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Investigation of Conventional and AI Techniques for Online Application to Solve ELD, MED and CEED Problems

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Abstract
In this paper, one conventional and two AI techniques are investigated to find their suitability for ON-LINE application to solve Economic Load Dispatch (ELD), Minimum Emission Dispatch (MED) and Combined Economic and Emission Dispatch (CEED) problem. In this paper, three techniques, Classical Lambda Iteration method, Particle Swarm Optimization (PSO) and Hopfield Neural Network (HNN) are applied to obtain ELD, MED and CEED problem solutions for three, six and fifteen unit test systems. The results obtained show the superiority of HNN technique over the other two techniques. The solutions obtained are quite encouraging. The algorithm and simulations are carried out using MATLAB software.
Keywords: ELD, MED, CEED, Conventional Lambda Technique, Particle Swarm Optimization (PSO), Hopfield Neural Network (HNN), Price Penalty Factor-PPF.

I. Introduction

One of the most important problems in electric power systems is the operation of power system at minimum cost. This problem, known as Economic Load Dispatch (ELD), minimizes system cost by properly allocating the real power demand amongst the online generating units. Economic load dispatch is one of the principal functions of energy management systems.

The main objective of the ELD problem is to determine the optimum combination of power outputs of all generating units which minimizes the total fuel cost while satisfying the system constraints. The objective of Emission Dispatch problem is to minimize the total environmental degradation of the power system while satisfying the system constraints. Both the objectives of Economic Dispatch and Emission Dispatch problems are considerably different, as the ELD problem deals with minimizing the total fuel cost at an increased emission level whereas MED deals with minimizing the emission level at an increased system operating cost. Therefore, there should be an operating point that strikes a balance between the cost and emission. This is achieved by Combined Economic and Emission Dispatch (CEED) problem.

The objective of CEED problem is to minimize the total operating cost of the power system while satisfying demand and generating limit constraints. The bi-objective CEED is converted into a single optimization problem by introducing a term called Price Penalty Factor.

The proposed techniques are applied to obtain ELD, MED and CEED solutions of three test systems (3-Gen., 6-Gen. and 15-Gen. Unit Test Systems). Investigation of these three techniques is carried out w.r.t Total Operating Cost, Total Emission, Minimum Emission, System Losses and Computation- Time.

II. Problem Formulation

A. Economic Dispatch Formulation

Consider a power generation system with 'i' generators. The ELD problem is to find the optimal combination of power generation that minimizes the total cost while satisfying the total demand. The cost function of ELD which is to be optimized is defined as follows:

$$F = \sum_{i} f_i(P) = (a_i P_i^2 + b_i P_i + c_i) \qquad (1)$$

where F is the total fuel cost in Rs/hr, $f_i(P_i)$ is the cost of the i^{th} generator in Rs/hr; P_i the power output of generator i in MW; a_i, b_i and c_i are the cost coefficients of the i^{th} generator.

B. Emission Dispatch Problem

The total emission of atmospheric pollutants caused by fossils-fuelled thermal units can be expressed as

$$E = \sum_{i} (\alpha_i P_i^2 + \beta_i P_i + \gamma_i) \qquad (2)$$

where E is the total emission level in Kg/hr, α_i, β_i and γ_i are the emission coefficients of the i^{th} generator.

C. Problem Constraints

For stable operation of power system, the power output of each generator is restricted within its lower and upper limits, i.e.,

$$P_{i\,min} \le P_i \le P_{i\,max} \qquad (3)$$

And the total active power generation must balance the predicted load demand plus losses, at each time interval over the scheduling time horizon.

$$\sum P_i = P_D + P_L \qquad (4)$$

D. Combined Economic and Emission Dispatch Problem

The bi-objective CEED problem, which minimizes the total operating cost, is converted into single optimization problem by introducing Price Penalty Factor, h. The price penalty factor is the ratio between the maximum fuel cost and maximum emission of the corresponding generator.

$$h_i = F\,(P_{i\,max}) / E\,(P_{i\,max}) \quad i=1,2\ldots.n \qquad (5)$$

III. Particle Swarm Optimization (PSO)

In 1965, Kennedy and Eberhart [1995] first introduced the Particle Swarm Optimization (PSO) method, motivated by social behavior of organisms such as fish schooling and bird flocking.PSO, as an optimization tool, provides a population – based search procedure in which individuals called particles change their positions (states) with time. In a PSO system particles lie around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighboring particles, making use of the best position encountered by itself and its neighbors. The swarm direction of a particle is defined by the set of particles neighboring the particle and its history experience.

