, B_{00} :	Transmission loss formula coefficients
N:	Number of online generating units
M_i:	Number of fuel cost functions for generating unit i
P_D :	Total load demand of the system (MW)
P_L :	Total network loss of the system (MW)
Pi:	Output power of unit i (MW)
$P_{i,min}$, $P_{i,max}$:	Lower and upper generation limits of unit i (MW)
U_i:	input of continuous neuron i corresponding to the output Vi
U_λ :	input of multiplier neuron corresponding to the out-put V_λ
V_i:	Output of continuous neuron i representing for out-put power P_i
V_λ:	Output of multiplier neuron representing Lagrangian multiplier λ
λ:	Lagrange multiplier associated with power balance
w_1, w_2	Weights corresponding to the fuel cost and CO2 emission objectives.

1. Introduction

The operation cost in power systems needs to be minimized at each time via economic dispatch (ED). In practical power system operation conditions, many thermal generating units, especially those units which are supplied with multiple fuel sources like coal, natural gas, and oil require that their fuel cost functions may be segmented as piecewise quadratic cost functions for multiple fuel options [1]. The ED problem with multiple fuel options is to minimize total fuel cost among the available fuels for each unit while satisfying load demand and generation limits. Nowadays, emission control is also an important objective to considered along with fuel cost and utility planners are trying to improve their operating strategies to reduce pollution [2]. In fact, apart from heat, thermal units produce particulates and gaseous emissions. A number of substances such as CO2, SO2, NOx, dust particles etc. are emitted during the operation of thermal units. Society demands adequate and secure electricity not only at the cheapest possible price, but also at minimum level of pollutant's emission. ELD problem with multi fuel options can be recognized as a multi-objective constrained optimization problem with two conflicting objectives, *i.e.*, the minimum fuel cost and the minimum gaseous emission effects [2].

In the past decades, all conventional methods have been used to solve classical ELD problem with multiple fuel options neglecting environment aspects. The lambda-iteration method [3], base point and participation factors method and gradient method have been employed to solve the simple ELD problem with single quadratic function. The lamda-iteration has been used again and reached best solution compared to others shown in [4]. This method can be valued as a simple and effective one. However, the disadvantage of the method is that value of lamda set up initially. The best solution has gained within 93 trials with various values of lamda and fuel type k are set initially. The simulation time for each trial is short but total time for whole is long. The application of the Hopfield neural network (HNN) [5] with its merit of simplicity has created difficulties in handling some kinds of inequality constraints and dealing with large-scale problems with many constraints. Moreover, the final solution of the HNN method is also sensitive to the choice of penalty factors associated with constraints. For solving the problem by the enhanced Lagrangian neural network (ELANN) [6] method, the dynamics of Lagrange multipliers including equality and inequality constraints were improved to guarantee its convergence to the optimal solutions, and the momentum technique was also employed in its learning algorithm to achieve fast computational time. Both HNN [5] and ELANN [6] were involved a large number of iterations for convergence.

Particle swarm optimization (PSO) [7] has been widely applied in power system optimization problems. Although this technique can generate high-quality solutions within shorter calculation time and stable convergence characteristic than some other methods, it seems to be sensitive to the tuning of some weights or parameters. Self-Adaptive Differential Evolution (SDE) [8] is a good method to solve ELD problem with Valve-Point Effects. The genetic algorithm (GA) [8-10] is critically dependent on the fitness function and sensitive to the mutation and crossover rates, the encoding scheme of its bits, and the gradient of the search space curve leading toward solutions. With a parallel searching mechanism, the evolutionary programming (EP) [11] method has a high probability of finding an optimal solution. The Differential Evolution (DE) [12] algorithm is found to be a powerful evolutionary algorithm for global optimization in many real problems. However, there is no guaranty for this method to always obtain optimal solution. Moreover, the DE method is also slow when dealing with large-scale problems. An augmented Lagrange Hopfield network (ALHN) method [13] is a continuous Hopfield neural network with its energy function based on augmented Lagrange function. The advantages of ALHN over the conventional Hopfield neural network are simpler use, more general applications, faster convergence, better optimal solution, and larger scale of problem implementation. Combining ALHN and equivalent fuel cost coefficients [14] reduces the complex of multiple fuel options problem. Consequently, more constraints have been taken into account in EED problem with multiple fuel options.

