ENVIRONMENTAL ECONOMIC LOAD DISPATCH USING HOPFIELD NEURAL NETWORK

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By:
Divya Gupta
(Regn. No. 80641006)

Under the supervision of:
Dr. Sanjay K. Jain
Assistant Professor, EIED

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ELECTRICAL & INSTRUMENTATION ENGINEERING DEPARTMENT
THAPAR UNIVERSITY
PATIALA – 147004

CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, **"Environmental Economic Load Dispatch Using Hopfield Neural Network"**, in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Power Systems & Electric Drives* submitted in Electrical & Instrumentation Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Sanjay K. Jain,** Assistant Professor, EIED. The matter presented in this thesis has not been submitted for the award of any other degree of this or any other university.

(Divya Gupta)
Regn.No.80641006

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

(Dr. Sanjay K. Jain)
Assistant Professor
Electrical & Instrumentation Engg. Department
Thapar University
Patiala

Countersigned by

S. Ghosh
12/8/08
(Dr. Smarajit Ghosh)
Professor & Head
Electrical & Instrumentation Engg. Department
Thapar University
Patiala

(Dr. R.K.Sharma)
Dean(Academic Affairs)
Thapar University,
Patiala.

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DIVYA GUPTA
80641006

ABSTRACT

The economic load dispatch (ELD) is one of the most important optimization problems from the view point of power system to derive optimal economy. Classically, it is to identify the optimal combination of generation level of all generating units which minimizes the total fuel cost while satisfying the load. This classical ELD formulation have been solved by various methods like Lagrange method, Newton's method etc.

As the time progresses, the environmental constraints are becoming foremost important in deciding the operation of thermal units. Therefore, conventional load dispatch problem has to be solved to find the generation level that minimise the cost or minimise the emission level or their combination subjected to load balance. Even the environmental emission can be taken as the constraints in cost optimisation problem. Therefore, an efficient and diversified model is needed to handle the above variations in the problem.

The solutions to the above problems is attempted using Modified Hopfield Neural Network (HNN), which works on the principal of minimizing the energy function as conventional HNN and therefore sure to converge but differs from conventional HNN. In the conventional HNN, equality constraint on load is combined into objective cost after assigning suitable weightage factors. The computational procedures include selection of weighting factors and thus the convergence depends on the weight selection. In the modified HNN, there is flexibility of taking objective function and the constraints separately. The internal parameters of neural networks are computed using valid subspace approach, which guarantee the convergence of solution at equilibrium points.

In this thesis, the environmental economic dispatch is considered and the following has been attempted

1. Cost optimisation with load balance constraint
2. NOx emission optimisation with load balance constraint
3. SOx emission optimisation with load balance constraint
4. Cost optimisation with SOx and NOx emissions and load balance as constraint

The results are presented for the above using Modified HNN. The results are also compared with classical λ and classical HNN methods for cost optimisation.

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CHAPTER-1

INTRODUCTION

1.1 OVERVIEW

One of the most important operational functions of modern day energy management system is Economic Load Dispatch (ELD). It aims to minimize the total cost of real power generation from thermal power plants at various stations while satisfying the loads and losses in power transmission system. The objective is to distribute the total load demand and total loss among units connected while simultaneously minimizing generation costs and satisfying power balance equations and other constraints.

The operation of thermal power plants depends on combustion of fossil fuels which produces SOx and NOx emissions. These emissions have given rise to environmental concerns. Even the Clean air act [133] persuades the utilities to change their practices to meet the environmental emission norms. Thus it becomes important to perform the emission dispatch or include the emission constraints into the economic dispatch.

A minimum emission dispatch is performed in much the same way as an economic dispatch with the end goal being to reduce emissions like SOx and NOx emissions instead of costs. The fuel cost objective function is replaced by an emissions objective function. The constraints are the same but the optimal solution will produce the lowest total emissions as opposed to the lowest total cost. For most utilities the overall objective is to produce their product at the lowest possible cost while adhering to all environmental constraints. In this sense emission restrictions can be treated as an additional constraint.

1.2 LITERATURE REVIEW

The work carried out by various researchers on the economic load dispatch and environmental economic dispatch is briefly reviewed to find the scope of work.