PSO Algorithm

Step1: Initial Swarm and velocities of each particle/agent are randomly generated within the allowable search range. The current searching point is set to pbest (particle best) for each agent. The best evaluated value of pbest is set to gbest (global best).

Step2: The objective function value is calculated for each agent/particle. If the current value is better than previous pbest of the particle, then the pbest value is replaced by the current value. If the best value of pbest is better than the previous gbest, the gbest is replaced by the current gbest value.

Step3: The current searching point of each agent/particle is changed using

$$v_{ij}^{r+1} = w^*v_{ij}^{r} + C_1{}^*R_1{}^*(Pb_{ij}^{r} - P_{ij}^{r}) + C_2{}^*R_2{}^*(G_j^{r} - P_{ij}^{r}) \qquad (6)$$

i=1,2,……,NP;

j=1,2,…….NG.

$$P_{ij}^{r+1} = P_{ij}^{r} + v_{ij}^{r+1} \qquad (7)$$

In general, the inertia weight w is set according to the following equation:

$$w = w^{max} - \frac{w^{max} - w^{min}}{IT^{max}} * IT \qquad (8)$$

where,

IT^{max} is the maximum number of iterations (generations), and IT is the current number of iterations.

Step4: Check the Stopping Criterion.

IV. Modified Hopfield Neural Network

In this paper, a Modified Hopfield Neural Network Method is employed with Linear Input-Output Function. The Power mismatch (Pm), can be predetermined at any small value one expects such that the dynamic equation of a neuron has the merit that it is not related to any other neurons. Consequently, each neurons dynamic performance can be simply described using a first order differential equation.

To solve the CEED problem without Losses using Modified HNN Method, energy function including both power mismatch (P_m), and total operating cost F_t is defined as follows:

$$E = (D/2)[(P_D+P_L)-\sum P_i]^2 + (G/2) \sum(A_iP_i^2+B_iP_i+C_i)$$

$$E = (D/2)P_m^{\,2} + (G/2)\,\phi \qquad (9)$$

where, $A_i = a_i + h\alpha_i$

$B_i = b_i + h\beta_i$ and $C_i = c_i + h\gamma_i$

$$\frac{d\phi(P_i)}{dP_i} = 2A_iP_i + B_i \qquad (10)$$

D and G are positive weighting factors. By comparing (9) with the energy function of the conventional HNN, we get

$T_{ii} = -D-GC_i$ (11)

$T_{ij} = -D$ (12)

$I_i = DP_D – GB_i/2$ (13)

The dynamic equation of a neuron is given as

$$\frac{dU_i}{dt} = \sum_j T_{ij} P_j + I_i \quad (14)$$

Substituting (11), (12) and (13) into (14) the dynamic equation becomes

$$dU_i / dt = DP_m - (G/2)(d\phi_i / dP_i) \quad (15)$$

The dynamic equation is obtained by substituting eq.10 into eq. 15

$$dUi/ dt= DP_m-(G/2) [B_i + 2A_i(K_{1i}U_i+ K_{2i})]$$

$$=K_{3i}\ U_i +K_{4i} \quad (16)$$

where $K_{3i} = -GC_i\ K_{1i} =-GA_i(P_{imax} -P_{imin})/ (U_{max}-U_{min})$

$K_{4i} =DP_m-(G/2) B_i- GA_iK_{2i}$

Here, K_{3i} has relation to decaying speed, and its value is negative. Solving (16), the neurons input function, $U_i(t)$ is obtained as

$U_i(t)= [U_i(0)+(K_{4i}/K_{3i})]e^{K3it} +(-K_{4i}/K_{3i})$ (17)

The neurons output function, $P_i(t)$, is obtained as

$P_i(t)= (K_{1i}\ U_i(0) + K_{2i}- [(2K_{AB}P_m - B_i)/(2A_i)])e^{k3it} + [(2K_{AB}P_m-B_i)/(2A_i)]$ (18)

where $K_{AB} = A/B$.