As mentioned in [2], a number of substances such as So2, Nox, dust particles etc. are emitted during the operation of thermal units. Therefore, the paper proposes that ELD problem should be added with emission objectives. Finally, in addition to minimizing fuel cost, minimizing emissions is regarded as the second important mission while operating thermal plants. However, there often exists a conflict among the objectives. If only one objective obtains minimum, the minimum for all objectives can not be reached. Thus, finding the best compromise solution for a multi-objective problem is a very important task. One of the methods to find the best compromise solution from Pareto-optimal front is fuzzy satisfying method [13]. In this paper, a simple method based on quadratic programming (QP) and Hopfield Lagrange network has been proposed to solve EELD problem with multi fuel options. In order to demonstrate the effectiveness of HLN proposed method, it is tested on one system consisting of ten generating units with various load demands and compared to other methods in case of economic dispatch. In case of economic-emission dispatch, the set of obtained solutions and the best compromise from the set is found and compared to those from LI method also carried out in the paper.

2. Related Work

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 HLN method, its energy function augmented by Hopfield terms from the continuous Hopfield network could damp out oscillation of the conventional Hopfield network during the convergence process. Consequently, the proposed HLN can overcome the disadvantages of the conventional Hopfield network [5] in solving optimization problems for its simpler implementation, better global solution, faster convergence time, and larger scale applications. It has been used to solve hydrothermal scheduling problem [14] and obtained good solution including computation time, 0.15 seconds for a large scale system with two thermal plants and two hydro plants over 24 intervals scheduling. Then, HLN is developed to solve problem having more complicated input data with inequality function. The development is successful by V.N Dieu *et al.*, in [1, 14].

In paper [14], basing on another study, the authors have proposed equivalent fuel cost function and applied the function to ELD problem with prohibit zone. As a result, good solution has been obtained and compared to those from other methods. However, emission objective is not considered in the paper. Unlike ALHN [1, 14], lamda-iteration has been a classical method for solving many optimal problems for long time. ELD problem with single quadratic cost functions has been solved by LI in [3]. Then, LI has been modified and applied to solve ELD problem with multiple fuel options [4].93 trials have been done, the best solution has been chosen and compared to those from others including ALHN. The comparison has shown that LI is a good method.

In this paper, two methods based on combination of equivalent fuel cost function [15] and HLN [14] and combination of equivalent fuel cost function [15] and LI [3] are proposed to solve ELD problem with piecewise quadratic cost functions. The results are then compared to other methods have demonstrated that the methods are effective. Then, emission is added to the main objective, making ELD problem become economic emission dispatch problem. The best compromise obtained from a set of 11 dominated solutions using HLN and LI are compared and then the comparison has been discussed.

3. Problem Formulation

The objective of the ED problem with multiple fuel options is only to minimize the total cost of thermal generating units. In the EED problem, the objective is to find a suitable fuel for each generating unit in order to minimize both the total cost and the emissions given off from thermal generating while satisfying different constraints including power balance and generation limits.

Mathematically, the problem is formulated as follows:

$$Min\,F = \sum_{i=1}^{N} w_1 F_{1ik}(P_i) + w_2 F_{2ik}(P_i) \tag{1}$$

Where:

$$F_{1i}(P_i) = \begin{cases} c_{i1}P_{i1}^2 + b_{i1}P_{i1} + a_{i1} \\ \quad if\;\; P_{i1}^{\min} \le P_{i1} \le P_{i1}^{\max}\;\; for\; fuel\, 1 \\ \vdots \\ c_{ik}P_{ik}^2 + b_{ik}P_{ik} + a_{ik} \\ \quad if\;\; P_{ik}^{\min} \le P_{ik} \le P_{ik}^{\max}\;\; for\; fuel\; k \end{cases} \tag{2}$$

$$F_{2i}(P_i) = \begin{cases} f_{i1}P_{i1}^2 + e_{i1}P_{i1} + d_{i1} \\ \quad if\;\; P_{i1}^{\min} \le P_{i1} \le P_{i1}^{\max}\;\; for\; fuel\, 1 \\ \vdots \\ f_{ik}P_{ik}^2 + e_{ik}P_{ik} + d_{ik} \\ \quad if\;\; P_{ik}^{\min} \le P_{ik} \le P_{ik}^{\max}\;\; for\; fuel\; k \end{cases} \tag{3}$$

Subject to:

1. Power balance constraints:

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

$$P_{Lk} = \sum_{i=1}^{N_1}\sum_{j=1}^{N_1} P_i B_{ij} P_j + \sum_{i=1}^{N} B_{0i} P_i + B_{00} \tag{5}$$