In power system, the operation cost at each time needs to be minimized via economic load dispatch (ELD) i.e. how the real power output of each controlled generating unit in an area is selected to meet a given load and to minimise the total operating costs in the area [102]. This is one of the important optimization problems in a power system. Many approaches [3-132] have been listed to formulate and solve this problem. These approaches include combining emission dispatch with the economic load dispatch [22-34], includes use of Hopfield neural network [1-22], fuzzy approach [33,125], Evolutionary Algorithms[35-75] and hybrid methodologies[71, 75, 122]. Evolutionary Algorithms constitutes Genetic algorithms [35-65], Particle Swarm Optimisation [129-132] and simulated annealing [126].

Power utilities seek to provide reliable supply of electrical energy at a reasonable cost while operating to meet the environment limits and constraints. Decisions must be made affecting the deployment of each generating unit along with evaluating the need for additional or new sources of generation. Combustion of fossil fuels produces NOx and SOx emissions. Possible means of meeting these standards include burning higher quality fuel, replacing older plants with new efficient cleaner plants, considering emission-free alternate forms of energy, upgrading existing plants. In many jurisdictions, provisions are made for utilities to trade unused portions of their emission allowances [26]. Thus the emission levels can be reduced through economic/environmental dispatching of thermal generating units.

Concerns about the environment and air pollution are not a product of the 1990s. Air pollution in urban centers has always been an issue of importance. In [27], researchers provided a summary of economic/environmental dispatching algorithms dating back to 1970 using conventional optimization methods. In most cases the authors used the Newton-Raphson method to find a solution. This method is noted for its fast rate of convergence, however difficulty can arise when dealing with system constraints. In most cases a nonlinear programming technique can prove quite successful. Several models have been used to represent emission levels. Zahavi and Eisenberg [28] used a second order polynomial, while Kermanshahi, et al. [24] used the sum of a quadratic and an exponential term. Gent and Lamont [25] used a combination of a straight line and an exponential term. Many areas of power systems engineering such as load forecasting, security assessment and diagnostics [112, 113] have applied neural networks. Park et.al., [10] applied a Hopfield neural network to economic dispatching using a piecewise quadratic cost function and Fukuyama et. al., [77] applied a hopfield neural network to solve dynamic economic load dispatching.

Various neural approaches including Fuzzy and Hopfield neural methodology for solving economic/environmental dispatch have been listed. Dhillon et.al., [33] formulated the problem considering uncertainties in system production cost and random nature of load demand. The authors used the weighted min max technique to obtain trade-off relation between the conflicting objectives and fuzzy set theory is subsequently used to help the operator choose an optimal operating point. Song et.al., [125] used a fuzzy logic controlled Genetic algorithm for solving the environmental/economic dispatch where the crossover and mutation probabilities were adjusted based on the average fitness of the population. The multiobjective problem was converted to a scalar optimization problem with weighted constraints.

One of the milestones for the current renaissance in the field of neural networks is the associative model proposed by Hopfield at the beginning of the 1980s. No synchronization is required, each unit behaving as a kind of elementary system in complex interaction with the rest of the ensemble. An energy function must be introduced to harness the theoretical complexities posed by such an approach. The important property of the Hopfield neural network is the decrease in energy by finite amount whenever there is any change in inputs. Thus the hopfield neural network can be used for optimisation. Different approaches have been introduced to solve the economic dispatch problem with Hopfield approach [1-22]. Comparison of different algorithms implied to solve the economic load dispatch problem is listed in [9]. Conventional ways of solving it is given in [1-6, 10-20]. In [6] an energy function composing power mismatch, total fuel cost and the transmission line losses is defined. The weighting factors associated with the terms of the energy function can be either appropriately selected or directly estimated in the model which however is determined by trial and error. To minimise the value of energy function, the computational procedures including the series of adjusting the weighting factor associated with the transmission line losses and updating the unit generations and power losses are carried out. Because the weighting factors are governed by some relationships developed, adjustment of the weighting factor is much simpler and more effective in steadily achieving solutions than adjustment of the λ-multiplier in the lambda-iteration method for economic dispatch problems. Hopfield method of solving can be further extended to Environmental dispatching [11]. Another way of using this neural network is augmented hopfield approach listed in [4]. Cost function used can be linear, non linear or piecewise quadratic type [10]. Constraints used in this methodology can be losses, power mismatch and prohibited zones [13] and other equality and inequality constraints [16]. Other approaches are improved hopfield model [18] and adaptive approach [20]. The latter develops two different methods, which are the slope adjustment and bias adjustment methods, in order to speed up the convergence of the hopfield neural network system. Adaptive learning rates are also developed by using energy functions and applied to the slope and bias adjustment methods. Improved hopfield can further be used for environmental dispatching [22]. The best method of using hopfield is modified hopfield model using valid subspace model discussed in [7, 14]. The benefit is that there is no need of adjusting weighting factors which otherwise is very cumbersome to handle.

