ECONOMIC LOAD DISPATCH BY INTEGRATION OF LAGRANGE NEURAL NETWORK AND FEEDFORWARD NEURAL NETWORK

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Abstract

This paper presents a novel integrated approach to find the load dispatch for economic power generation in a grid of thermal power plants. A synergy of feedforward neural network (FNN) and Lagrange neural network (LNN) has been introduced in an innovative way. Backpropagation algorithm is used for training the FNN. The data required for training and testing FNN is obtained by LNN. Transmission loss, equality and inequality constraints of economic power generation are appropriately considered in the formulation of solution algorithm. The cost of electricity generation by a generating unit is expressed exponentially with respect to active power output of the corresponding generating unit. The generation schedule obtained by LNN is most economical whereas a FNN trained by backpropagation algorithm produced results practically in no time. Therefore, the proposed approach produced most economical results in less computation time.

Keywords: Load Dispatch, Neural Network, Feedforward, Lagrange Neural Network, Back-propagation Algorithm, Equality Constraint, Inequality Constraint.

1. Introduction

In the present age of fast digital computers with large memories various methods and algorithms have been developed to solve some complicated problems. Each method has its own advantages and drawbacks. A method which was considered state-of-the-art few years back now becomes obsolete. Presently for achieving better solution of complex problems, a trend of integrating two or more methods, commonly termed as hybridization, is more common. Hybrid approach deals with the synergetic integration of two or more methods. The general approach in these methods is that first, one or more methods are employed for finding a solution close to optimal value followed by another method which is used to obtain the final optimal value.

It is everyone's social responsibility to ensure that electricity is consumed as effectively as possible. In the midst of development of integrated power systems, dearth of energy resources, day by day increasing demand of electricity, it becomes essential to minimize the running charges of generating the electricity for satisfying a typical load demand [1,3]. In the past several authors and researchers have published papers to find improved solutions in terms of speed, accuracy of results, computer memory, and economy while solving economic load dispatch (ELD) problems using hybrid techniques. Systems based on neural networks (NN) have high computational rates due to the involvement of large number of processing units (neurons) and the high degree of connectivity between them [4]. Ravi *et al*. [8] proposed a hybrid intelligent technique using a NN and evolutionary programming (EP). EP was used to find global ELD solution where as an auto configuring NN was used to speed up the computation. Sendaula *et al.* [9] employed a combination of the Hopfield and the Chua-Lin NN to solve ELD problem and got better results in terms of accuracy and speed. Tsai *et al.* [10] proposed a hybrid Taguchi-Genetic algorithm approach for tuning the structure and parameters of a FNN. Taguchi method was used to improve the results obtained by genetic algorithm. As per authors' claim improved results were obtained when compared to the results obtained by classical existing method. Therefore, in the present paper with the aim of minimizing cost of generation as well as time of computation an integrated approach of LNN and FNN is proposed.

2. Economic Load Dispatch Using Exponential Cost Function

Consider a typical power system consisting of *n* generating units supplying electrical power to a load and compensating transmission loss as shown in Figure-1 [1].

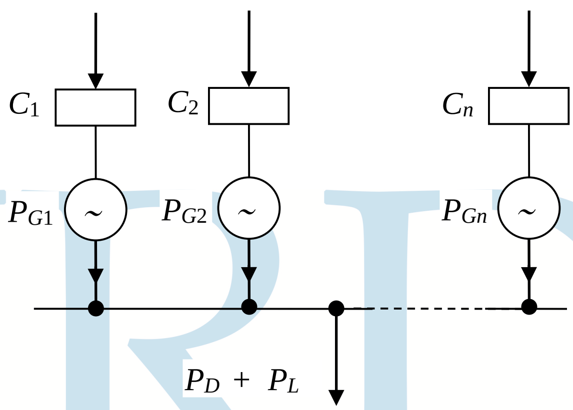


Figure -1 Generating units connected to common bus

Let $C_1, C_2, \dots, C_n$ be the operating costs of individual generating units for the corresponding active power outputs $P_{G1}, P_{G2}, \dots, P_{Gn}$ respectively. If C is the total operating cost of the entire system and P_D is the total power demand, then the problem of ELD can be stated as follows [3],

Minimize,

$$C = C_1 + C_2 + \cdots + C_n = \sum_{i=1}^{n} C_i. \qquad \text{(objective function)} \qquad \dots (2.1)$$

Where C_i is the operating cost corresponding to active power output P_{Gi} for the *i*th generating unit.

$$C_i = \alpha_i \exp(\beta_i P_{Gi}). \ \$/h \quad \text{for } i = 1,2,\dots,n \qquad \dots (2.2)$$

Where α_i and β_i are the constants which are calculated based on the physical and environmental conditions of the system.