2. Generator operating limits:

$$P_i^{\min} \le P_{ik} \le P_i^{\max} \tag{6}$$

3. Weight constraint [16]:

$$w_1 + w_2 = 1 \tag{7}$$

4. Implementation of QP-HLN

4.1. Equivalent Fuel Cost and Emission Coefficients

The equivalent fuel cost coefficients for each unit can be calculated via composite generation production cost curve [15] or average value of all fuel cost curves. In this paper, the equivalent fuel cost coefficients and emission coefficients for each unit are based on the average value of their fuel cost and emission curves. The purpose of this task is to make the piecewise quadratic fuel cost and emission functions become linear functions. After solving the first iterative algorithm, the most optimal fuel of each generating unit is found and final best solutions is then also found after running the second iterative algorithm. The equivalent cost coefficients are reformulated as follows:

$$a_{i,me} = \frac{\sum_{k=1}^{M_i} a_{ij}}{M_i} \tag{8}$$

$$b_{i,me} = \frac{\sum_{k=1}^{M_i} b_{ij}}{M_i} \tag{9}$$

$$c_{i,me} = \frac{\sum_{k=1}^{M_i} c_{ij}}{M_i} \tag{10}$$

$$d_{i,me} = \frac{\sum_{k=1}^{M} d_{ij}}{M_i} \tag{11}$$

$$e_{i,me} = \frac{\sum_{k=1}^{M} e_{ij}}{M_i} \tag{12}$$

$$f_{i,me} = \frac{\sum_{k=1}^{M} f_{ij}}{M_i} \tag{13}$$

4.2. HLN Implementation

4.2.1. HLN for Optimal Solutions

After obtaining the appropriate fuel cost and emission curves for each unit, the problem will become a MO-ED problem with the objective as follows:

$$L = \sum_{i=1}^{N} [w_1 F_{1i,me}(P_i) + w_2 F_{2i,me}(P_i)] + \lambda(P_D + P_L - \sum_{i=1}^{N} P_i) \tag{14}$$

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

$$E=\sum_{i=1}^{N}[w_1F_{1i,me}(V_i)+w_2F_{2i,me}(V_i)]+\lambda(P_D+P_L-\sum_{i=1}^{N}V_i)\ +\sum_{i=1}^{N}\int_0^{V_i}g^{-1}(V)dV \quad (15)$$

Where:

$$F_{1i,me}(V_i)=(c_{i,me}V_i^2+b_{i,me}V_i\ +a_{i,me}) \quad (16)$$

$$F_{2i,me}(V_i)=(f_{i,me}V_i^2+e_{i,me}V_i\ +d_{i,me}) \quad (17)$$

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

$$E=\sum_{i=1}^{N}(c_iV_i^2+b_iV_i\ +a_i)+\lambda(P_D+P_L-\sum_{i=1}^{N}V_i)\ +\sum_{i=1}^{N}\int_0^{V_i}g^{-1}(V)dV \quad (18)$$

Where:

$$a_i=w_1a_{i,me}+w_2d_{i,me} \quad (19)$$

$$b_i=w_1b_{i,me}+w_2e_{i,me} \quad (20)$$

$$c_i=w_1c_{i,me}+w_2f_{i,me} \quad (21)$$

Form energy function (18), the dynamics of the model for updating neuron inputs are defined as follows:

$$\frac{\partial E}{\partial V_i}=(b_i+2c_iV_i)-V_\lambda(1-\frac{\partial P_L}{\partial V_i})+U_i \quad (22)$$

$$\frac{\partial E}{\partial V_\lambda}=\Delta P=\sum_{i=1}^{N}P_i-P_L-P_D \quad (23)$$

$$\frac{\partial P_L}{\partial V_i}=2\sum_{j=1}^{N}B_{ij}V_j+B_{i0} \quad (24)$$

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

$$U_i^{(n)}=U_i^{(n-1)}-\alpha_i\frac{\partial E}{\partial V_i} \quad (25)$$

$$U_\lambda^{(n)}=U_\lambda^{(n-1)}+\alpha_\lambda\frac{\partial E}{\partial V_\lambda} \quad (26)$$

The outputs of continuous neurons are determined as follows:

$$V_i=g(U_i)=\left(\frac{P_i^{\max}-P_i^{\min}}{2}\right)[1+\tanh(\sigma U_i)]+P_i^{\min} \quad (27)$$

Where σ is slope of sigmoid function that determines the shape of the sigmoid function [17]. The output of the multiplier neuron is determined by a transfer function as follows:

$$V_\lambda=g(U_\lambda)=U_\lambda \quad (28)$$

4.2.2. Selection of Parameters

By experiment, the value of σ is fixed at 10000 for all test systems. Pairs of α_i and α_λ is differently chosen and vary depending on the data being processed.