Methods arising from evolutionary computation particularly, for solving multiobjective optimization methods, are fast and effective techniques capable of finding a well-distributed set of diverse trade-off solutions, with little or no more effort than sophisticated single-objective optimizers would have taken to find a single one. Several evolutionary algorithms are listed [35-75, 129-132, 126-128]. The methods include Genetic Algorithm approach, Particle Swarm Optimisation and Simulated annealing methods. Yalcinoz and Altun [41] proposed a solution to the environmental economic dispatch using a modified genetic algorithm which is based on arithmetic crossover operator with real valued genes. This approach also expressed the fitness function (overall objective) as a weighted sum of the total fuel cost and emission (SO_2 and NOx) objectives. Genetic algorithm is an attractive tool for economic dispatch problems. Sheble et.al., [60] presented papers where Genetic Algorithm solves the economic dispatch. In the papers, an example with three units was explored. Chang et.al., [36] have presented a genetic algorithm for solving economic dispatch problem. This method can take into account network losses, ramp rate limits and valve point zone. A fuzzy logic controlled genetic algorithm [125] has been applied to environmental/economic dispatch by Song et. al. In [129], authors used Particle Swarm Optimisation (PSO) algorithm to solve the problem of combined economic and emission dispatch. Penalty factors are defined which blend the emission costs with the fuel costs. The familiar quadratic form of objective functions are used which gives the optimal dispatch directly. The capacity limits (lower and upper) of plants are treated as the operating constraints and the total generation which is a function of load plus transmission losses is considered as the demand constraint.

1.3 SCOPE OF WORK

As the time progresses, the environmental constraints are becoming foremost important in deciding the operation of thermal units. The conventional load dispatch may therefore be looked into as identifying the generation level with minimising the cost, or minimising the emission level or their combination subjected to load balance. Even the environmental emission can be taken as the constraints in cost optimisation problem. Therefore it requires an efficient and diversified model which can handle the above variations in the problem. The above problems are attempted using Modified Hopfield Neural network

1.4 ORGANIZATION OF THE THESIS

The work carried out has been summarized in six chapters. The Chapter 1 highlights the brief introduction, summary of work carried out by various researchers. The scope of the work is also identified and the outline of the thesis is also given in this chapter. The Chapter 2 explains the Environmental Economic Load Dispatch formulation and Economic Load Dispatch solution using Lagrange Multiplier Method. The Chapter 3 briefly describes Hopfield Neural Network and presents the mapping of Economic Load Dispatch problem in Hopfield Neural Network. The Chapter 4 discusses the Modified Hopfield Neural Network and the formulation of Environmental Economic Load Dispatch through Modified Hopfield Neural Network. The Chapter 5 details the results pertaining to various cases and the comparison of results obtained for various methods. The conclusions and the scope of further work are detailed in Chapter 6.

CHAPTER-2

ENVIRONMENTAL ELD FORMULATION

This Chapter covers Environmental Economic Load Dispatch problem formulation and Economic Load Dispatch (ELD) solution using classical Lagrange Multiplier method.

2.1 ECONOMIC LOAD DISPATCH

The Economic Dispatch can be defined as the process of allocating generation levels to the generating units, so that the system load is supplied entirely and most economically. The objective of Economic Load Dispatch is to minimise the overall cost of generation, i.e.,

minimise $$C_t = \sum_{i=1}^{NG} C_i \tag{2.1}$$

where NG is the set of dispatchable generating units.