Because of $K_{3i}< 0$ the exponential term on the right side of the above Eqn. (8.11) is of transient existence. This term decays exponentially and finally becomes vanishingly small eventually setting $t=\infty$ for (18) then

$P_i(\infty)= (2K_{AB}P_m -B_i)/2A_i$ (19)

Here $P_i(\infty)$ represents the optimal generation level for unit i. The power mismatch P_m which is defined as the power demand less the total generating power is expressed as

$P_m = [P_D+ (1/2)\sum(B_i/A_i)] / [K_{AB}\sum(1/A_i)+1]$

Appropriately selecting K_{AB} , we have

$K_{AB}\sum(1/A_i) >>1$

Finally, an useful approximate formula for P_m can be written as

$P_m =[P_D+ (1/2)\sum(B_i/A_i)] / [K_{AB}\sum(1/A_i)]$

V. Results and Analysis

Case1: 3-Generating Unit Test System

The 3-Gen. Unit Test System consists of three generators with a load demand of 500 MW [16].Owing to the limit of space, the parameters of the units and the B loss coefficients matrix cannot be listed.

Table 1: Results of ELD without Losses for a Power Demand of 500 MW

P_D (MW)	Description	Λ method	PSO	HNN
500	**Total Cost (Rs./hr)**	24924.1263	24580.1364	24924.1218

Computation-Time in Seconds	
Conventional Lambda Method	0.047506
Particle Swarm Optimization	0.23164
Hopfield Neural Network	0.007342

P_D (MW)	Gen. Unit No.	λ-Method	PSO	HNN
500	P_{G1}	97.2251	92.5867	97.22505
	P_{G2}	210.159	236.4381	210.1589
	P_{G3}	192.616	181.643	192.6159

Table 2: Results of ELD with Losses for a Power Demand of 500 MW

P_D (MW)	Description	λ-Method	PSO	HNN
500	**Total Cost (Rs./hr)**	25467.3289	23074.777	25465.4307
	Loss (MW)	11.9933	8.8139	11.9143
Computation-Time in Seconds				
Conventional Lambda Method		0.049058		
Particle Swarm Optimization		0.564688		
Hopfield Neural Network		0.038041		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
500	P_{G1}	99.80379	83.086	105.8804
	P_{G2}	214.4906	297.73	212.7289
	P_{G3}	197.6889	137.62	193.3042

Table 3: Results of MED without Losses for a Power Demand of 500MW

P_D (MW)	Description	λ-Method	PSO	HNN
500	**Total Emission (Kg/hr)**	296.8268	300.0031	296.7952
Computation-Time in Seconds				
Conventional Lambda Method		0.0605		
Particle Swarm Optimization		0.2387		
Hopfield Neural Network		0.0163		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
500	P_{G1}	129.8752	126.7495	128.0191
	P_{G2}	185.0624	196.8482	185.9904
	P_{G3}	185.0624	178.7558	185.9904

Table 4: Results of MED with Losses for a Power Demand of 500MW

P_D (MW)	Description	λ-Method	PSO	HNN
500	**Total Emission (Kg/hr)**	311.082	308.7924	311.0773
	Loss (MW)	11.6787	9.0963	11.6727
Computation-Time in Seconds				
Conventional Lambda Method		0.0589		
Particle Swarm Optimization		0.6011		
Hopfield Neural Network		0.043		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
500	P_{G1}	130.9659	84.6997	131.5437
	P_{G2}	190.3562	186.9572	190.264
	P_{G3}	190.3562	243.671	189.864

Table 5: Results of CEED without Losses for a Power Demand of 500MW

P_D (MW)	PPF (h) in Rs./Kg	Description	λ-Method	PSO	HNN
500	44.806	**Total Cost (Rs./hr)**	38264.488	37655.0977	38264.478
Computation-Time in Seconds					
Conventional Lambda Method			0.038223		
Particle Swarm Optimization			0.346507		
Hopfield Neural Network			0.004942		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
500	P_{G1}	124.9274	133.5104	124.9274
	P_{G2}	188.3903	170.663	188.3902
	P_{G3}	186.6823	197.802	186.6823

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Table 6: Results of CEED with Losses for a Power Demand of 500MW

P_D (MW)	PPF (h) in Rs./Kg	Description	λ-Method	PSO	HNN
500	44.806	**Total Cost(Rs./hr)**	39436.9253	39479.9062	39436.0592
		Loss (MW)	11.7035	11.7043	11.6935
Computation-Time in Seconds					
Conventional Lambda Method			0.03883		
Particle Swarm Optimization			0.396325		
Hopfield Neural Network			0.039649		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
500	P_{G1}	127.8382	129.91	128.8256
	P_{G2}	192.7562	192.30	192.5791
	P_{G3}	191.109	189.90	190.2853

Analysis: From case 1, it is observed that PSO technique provides better result in terms of total cost, reduced losses when compared to other two techniques for ELD, MED problems. In case of MED, PSO provides better emission than PSO and Conventional Lambda technique. For practical application HNN technique provides a better result in terms of total cost, reduced system losses as well as computationally fast.