Subject to the constraint that power generation should equal total power demands and transmission losses, i.e.,

$$P_D + P_L = P_{G1} + P_{G2} + \cdots + P_{Gn} = \sum_{i=1}^{n} P_{Gi}. \quad \text{(equality constraint)} \qquad \text{... (2.3)}$$

Where P_L is the transmission loss.

The inequality constraints binding by maximum and minimum active power generation are expressed as follows,

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}. \text{ for } i = 1,2, \dots, n \quad \text{(inequality constraint)} \qquad \text{... (2.4)}$$

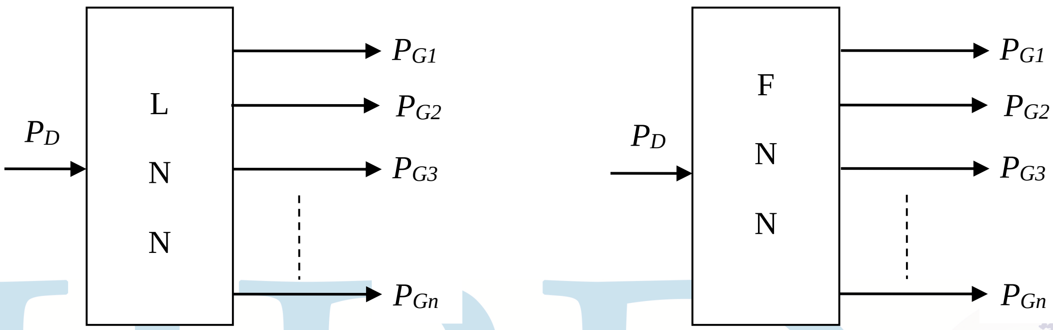
Where P_{Gi}^{max} and P_{Gi}^{min} are respectively the maximum and minimum active power output of the *i*th generating unit [3].

3. Methodology

The proposed integrated approach consists of two stages as shown in Figure-2. In the first stage, an LNN [2,6,12] is employed to find the active power output of generators for a particular load demand [7]. Sufficient number of the training patterns, i.e., input-output combinations of load demand and the output of generators are obtained, by changing the load demand in suitable steps from minimum to maximum generation capacity of generators taking into consideration the transmission losses.

In the second stage, the results obtained by LNN are used to train the FNN. Therefore, the output of LNN becomes the target values. During the training process, the weights of the FNN are modified in such a way that the error between the actual values of generators' output and the target values of generators' output is reduced to predefined minimum value. The trained network acquires the ability to generate the output for any value of load demand.

The Lagrange ANN is a two layer recursive network. The first layer known as the control layer, processes both the equality and inequality constraints while the second layer, known as the computing layer, computes the decision variables [5]. The constraint violations are looped back to adjust the state of the computing layer. The main aim of this neural network is to converge to the Kuhn-Tucker conditions defined for the problem.



(a) LNN used to generate training data

(b) FNN used to generate final results

Figure 2 Lagrange and Feedforward hybrid approach to solve ELD

4. Results and Discussion

Consider a typical power system comprising of six generating units [11]. The coefficients of exponential cost functions along with generators' active power limit are presented in Table-1 and loss coefficients are provided in Table-2.

Table-1 Data for exponential cost functions

Cost of *i*th unit	**Coefficients of Cost Function**	
C_i (\$/h)	**α_i (\$/h)**	**β_i (1/MWh)**
1	400	0.0050
2	200	0.0100
3	100	0.0200
4	600	0.0033

5	70	0.0207
6	45	0.0210

The inequality constraints for generating units are given as,

$10 \text{ MW } \leq P_{Gi} \leq 200 \text{ MW}$ for $i = 1,2,\ldots,6$.