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L \tag{2.2}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,\ldots,NG \tag{2.3}$$

The cost of generating unit C_i is expressed as

$$C_i = a_i P_i^2 + b_i P_i + c_i \tag{2.4}$$

where

a_i, b_i, c_i are cost coefficients for unit i,

C_t = total cost of generation

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

P_i^{min}, P_i^{max} = the minimum and maximum generating limits respectively for plant i.

2.2 ENVIRONMENTAL LOAD DISPATCH

Concerning environmental emission is important issue in the operation of modern power plants [134]. Operating at absolute minimum cost can no longer be the only criterion for dispatching electric power due to increasing concern of the environmental consideration. The generation of electricity from fossil fuel releases several contaminants, such as Sulphur oxides, Nitrogen oxides and Carbon dioxide, into the atmosphere. Since the text of the Clean Air Act Amendments of 1990 and similar Acts by European and Japanese governments, environmental constraints have topped the list of utility management concerns.

The overall goal for the NOx emission is to lower NOx emission by 2 million tons per year and the SOx emission by 8.9 million tons per year. The SOx laws were implemented in two phases. Phase I began in 1995. In this phase 262 generating units from 110 power plants are required to effectively limit their SOx emissions under 2.5lb /MBTU. In Phase II, which started in 2000, all generating units are required to meet the 1.2 lb/MBTU limit. Also, a national cap of 8.9 million tons per year on SOx emission will be enforced, and the utilities will be allowed to trade and bank the emission allowances. These two provisions create opportunities for utilities that can control emissions to sell excess allowances to other utilities with higher emissions. Because it is now a system's total tonnage of emissions that matters, not the .emission rate at particular units, new options for compliance are opened up. These include the purchase and sale of allowances among utilities and emission dispatch.

Now the limiting levels of emissions [129] over a scheduling horizon represent additional operational constraints that are to be satisfied when finding the optimal solution for the economic dispatch problem. The characteristics of emissions of different pollutants are different and are usually highly nonlinear. This increases the complexity of the Environmentally Constrained Economic Dispatch problem. The primary objective of this problem is to determine the most economic loadings of the generators such that the load demands in the intervals of the generation scheduling horizon can be met and the operation constraints of the generators are satisfied. In addition, the total emissions over the scheduling horizon need to satisfy the allowable emission limit over the same horizon. The harmful ecological effects by the emission of particulate and gaseous pollutants from fossil fuel power plants can be reduced by proper load allocation among the various generating units of the plants.

2.2.1 NOx Emissions Optimization

The objective of NOx optimisation [68] in Environmental Load Dispatch is to

minimise $E_{Nt} = \sum_{i=1}^{NG} e_{iN}$ (2.5)

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad i = 1,\ldots,NG$$

where $e_{iN} = a_{iN} P_i^2 + b_{iN} P_i + c_{iN} \quad for\ i = 1,2 \ldots NG$ (2.6)

a_{iN}, b_{iN} and c_{iN} = emission coefficients of the objective function

E_{Nt} = Total NOx emissions of the generating units

e_{iN} = NOx emissions of generator i, for i = 1, 2 ……NG

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

P_i^{min}, P_i^{max} = the minimum and maximum generating limits respectively for plant i.

NG = total number of generating units

2.2.2 SOx Emissions Optimization

The objective of SOx optimisation in Environmental Load Dispatch [68] is to

minimise $E_{St} = \sum_{i=1}^{NG} e_{iS}$ (2.7)

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad i = 1,\ldots,NG$$

where $e_{iS} = a_{iS} P_i^2 + b_{iS} P_i + c_{iS} \quad for\ i = 1, 2 \ldots NG$ (2.8)

a_{iS}, b_{iS} and c_{iS} = emission coefficients of the objective function

E_{St} = Total SOx emissions of the generating units

e_{iS} = SOx emissions of generator i, for i = 1, 2 ……NG

P_D = load demand

P_L = total system transmission loss

P_i = generation of i^{th} plant and

P_i^{min}, P_i^{max} = the minimum and maximum generating limits respectively for plant i.

2.3 ECONOMIC LOAD DISPATCH USING LAGRANGE MULTIPLIER METHOD

This section discusses the Economic Load Dispatch formulation by applying Lagrange Multiplier method.