4.2.3. Initialization

The algorithm of HLN requires initial conditions for all neurons. For the continuous neurons, their outputs are randomly initialized as follows:

$$V_i^{(0)} = P_D \frac{P_i^{\max}}{\sum_{i=1}^{N} P_i^{\max}} \tag{29}$$

$$U_i^{(0)} = real\left(\frac{\ln\left(\frac{V_i^{(0)} - P_i^{\min}}{P_i^{\max} - V_i^{(0)}} \right)}{2\sigma} \right) \tag{30}$$

$$\Delta P = P_D - \sum_{i=1}^{N} V_i \tag{31}$$

$$V_\lambda^{(0)} = \frac{1}{N} \sum_{i=1}^{N} \frac{b_i + 2c_i V_i^{(0)}}{(1 - \frac{\partial P_L}{\partial V_i})} \tag{32}$$

The initial input of the multiplier neuron is set to its output value:

$$U_\lambda^{(0)} = V_\lambda^{(0)} \tag{33}$$

4.2.4. Termination Criteria

In the proposed HLN network, the errors at step *n* are calculated from the follows:

Constraint errors:

$$\Delta P = \left| \sum_{i=1}^{N_1} V_i - P_L - P_D \right| \tag{34}$$

Iterative errors:

$$\Delta V_i = \left| V_i^{(n)} - V_i^{(n-1)} \right| \tag{35}$$

$$\Delta V_\lambda = \left| V_\lambda^{(n)} - V_\lambda^{(n-1)} \right| \tag{36}$$

The maximum error of the model is determined:

$$Err_{\max} = \max\{\Delta P, \Delta V_i, \Delta V_\lambda\} \tag{37}$$

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.

4.3. Overall Procedure

The first algorithm of the HLN for searching the best fuel is as follows.

Step 1: Determine equivalent cost and emission coefficients for all generating units by using their average value of all fuel cost and emission curves as in Section 4.1.

Step 2: Select parameters for the model in Section 4.2.2.

Step 3: Initialize inputs and outputs of all neurons using (29)-(33) as in Section 4.2.3

Step 4: Set $n = 1$.

Step 5: Calculate dynamics of neurons using (22)-(24).

Step 6: Update inputs of neurons using (25)-(26).

Step 7: Calculate output of neurons using (27)-(28).

Step 8: Calculate errors as in section 4.2.4.

Step 9: If $Err_{max} > \varepsilon$ and $n < N_{max}$, $n = n + 1$ and return to Step 5. Otherwise, print out generation power for ten units and go to the second algorithm.

The second algorithm of the HLN for finding the optimal fuel cost and emission is as follows.

Step 1: Determine appropriate fuel cost and emission curves for each unit based on the optimal solution obtained from the first algorithm.

Step 2- step 9: Calculate similarly as from step 2 to step 9 of the first algorithm.

5. Overall Procedure of QP and lamda-iteration based method

The overall algorithm of the Lamda-iteration is as follows:

Step 1: The average cost and emission functions are obtained from section 4.1

Step 2: Calculate generation powers for each unit using the iterative algorithm [3].

Step 3: Determine appropriate fuel cost and emission curves for each unit based on the optimal solution obtained from step 2.

Step 4: Calculate the most optimal generation powers for each unit using the iterative algorithm [3].

6. Best Compromise Solution by Fuzzy-Based Mechanism

In a multi-objective problem, there often exists a conflict among the objectives. If only one objective obtains minimum, the minimum for all objectives can not be reached. Therefore, finding the best compromise solution for a multi-objective problem is a very important task. To deal with this issue, a set of optimal solutions known as Pareto-optimal solutions is found instead of only one optimal solution. The Pareto optimal front of a multi-objective problem provides decision maker several options for decision making. One of the methods to find the best compromise solution from Pareto-optimal front is fuzzy satisfying method [13]. The fuzzy goal is represented in linear membership function as follows [13]:

$$\mu(F_j) = \begin{cases} 1 & if \quad F_j \le F_j^{\min} \\ \dfrac{F_j^{\max} - F_j}{F_j^{\max} - F_j^{\min}} & if \quad F_j^{\min} \le F_j \le F_j^{\max} \\ 0 & if \quad F_j \ge F_j^{\max} \end{cases} \quad (38)$$

Where F_j is the value of objective j; F_{jmax} and F_{jmin} are maximum and minimum values of objective j, respectively.

For each k non-dominated solution, the membership function is normalized as follows [16]:

$$\mu_D^k = \sum_{i=1}^{Nobj} \mu(F_i^k) \Bigg/ \sum_{k=1}^{Np} \sum_{i=1}^{Nobj} \mu(F_i^k) \quad (39)$$

where μ^k_D is the cardinal priority of kth 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^k_D in the fuzzy set is chosen as the 'best' solution based on cardinal priority ranking:

$$\text{Max } \{\mu^k_D: k = 1, 2, \ldots, N_p\} \quad (40)$$

7. Results and Discussions

The algorithm of HLN and LI are implemented in Matlab 7.2 programming language and executed on an Intel 2.0 GHz PC. For termination criteria, the maximum tolerance Err_{max} is set to 10^{-5} and to 10^{-2} for HLN and LI, respectively. In the section 7.1, the economic dispatch problem corresponding to w_1=1 and w_2=0 is solved by HLN and LI and compared to others. The economic emission dispatch problem is solved by HLN and LI, and then the best compromise from the set of 11 non-dominated solutions is found in the section 7.2.