Case 2: 6- Generating Unit Test System

An IEEE-30 bus system is considered, which consists of 6 generators for a Power Demand of 900MW. The system parameters, Loss Coefficients are presented in [17].

Table7: Results of ELD without Losses for a Power Demand of 900 MW

P_D (MW)	Description	λ-Method	PSO	HNN
900	**Total Cost(Rs./hr)**	45464.157	45399.9543	45464.1521
Computation-Time in Seconds				
Conventional Lambda Method		0.032178		
Particle Swarm Optimization		0.315269		
Hopfield Neural Network		0.009853		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	32.4969	41.449	32.4969
	P_{G2}	10.81598	20.947	10.81597
	P_{G3}	143.6467	224.3	143.6467
	P_{G4}	143.0317	136.45	143.0316
	P_{G5}	287.1036	275.31	287.1036
	P_{G6}	282.9051	209.94	282.9051

Table 8: Results of ELD with Losses for a Power Demand of 900 MW

P_D (MW)	Description	λ-Method	PSO	HNN
900	**Total Cost (Rs./hr)**	47065.5716	44982.3142	47035.1907
	Loss (MW)	32.931	29.4422	31.7216
Computation-Time in Seconds				
Conventional Lambda Method		0.04087		
Particle Swarm Optimization		0.754222		
Hopfield Neural Network		0.038594		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	33.67818	41.666	38.34618
	P_{G2}	12.51721	24.937	21.38999
	P_{G3}	150.0723	161.65	163.4752
	P_{G4}	148.1109	124.32	152.8626
	P_{G5}	295.6356	314.34	283.5868
	P_{G6}	292.9168	309.89	272.0664

Table 9: Results of MED without Losses for a Power Demand of 900 MW

P_D (MW)	Description	λ-Method	PSO	HNN
900	**Total Emission (lb/hr)**	698.5438	701.046	646.1284
Computation-Time in Seconds				
Conventional Lambda Method		0.03446		
Particle Swarm Optimization		0.32018		
Hopfield Neural Network		0.00902		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	55.58136	105.32	116.9927
	P_{G2}	55.58136	128.39	116.9927
	P_{G3}	161.9423	120.82	135.6939
	P_{G4}	161.9423	126.47	135.6939
	P_{G5}	232.4763	181.2	197.3133
	P_{G6}	232.4763	268.28	197.3133

Table 10: Results of MED with Losses for a Power Demand of 900 MW

P_D (MW)	Description	λ-Method	PSO	HNN
900	**Total Emission (lb/hr)**	679.0766	717.6656	678.9358
	Loss (MW)	24.7979	26.3243	24.5913
Computation-Time in Seconds				
Conventional Lambda Method		0.035832		
Particle Swarm Optimization		0.71995		
Hopfield Neural Network		0.034848		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	121.9083	13.421	124.1611
	P_{G2}	121.9083	62.089	125.1892
	P_{G3}	138.7095	200.47	138.99
	P_{G4}	138.7095	207.2	138.1487
	P_{G5}	201.7811	256.87	199.3437
	P_{G6}	201.7811	189.43	198.7581

Table 11: Results of CEED without Losses for a Power Demand of 900 MW

P_D (MW)	PPF(h) in Rs./Kg	Description	λ-Method	PSO	HNN
900	47.822	**Total Cost (Rs./hr)**	78208.674	78050.8478	78208.6623
Computation-Time in Seconds					
Conventional Lambda Method		0.064037			
Particle Swarm Optimization		0.514841			
Hopfield Neural Network		0.005864			

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	88.63243	92.342	88.63242
	P_{G2}	89.67917	98.81	89.67915
	P_{G3}	144.4325	75.32	144.4325
	P_{G4}	144.3562	115.30	144.3562
	P_{G5}	217.0664	221.18	217.0664
	P_{G6}	215.8333	302.77	215.8332

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Table 12: Results of CEED with Losses for a Power Demand of 900 MW