2.3.1 Economic Load Dispatch without Losses

The simplest economic dispatch problem [99] is the case when transmission line losses are neglected. Due to this the total demand P_D is the sum of all generations. A cost function C_i is assumed to be known for each plant. The problem is to find the real power generation, P_i for each plant such that the total operating cost C_t is minimum and the generation remains within the lower generation P_{imin} and upper generation P_{imax}. The objective function is given by equation (2.1). It is subjected to,

$$\sum_{i=1}^{NG} P_i = P_D \tag{2.9}$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1, \ldots, NG \tag{2.10}$$

The cost of generating unit C_i is expressed as given in equation (2.4)

A typical approach is to augment the constraints into objective function by using the Lagrange multiplier method. The augmented function is

$$L = C_t + \lambda \left(P_D - \sum_{i=1}^{NG} P_i \right) \tag{2.11}$$

The minimum of this unconstrained function is found at the point where its partial derivative with respect to its variables are zero, that is,

$$\frac{\partial L}{\partial P_i} = 0 \tag{2.12}$$

$$\frac{\partial L}{\partial \lambda} = 0 \tag{2.13}$$

The condition given by (2.12), results as

$$\frac{\partial C_t}{\partial P_i} + \lambda(0-1) = 0$$

As

$$C_t = C_1 + C_2 + \ldots + C_{NG}$$

then

$$\frac{\partial C_t}{\partial P_i} = \frac{dC_i}{dP_i} = \lambda$$

i.e., $$\frac{dC_i}{dP_i} = \lambda \quad for \quad i = 1,\ldots, NG \tag{2.14}$$

or

$$b_i + 2a_i P_i = \lambda \tag{2.15}$$

The equation (2.13) results into

$$\sum_{i=1}^{NG} P_i = P_D \tag{2.16}$$

Equation (2.16) is precisely the equality constraint that is to be imposed. Thus when losses are neglected, for most economical operation, all plants must operate at equal incremental fuel cost while satisfying the equality constraint given by equation (2.16). In order to find the solution, equation (2.15) is solved for P_i

$$P_i = \frac{\lambda - b_i}{2a_i} \quad for\ i = 1,\ldots, NG \tag{2.17}$$

The relations given by equation (2.17) are known as coordination equations. They are functions of λ. An analytical solution can be obtained for λ by substituting for P_i in (2.17) i.e.,

$$\sum_{i=1}^{NG} \frac{\lambda - b_i}{2a_i} = P_D \tag{2.18}$$

or

$$\lambda = \frac{P_D + \sum_{i=1}^{NG} \frac{b_i}{2a_i}}{\sum_{i=1}^{NG} \frac{1}{2a_i}} \tag{2.19}$$

The value of λ found from (2.19) is substituted in (2.17) to obtain the optimal scheduling of generation. The whole process of calculating power generations and minimising total operating cost neglecting losses is given in the algorithm and flow chart below.

2.3.1.1 Algorithm

Following steps presents the method of performing Economic Load Dispatch through given model:

1. Input the values of load demand P_D and cost coefficients a_i, b_i and c_i for i =1, 2…..NG.
2. Calculate λ using equation (2.19).
3. Calculate P_i’s using equation (2.17).
4. Calculate the fuel cost of each unit, C_i using equation (2.12).
5. Print the values of Pi’s, C_i’s and C_t.

The process of performing Economic Dispatch without losses using Lagrange Multiplier method is depicted in flow chart shown in fig. 2.1.