7.1. Economic Dispatch

In the section, the two proposed methods have been tested on one system consisting of 10 generating units [6], each with two or three piecewise quadratic cost functions representing different fuel types. Total demands are gradually changed from 2,400 MW to 2,700 MW in steps of 100 MW neglecting power loss with the case of economic dispatch *i.e.*, w_1=1, w_2 = 0 in equation (1). The Best solution by HLN and LI are given in tables 1 and 2, respectively. The best total costs (TC) and computational times (CT) obtained compared to those from EALHN [1], HNN [5], ELANN [6], SDE [8], ARCGA [9], IEP [11], DE [12] are given in tables 3-6. Clearly, total cost by HLN and LI nearly equal for all cases. However, HLN has shorter computation time than LI for all cases. The two proposed methods obtain better solutions than HNN [5], ELANN [6], SDE [8], ARCGA [9], IEP [11] and obtain equal quality solutions compared to others at 2,400 MW case. The proposed methods also obtains better solution than others except the EALHN [1], HNN [5], IEP [11] at 2500 MW case. Note the HNN [5] is not satisfied power balance constraint. The proposed methods have slightly higher total cost than others at 2600 MW case. Note the HNN [5] is not satisfied power balance constraint. At 2700 MW load case, HLN and LI get the lower total cost than HNN [5], ELANN [6], SDE [8], ARCGA [9], IEP [11] and nearly equal total cost compared to others at 2700MW case.

Clearly, HNN [5] violates power balance constraint for all cases of load. Furthermore, both fuel cost and computation time by HNN [5] is worse than other methods. ALHN [15] seems to be a good method for solving ELD problem. In fact, it gets good solution for four load cases and takes short computation time. Fuel cost from LI and HLN are nearly equal and equal to those form rest of methods four all cases.

For CPU time, it can be seen that the HLN proposed method is faster than almost methods except ALHN [15]. In this regard, LI is not as effective as HLN. HNN [5] takes the longest time within 60 seconds. ELANN [6] is faster than HNN [5]. However, ELANN [6] is lower than both LI and HLN. Computation time from other methods is not reported, so the comparison is not performed.

Table 1. Best Solutions by HLN for 10-unit System with Case of Economic Load Dispatch (w_1=1, w_2=0)

Unit	P_D=2400 MW		P_D=2500 MW		P_D=2600 MW		P_D=2700 MW	
	Fuel	Gen	Fuel	Gen	Fuel	Gen	Fuel	Gen
1	1	189.7402		206.5192	2	209.7882	2	218.2501
2	1	202.3427		206.4572	1	207.9078	1	211.6626
3	1	253.8953		265.7391	1	269.9145	1	280.7228
4	3	233.0456		235.9531	3	236.9782	3	239.6315
5	1	241.8298		258.0178	1	263.7247	1	278.4973
6	3	233.0456		235.9531	3	236.9782	3	239.6315
7	1	253.2751		268.8635	1	274.359	1	288.5845
8	3	233.0456		235.9531	3	236.9782	3	239.6315
9	1	320.383		331.4875	1	402.7945	3	428.5212
10	1	239.3972		255.0563	1	260.5768	1	274.8669
TP (MW)	2400		2500		2600		2700	
TC ($)	481.7226		526.2388		574.7413		623.8092	
CT (s)	0.124		0.11		0.152		0.225	

Table 2. Best Solutions by LI for 10-unit System with Case of Economic Load Dispatch (w_1=1, w_2=0)

Unit	P_D=2400 MW		P_D=2500 MW		P_D=2600 MW		P_D=2700 MW	
	Fuel	Gen	Fuel	Gen	Fuel	Gen	Fuel	Gen
1	1	189.7403		206.5191	2	209.788	2	218.2499
2	1	202.3426		206.4573	1	207.9078	1	211.6626
3	1	253.895		265.7392	1	269.9146	1	280.7227
4	3	233.0455		235.9532	3	236.9782	3	239.6315
5	1	241.8293		258.0178	1	263.7247	1	278.4972
6	3	233.0455		235.9532	3	236.9782	3	239.6315
7	1	253.2746		268.8636	1	274.3591	1	288.5845
8	3	233.0455		235.9532	3	236.9782	3	239.6315
9	1	320.3829		331.4878	1	402.7945	3	428.5215
10	1	239.3966		255.0563	1	260.5767	1	274.8666
TP(MW)	2399.9978		2500.001		2600		2699.9995	
TC ($)	481.7217		526.239		574.7412		623.8089	
CT (s)	7.84		2.508		6.871		6.221	