Table-2 Transmission loss coefficient matrix

Bus Numbers	**1**	**2**	**3**	**4**	**5**	**6**
1	0.000200	0.000010	0.000015	0.000005	0.000000	-0.00003
2	0.000010	0.000300	-0.00002	0.000001	0.000012	0.000010
3	0.000015	-0.00002	0.000100	-0.000010	0.000010	0.000008
4	0.000005	0.000001	-0.000010	0.000015	0.000006	0.000050
5	0.000000	0.000012	0.000010	0.000006	0.000250	0.000020
6	-0.00003	0.000010	0.000008	0.000050	0.000020	0.000210

FNN is trained using the training data obtained by LNN. LNN is a sensitive network. Its performance is greatly affected by the choice of learning rate parameters (μ) and (ρ). If these parameters are small, convergence will be extremely slow. On the other hand, oscillations are likely to occur if the parameters are too large. Momentum factor (α) is added to speed up the convergence. Typical values considered for different parameters are as under:

$\alpha = 0.02$, $\xi = 0.004$, $\varepsilon = 0.001$, $\rho = 0.90$, $\mu = 0.5$ to 1.0

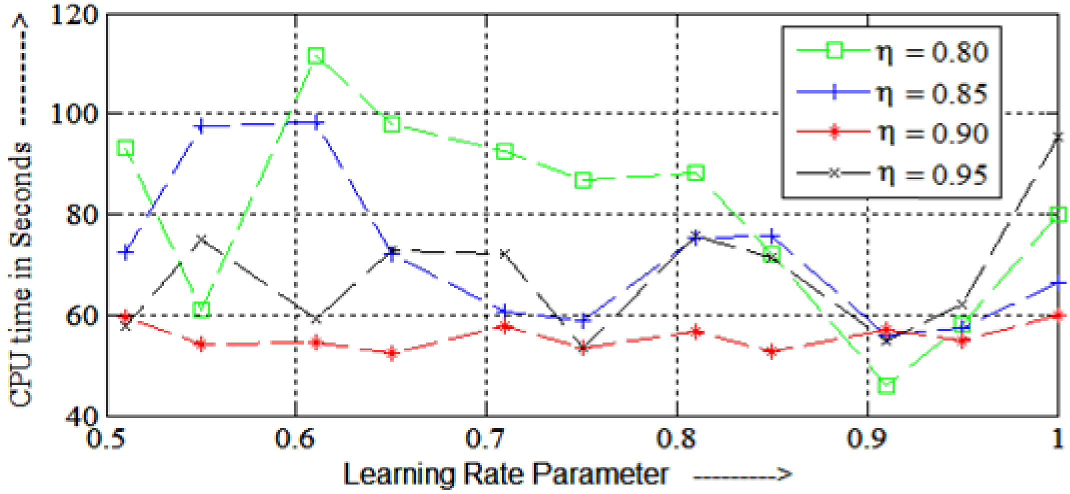


Figure-3 CPU time with learning rate parameter for different values of momentum factor

While training FNN for a given load demand, variation of CPU time w.r.t. learning rate parameter (η) for different values of momentum factor (μ) is shown in Figure-3. It is evident from Figure-3 that time taken by CPU is less for η = 0.90 and it is fairly constant when μ is changed from 0.5 to 1.0. During training phase of FNN, the load on the system is varied from 400 MW to 850 MW with an interval of 50 MW. Table-3 shows the results obtained by LNN and FNN.

Table-3 Results produced by hybrid method

Load (MW)	**P_{G1} (MW)**			**P_{G2} (MW)**			**P_{G3} (MW)**		
	LNN	**FNN**	**Error**	**LNN**	**FNN**	**Error**	**LNN**	**FNN**	**Error**
400	86.80	87.13	-0.082	43.40	44.50	-0.275	21.70	21.70	0.000
450	100.39	99.73	0.147	50.20	50.22	-0.006	25.10	24.71	0.087
500	117.27	17.73	-0.091	58.64	58.61	0.006	29.32	29.24	0.016
550	140.67	140.26	0.075	70.33	69.21	0.204	35.17	35.10	0.012
600	164.23	165.10	-0.145	82.11	81.02	0.183	41.06	41.55	-0.083
650	187.96	187.16	0.123	93.98	94.12	-0.022	46.99	48.10	-0.171
700	200.00	198.09	0.273	110.58	110.74	-0.024	55.29	55.34	-0.007

750	200.00	199.92	0.010	132.07	132.79	-0.096	66.03	64.68	0.180
800	200.00	200.00	0.000	153.74	156.05	-0.289	76.87	76.53	0.042
850	200.00	00.00	0.000	175.60	172.54	0.361	87.80	88.42	-0.072

Table 3 Results Produced by Hybrid Method (Contd.)