P_D (MW)	PPF (h) in Rs./Kg	Description	λ-Method	PSO	HNN
900	47.822	**Total Cost (Rs./hr)**	81354.4119	81355.726	81333.9164
		Loss (MW)	26.6391	26.6398	26.3069
Computation-Time in Seconds					
Conventional Lambda Method			0.046405		
Particle Swarm Optimization			0.600675		
Hopfield Neural Network			0.043807		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
900	P_{G1}	92.40464	92.405	95.39424
	P_{G2}	94.02537	94.025	98.86849
	P_{G3}	148.1855	148.19	149.1057
	P_{G4}	148.0321	148.03	147.5048
	P_{G5}	222.5762	222.58	218.8518
	P_{G6}	221.4151	221.42	216.5777

Analysis: From case 2, i.e., 6 Gen. Unit Test System for a power demand of 900 MW, it is observed that PSO technique provides a better cost, reduced system losses when compared to other two techniques for an ELD problem. In case of MED, HNN technique provides better emission than other two techniques. For CEED problem, HNN technique gives better result in terms of total operating cost, minimum emission, reduced losses as well as computationally fast.

Case 3: 15 Generating Unit Test System

15- Generating Unit Test System consists of 15 generators for a Power Demand of 2630 MW.

Table 13: Results of ELD without Losses for a Power Demand of 2630MW

P_D (MW)	Description	λ-Method	PSO	HNN
2630	**Fuel Cost (Rs./hr)**	32257	31792	32257
Run-Time Comparison in Seconds				
Conventional Lambda Method		0.03334		
Particle Swarm Optimization		0.6573		
Hopfield Neural Network		0.0409		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	455	438.04	455
	P_{G2}	455	300.67	455
	P_{G3}	130	106.85	130
	P_{G4}	130	30.115	130
	P_{G5}	271.18	434.06	271.18
	P_{G6}	460	459.76	460
	P_{G7}	465	417.99	465
	P_{G8}	60	68.283	60
	P_{G9}	25	80.735	25
	P_{G10}	25	33.768	25
	P_{G11}	43.389	79.987	43.3887
	P_{G12}	55.431	40.21	55.4311
	P_{G13}	25	35.601	25
	P_{G14}	15	50.241	15
	P_{G15}	15	54.454	15

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Table 14: Results of ELD with Losses for a Power Demand of 2630 MW

P_D (MW)	Description	λ-Method	PSO	HNN
2630	**Fuel Cost (Rs./hr)**	32560	32832	32670.6254
	Loss (MW)	28.835	38.615	28.777
Run-Time Comparison in Seconds				
Conventional Lambda Method	0.78400			
Particle Swarm Optimization	1.4167			
Hopfield Neural Network	0.0395			

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	455	275.47	150
	P_{G2}	455	437.72	455
	P_{G3}	130	101.69	130
	P_{G4}	130	118.38	130
	P_{G5}	297.53	440.73	470
	P_{G6}	460	322.53	460
	P_{G7}	465	399.32	465
	P_{G8}	60	166.85	60
	P_{G9}	25	136.98	25
	P_{G10}	25	37.663	98.7769
	P_{G11}	44.895	54.414	80
	P_{G12}	56.411	72.638	80
	P_{G13}	25	76.121	25
	P_{G14}	15	32.54	15
	P_{G15}	15	16.364	15

Table 15: Results of MED without Losses for a Power Demand of 2630 MW

P_D (MW)	Description	λ-Method	PSO	HNN
2630	**Total Emission (lb/hr)**	3427.2905	7933.3166	3427.2902
Run-Time Comparison in Seconds				
Conventional Lambda Method	0.039347			
Particle Swarm Optimization (PSO)	0.682377			
Hopfield Neural Network (HNN)	0.029945			

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	455	434.8853	455
	P_{G2}	368.6461	434.3304	368.646
	P_{G3}	45.15943	78.4912	45.15943
	P_{G4}	130	124.2692	130
	P_{G5}	130	344.487	150
	P_{G6}	150	438.4005	135
	P_{G7}	135	293.1891	369.1944
	P_{G8}	369.1945	204.263	300
	P_{G9}	300	30.4301	162
	P_{G10}	162	156.2781	160
	P_{G11}	160	55.7061	80
	P_{G12}	80	78.8129	80
	P_{G13}	80	62.4025	85
	P_{G14}	85	41.4214	55
	P_{G15}	55	42.4821	55