Table 3. Comparison of Fuel Cost and CPU Time for Load Demand of 2,400 MW

Method	Total power	Cost ($/h)	CPU time (s)
HNN [5]	2,399.8	481.87	~60
ELANN[6]	2,400	481.74	11.53
SDE [8]	2,400	481.8628	
ARCGA [9]	2,400	481.743	0.85
IEP [11]	2,400	481.779	-
DE [12]	2,400	481.723	-
ALHN [15]	2,400	481.723	0.008
LI	2,399.9978	481.7217	7.84
HLN	2,400	481.7226	0.124

Table 4. Comparison of Fuel Cost and CPU Time for Load Demand of 2,500 MW

Method	Total power	Cost ($/h)	CPU time (s)
HNN [5]	2,499.8	526.13	~60
ELANN [6]	2,500	526.27	12.25
SDE [8]	2,500	526.3232	-
ARCGA [9]	2,500	526.259	0.85
IEP [11]	2,500	526.304	-
DE [12]	2,500	526.239	-
ALHN [15]	2,500	526.239	0.043
LI	2,500	526.239	2.508
HLN	2,500	526.2388	0.11

Table 5. Comparison of Fuel Cost and CPU Time for Load Demand of 2,600 MW

Method	Total power	Cost ($/h)	CT (s)
HNN [5]	2,599.8	574.26	~60
ELANN [6]	2,600	574.41	~9.99
SDE [8]	2,600	574.538	-
ARCGA [9]	2,600	574.405	0.85
IEP [11]	2,600	574.473	-
DE [12]	2,600	574.381	-
ALHN[15]	2,600	574.381	0.047
LI	2,600	574.7412	6.871
HLN	2,600	574.7413	0.152

Table 6. Comparison of Fuel Cost and CPU Time for Load Demand of 2,700 MW

Method	Total power	Cost ($/h)	CT (s)
HNN [5]	2,700	626.12	~60
ELANN [6]	2,699.7	623.88	21.36
SDE [8]	2,700	623.9225	-
ARCGA [9]	2,700	623.828	0.85
IEP [11]	2,700	623.851	-
DE [12]	2,700	623.809	-
ALHN[15]	2,700	623.809	0.057
LI	2699.9995	623.8089	6.221
HLN	2,700	623.8092	0.225

7.2. Determination of the Best Compromise Solution

In the section, the objective is to minimizing both fuel cost and emission. There often exists a conflict among the objectives. If only one objective obtains minimum, the minimum for all objectives can not be reached. Therefore, in order to find the best compromise, the weights w_1 and w_2 in equation (1), respectively, are varied in the range 0-l.0 in step of 0.1 so that their sum is 1.0. The best compromises are found form a ten generating unit system above for four load cases. The fuel cost data of ten units are from [6], the data of CO2 emission are given in Table 7.

The set of 11 non-dominated solutions for load cases of from 2400 MW to 2700 MW found by using HLN and LI algorithms are given in from Tables 8 to 11. The membership value μ_D are also listed in the same table. In the Table 12, the best compromises corresponding to the highest value of membership μ_D for all load cases for both HLN and LI have been shown. At load case of 2400 MW, the best compromises are found at w_1 = 0.9 and w_2 = 0.1 corresponding to μ_D = 0.11 and 0.1086 for HLN and LI respectively. For HLN, the total fuel cost for this case is $484.9916 and the total emission of 4797.629 kg CO2. For LI, the total fuel cost for this case is $484.9959 and the total emission of 4797.669 kg CO2. Clearly, the fuel cost and emission difference between HLN and LI are negligible. The fuel cost and emission corresponding to the best compromises using HLN and LI are nearly equal for the rest of load cases.

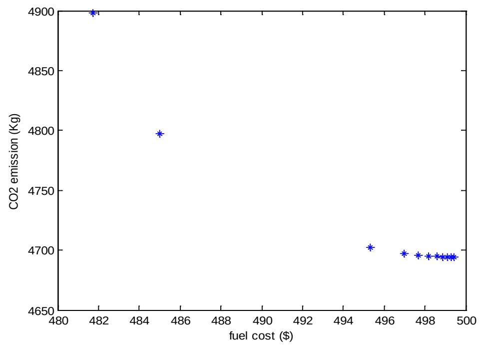

Figure 1. Pareto-optimal front for Fuel Cost and Emission

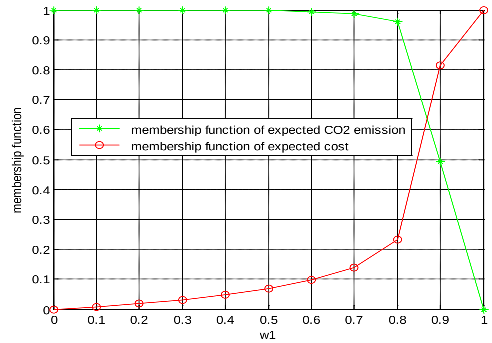

Figure 2. Variation of Membership Functions against Weight w_2=1- w_1 for 2400 MW Case

The Pareto-optimal front for 2400 MW case using HLN is given in Figure 1 and Figure 2 depicts the methodology to determine the best compromise solution based on the relationship between membership function and the weight of objective. Similarly, the best compromise solution for rest of load cases is determined in the same manner of the case.