P_{G4} (MW)			P_{G5} (MW)			P_{G6} (MW)			P_L (MW)		
LNN	**FNN**	**Error**	**LNN**	**FNN**	**Error**	**LNN**	**FNN**	**Error**	**LNN**	**FNN**	**Error**
163.41	163.05	0.090	36.53	36.21	0.080	56.37	55.94	0.106	8.21	8.92	-0.177
185.34	186.93	-0.354	39.82	39.46	0.080	59.60	59.32	0.064	10.45	10.21	0.054
200.00	197.08	0.585	43.90	44.10	-0.040	63.62	63.98	-0.072	12.75	12.18	0.112
200.00	199.47	0.096	49.55	49.78	-0.042	69.19	69.52	-0.059	14.91	14.79	0.022
200.00	199.90	0.017	55.24	55.79	-0.092	74.80	75.26	-0.076	17.44	17.66	-0.036
200.00	199.97	0.004	60.97	61.87	-0.138	80.45	81.13	-0.104	20.34	20.42	-0.012
200.00	199.99	0.001	68.99	68.81	0.025	88.36	88.06	0.043	23.20	23.09	0.016
200.00	200.00	0.000	79.37	78.02	0.180	98.59	97.38	0.161	26.06	26.06	0.000
200.00	200.00	0.000	89.84	89.63	0.026	109.0	109.0	0.000	29.36	29.54	-0.022
200.00	200.00	0.000	100.4	101.1	-0.072	119.3	119.8	-0.059	33.12	33.02	0.012

********* Result for Mean Square Error = 6.231863e-05 *********

The performance of the FNN during training is shown in Figure-4 which shows the variation of power outputs of various generators in the system for a load demand of 400 MW.

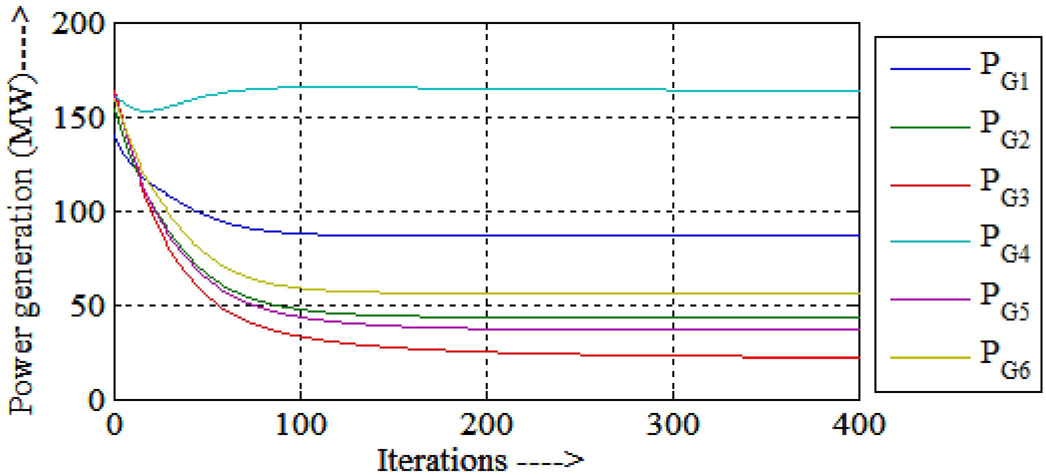


Figure-4 Power generation versus Iterations during training phase

5. Conclusion

In this paper, the ELD problem has been solved successfully with great accuracy by using a hybrid method of LNN and FNN. The salient features of the two NNs have been fully utilized in obtaining the solution of the proposed problem. Regular features of a generating unit like generator's minimum and maximum capacity constraints and transmission losses in the lines were suitably considered. Due to continuous change in the load demand classical methods of solving ELD problem sometimes fail to provide the results under varying conditions of load demand. On the other hand methods based on NN are capable of solving problem under varying conditions of load demand.

As the cost of generation associated with the results obtained by LNN is minimum, and now these results are used to train the FNN, therefore FNN also yields economical results. Further, trained FNN produced the desired results without any further iteration as in case of λ-iteration methods. Therefore, it is concluded that proposed hybrid method's result were fast and most economical. For future study, it is suggested to devise other hybrid models.

6. References

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