Table 16: Results of MED with Losses for a Power Demand of 2630 MW

P_D (MW)	Description	λ-Method	PSO	HNN
2630	**Total Emission (lb/hr)**	5770.7112	9058.7713	4384.4285
	Loss (MW)	388.4587	54.2608	387.761
Run-Time Comparison in Seconds				
Conventional Lambda Method		0.823596		
Particle Swarm Optimization (PSO)		1.4679		
Hopfield Neural Network (HNN)		0.041687		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	455	263.191	455
	P_{G2}	455	420.6357	455
	P_{G3}	130	70.4227	130
	P_{G4}	130	108.5654	130
	P_{G5}	191.0303	313.6179	150
	P_{G6}	215.2773	363.6523	135
	P_{G7}	465	457.4283	465
	P_{G8}	300	291.6469	300
	P_{G9}	162	123.9988	162
	P_{G10}	160	134.1981	160
	P_{G11}	80	36.8355	80
	P_{G12}	80	76.6688	80
	P_{G13}	85	28.615	85
	P_{G14}	55	43.9092	55
	P_{G15}	55	16.1217	55

Table 17: Results of CEED without Losses for a Power Demand of 2630MW

P_D (MW)	PPF (h) in Rs./Kg	Description	λ-Method	PSO	HNN
2630	13.2870	**Total Cost(Rs./hr)**	78744.81	105045.88	78744.80
Computation-Time in Seconds					
Conventional Lambda Method			0.05658		
Particle Swarm Optimization			0.50986		
Hopfield Neural Network			0.03197		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	454.8143	390.1487	455
	P_{G2}	366.6624	379.2113	366.5752
	P_{G3}	46.59585	128.8317	46.58659
	P_{G4}	130	127.9059	130
	P_{G5}	150	174.644	150
	P_{G6}	135	269.5435	135
	P_{G7}	369.9274	460.3626	369.8381
	P_{G8}	300	171.8644	300
	P_{G9}	162	158.5007	162
	P_{G10}	160	152.9686	160
	P_{G11}	80	75.5318	80
	P_{G12}	80	48.8405	80
	P_{G13}	85	50.1766	85
	P_{G14}	55	38.7588	55
	P_{G15}	55	45.6668	55

Table 18: Results of CEED with Losses for a Power Demand of 2630MW

P_D (MW)	PPF (h) in Rs./Kg	Description	λ-Method	PSO	HNN
2630	13.2870	**Total Cost (Rs./hr)**	113789.5217	145632.2137	94092.2341
		Loss (MW)	388.4787	145.1269	388.4787
Run-Time Comparison in Seconds					
Conventional Lambda Method			3.2543		
Particle Swarm Optimization			6.1056		
Hopfield Neural Network			0.05617		

P_D (MW)	Gen. Unit No.	λ-Method (MW)	PSO (MW)	HNN (MW)
2630	P_{G1}	455	330.7868	455
	P_{G2}	455	375.7288	455
	P_{G3}	130	121.6557	130
	P_{G4}	130	109.8083	130
	P_{G5}	190.9695	212.6889	150
	P_{G6}	215.4891	452.3237	135
	P_{G7}	465	433.4686	465
	P_{G8}	300	261.3454	300
	P_{G9}	162	87.7303	162
	P_{G10}	160	56.4719	160
	P_{G11}	80	52.4599	80
	P_{G12}	80	52.768	80
	P_{G13}	85	58.9815	85
	P_{G14}	55	47.0678	55
	P_{G15}	55	17.7119	55

Analysis: From case 3, i.e., 15 Gen. Unit Test System for a power demand of 2630 MW, it is observed that for a pure ELD problem PSO technique gives better solution in terms of cost and reduced losses. But computationally, HNN technique is faster than other two techniques. In case of MED problem, HNN technique provides minimum emission, minimum losses as well as computationally fast. For CEED problem, HNN technique gives a better optimum solution in terms of total operating cost, minimum emission level, reduced system losses and faster computation.

VI. CONCLUSIONS

From the case studies, it is observed that for pure ELD problem, the Particle Swarm Optimization (PSO) technique provides a better solution in terms of total cost and reduced system losses. But computationally, HNN technique is faster than other two techniques. For MED problem, PSO technique provides minimum emission in case of small generating unit test systems whereas HNN technique gives minimum emission level for large generating unit test systems. In case of CEED problem, HNN technique provides a better solution w.r.t. total operating cost, minimum emission, reduced system losses as well as computationally fast. Hence, Hopfield Neural Network (HNN) technique is suitable for ON-LINE application of power system whereas for pure ELD problem, PSO technique gives better solution in terms of total cost, reduced system losses.

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