The computational times for four load cases above are given in Tables 8-11. The total computational time here is the total time for calculation of 11 non-dominated solutions not including determination of the best compromise solution. Clearly, the computational time by HLN is much shorter than those by LI for all cases.

Table 7. The Data of CO2 Emission for Ten Units

Unit i	Fuel k	d_{ik}	e_{ik}	f_{ik}	P_{min}	P_{max}
1	1	323.64	-4.77	0.0264	100	196
1	2	253.56	-3.6708	0.0222	196	250
2	2	18.65	-0.399	0.0115	50	114
2	3	136.5	-1.98	0.016	114	157
2	1	1184	-12.69	0.042	157	230
3	1	358.11	-2.8044	0.01305	200	332
3	3	-25.884	0.3051	0.0072	332	388
3	2	-532.26	4.3776	0	388	500
4	1	13.881	-0.21805	0.00735	99	138
4	2	369.95	-4.4436	0.01925	138	200
4	3	1867.6	-16.366	0.04165	200	265
5	1	122.496	-0.76868	0.00924	190	338
5	2	877.888	-4.58128	0.01408	338	407
5	3	-475.112	3.92656	0.00132	407	490
6	2	35.694	-0.5607	0.0189	85	138
6	1	951.3	-11.4264	0.0495	138	200
6	3	4802.4	-42.084	0.1071	200	265
7	1	159.012	-1.113	0.00924	200	331
7	2	367.668	-1.90428	0.00966	331	391
7	3	-364.14	2.98956	0.0021	391	500
8	1	13.881	-0.21805	0.00735	99	138
8	2	369.95	-4.4436	0.01925	138	200

8	3	1867.6	-16.366	0.04165	200	265
9	3	128.07	-0.16335	0.0054	130	213
9	1	796.77	-5.1075	0.01395	213	370
9	3	128.07	-0.16335	0.0054	370	440
10	1	189.992	-1.35184	0.01496	200	362
10	3	635.256	-2.75264	0.01564	362	407
10	2	-831.368	6.91424	0.00068	407	490

Table 8. Non-dominated Solutions for Load Case of 2400 MW by HLN and LIM

			HLN			LIM		
Case	w_1	w_2	F_1 ($)	F_2 (Kg)	μ_D	F_1 ($)	F_2 (Kg)	μ_D
1	1	0	481.7226	4897.808	0.0841	481.7217	4897.799	0.0824
2	0.9	0.1	484.9916	4797.629	0.11	484.9959	4797.669	0.1086
3	0.8	0.2	495.3181	4702.236	0.1004	495.3151	4702.207	0.1029
4	0.7	0.3	496.9658	4697.012	0.0947	497.0996	4696.729	0.0974
5	0.6	0.4	497.6948	4695.623	0.0918	498.2491	4694.481	0.0934
6	0.5	0.5	498.202	4694.992	0.0897	499.0613	4693.518	0.0903
7	0.4	0.6	498.5751	4694.682	0.088	499.6512	4692.966	0.0881
8	0.3	0.7	498.8611	4694.525	0.0867	500.1061	4692.69	0.0862
9	0.2	0.8	499.087	4694.449	0.0857	500.4697	4692.58	0.0847
10	0.1	0.9	499.2702	4694.416	0.0848	500.7645	4692.535	0.0835
11	0	1	499.4218	4694.407	0.0841	501.0102	4692.545	0.0824
CT (s)			0.798488			77.246008		

Table 9. Non-dominated Solutions for Load Case of 2500 MW by HLN and LIM

			HLN			LIM		
Case	w_1	w_2	F_1 ($)	F_2 (Kg)	μ_D	F_1 ($)	F_2 (Kg)	μ_D
1	1	0	526.2388	5337.84	0.0823	526.239	5337.842	0.0823
2	0.9	0.1	530.3071	5230.867	0.1129	530.3073	5230.868	0.1129
3	0.8	0.2	542.7061	5153.652	0.1013	542.7032	5153.624	0.1013
4	0.7	0.3	544.7893	5147.152	0.0966	544.789	5147.149	0.0966
5	0.6	0.4	546.1429	5144.576	0.0929	546.138	5144.53	0.0929
6	0.5	0.5	547.0897	5143.397	0.09	547.0907	5143.407	0.09
7	0.4	0.6	547.7883	5142.816	0.0878	547.7877	5142.81	0.0878
8	0.3	0.7	548.3248	5142.523	0.086	548.3234	5142.511	0.086
9	0.2	0.8	548.7475	5142.38	0.0845	548.7459	5142.346	0.0846
10	0.1	0.9	549.0922	5142.318	0.0833	549.0939	5142.315	0.0833
11	0	1	549.3774	5142.302	0.0823	549.3788	5142.297	0.0823
CT (s)			0.741316			56.726297		

Table 10. Non-dominated Solutions for Load Case of 2600 MW by HLN and LIM

			HLN			LIM		
Case	w_1	w_2	F_1 ($)	F_2 (Kg)	μ_D	F_1 ($)	F_2 (Kg)	μ_D
1	1	0	574.7413	5777.503	0.0815	574.7412	5777.501	0.0815
2	0.9	0.1	579.2083	5660.883	0.1129	579.2086	5660.885	0.1129
3	0.8	0.2	582.1406	5642.818	0.1102	582.1413	5642.823	0.1102
4	0.7	0.3	596.2253	5577.8	0.0952	594.3471	5577.327	0.0953
5	0.6	0.4	595.5879	5576.207	0.0917	595.7431	5574.675	0.0917
6	0.5	0.5	596.5429	5574.018	0.0889	596.7164	5573.464	0.0889
7	0.4	0.6	597.2485	5573.432	0.0868	597.4373	5572.907	0.0867
8	0.3	0.7	597.7907	5573.135	0.0851	597.9875	5572.614	0.085
9	0.2	0.8	598.2185	5572.991	0.0837	598.4235	5572.48	0.0836
10	0.1	0.9	598.5674	5572.927	0.0825	598.769	5572.354	0.0825
11	0	1	598.8561	5572.911	0.0815	599.0633	5572.366	0.0815
CT (s)			1.175464			60.791237		

Table 11. Non-dominated Solutions for Load Case of 2700 MW using HLN and LIM

			HLN			LIM		
Case	w_1	w_2	F_1 ($)	F_2 (Kg)	μ_D	F_1 ($)	F_2 (Kg)	μ_D
1	1	0	623.8092	6262.249	0.0794	623.8089	6262.245	0.0798
2	0.9	0.1	628.2922	6121.833	0.1193	628.4246	6119.806	0.1188
3	0.8	0.2	633.8512	6103.832	0.1106	634.0017	6102.539	0.1097
4	0.7	0.3	635.7508	6097.909	0.1075	635.9284	6096.541	0.1065
5	0.6	0.4	648.6571	6051.959	0.0888	648.9309	6045.672	0.089
6	0.5	0.5	649.7493	6050.6	0.0863	650.0047	6044.314	0.0865
7	0.4	0.6	650.5564	6049.929	0.0843	650.8035	6043.716	0.0845
8	0.3	0.7	651.1768	6049.59	0.0827	651.4101	6043.375	0.083
9	0.2	0.8	651.6672	6049.424	0.0814	651.8907	6043.213	0.0817
10	0.1	0.9	652.0663	6049.352	0.0803	652.2801	6043.142	0.0807
11	0	1	652.3967	6049.333	0.0794	652.6028	6043.129	0.0798
CT (s)			2.036220			53.921774		

Table 12. The Best Compromises for all Cases of Load form 2400 to 2700 MW

			HLN			LIM		
Load	w_1	w_2	F_1 ($)	F_2 (Kg)	μ_D	F_1 ($)	F_2 (Kg)	μ_D
2400	0.9	0.1	484.9916	4797.629	0.11	484.9959	4797.669	0.1086
2500	0.9	0.1	530.3071	5230.867	0.1129	530.3073	5230.868	0.1129
2600	0.9	0.1	579.2083	5660.883	0.1129	579.2086	5660.885	0.1129
2700	0.9	0.1	628.2922	6121.833	0.1193	628.4246	6119.806	0.1188

8. Conclusion and Future Work

In this paper, the equivalent fuel cost coefficients and emission coefficients for each unit are obtained based on the average value of their fuel cost and emission curves, making the piecewise quadratic fuel cost and emission functions become linear functions. After solving the first iterative algorithm, the most optimal fuel of each generating unit is found and final best solutions is then also found after running the second iterative algorithm. The proposed method has been tested on one system for various load cases for economic dispatch in Section 7.1. The simulation results in terms of fuel cost and computation time compared to those from other methods have shown that HLN is a strongly effective method to solve ELD problem with Multiple Fuel options. Besides fuel cost, emission is added to the objective, making ELD problem becomes EELD problem in the Section 7.2. The best fuel cost and emission by HLN and LI corresponding to the best compromise found and compared to each other have indicated that the two methods have the same quality solutions. However, HLN is more effective than LI through comparisons of the computation time for the set of 11 non-dominated solutions and the maximum tolerance Err_{max}.

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. Therefore, the future work will divide the emission objective into three emission objectives and best compromise solution for two, three and four objectives will be obtained respectively.

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