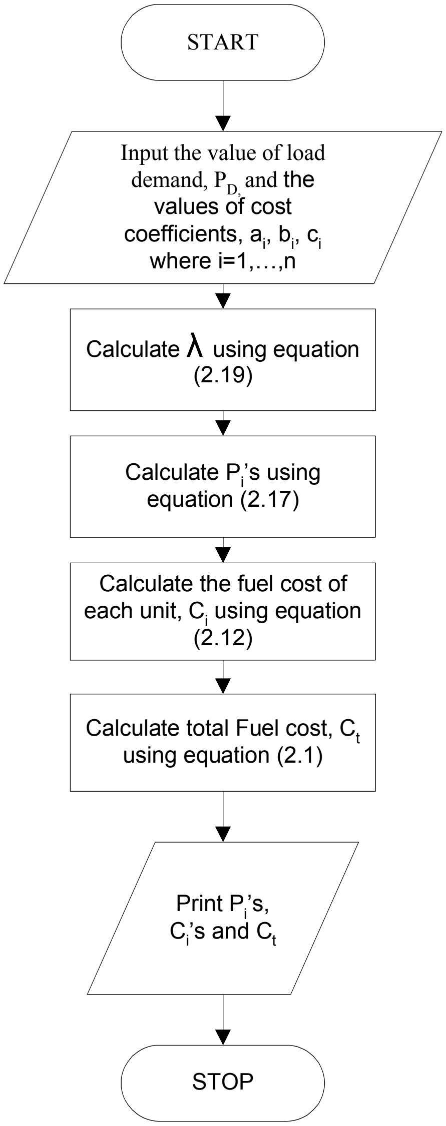

Fig. 2.1 Economic Load Dispatch neglecting losses using Lagrange Multiplier method

2.3.2 Economic Load Dispatch with Losses

Transmission losses may be neglected when transmission losses are very small but in a large interconnected network where power is transmitted over long distances, transmission losses are a major factor and affect the optimum dispatch of generation. One common practice for including the effect of transmission losses is to express the total transmission loss as a quadratic function of the generator outputs as

$$P_L = \sum_{i=1}^{NG}\sum_{j=1}^{NG} P_i B_{ij} P_j \qquad (2.20)$$

The coefficients B_{ij} are called loss coefficients or B-coefficients. The economic load dispatch problem is thus formulated as given in equations (2.1) to (2.4)

Using the Lagrange multiplier, the augmented function is,

$$L = C_t + \lambda(P_D + P_L - \sum_{i=1}^{NG} P_i) \qquad (2.21)$$

For minimisation of augmented function,

$$\frac{\partial L}{\partial P_i} = 0 \qquad (2.22)$$

$$\frac{\partial L}{\partial \lambda} = 0 \qquad (2.23)$$

The condition given by (2.22) results as,

$$\frac{\partial C_t}{\partial P_i} + \lambda(0 + \frac{\partial P_L}{\partial P_i} - 1) = 0 \qquad (2.24)$$

As

$$C_t = C_1 + C_2 + ... + C_{NG} \qquad (2.25)$$

then

$$\frac{\partial C_t}{\partial P_i} = \frac{dC_i}{dP_i} \qquad (2.26)$$

i.e.,

$$\frac{dC_i}{dP_i} + \lambda \frac{\partial P_L}{\partial P_i} = \lambda \qquad for\ i = 1,...,NG \qquad (2.27)$$

The term $\frac{dC_i}{dP_i}$ is called incremental fuel cost $(IC)_i$ and $\frac{\partial P_L}{\partial P_i}$ is known as the incremental transmission loss $(ITL)_i$, associated with i^{th} generating unit. Rearranging (2.27) results as,

$$\left(\frac{1}{1-\frac{\partial P_L}{\partial P_i}}\right)\frac{dC_i}{dP_i}=\lambda \qquad i=1,...,NG \tag{2.28}$$

or

$$L_i\frac{dC_i}{dP_i}=\lambda \qquad i=1,...,NG \tag{2.29}$$

where L_i is known as the penalty factor of plant i and is given by

$$L_i=\frac{1}{1-\frac{\partial P_L}{\partial P_i}} \tag{2.30}$$

Equation (2.21) shows that the minimum cost is obtained when the incremental cost of each plant multiplied by its penalty factor is same for all plants. Equation (2.28) is also written in alternative form as [133],

$$(IC)_i=\lambda[1-(ITL)_i] \quad for\ i=1,2,\ldots NG \tag{2.31}$$

This equation is referred to as the exact coordination equation. Thus it is clear that to solve the economic load dispatch problem, it is necessary to compute ITL for each plant and therefore functional dependence of transmission loss on real powers of generating plants must be determined. There are several methods, approximate and exact, for developing a transmission loss model. One of the most important, simple but approximate methods of expressing transmission loss as a function of generator powers is through B-coefficients. This method is reasonably adequate for treatment of loss coordination in economic scheduling of load between plants. The general form of loss formula using B-coefficients is given in (2.20)

Simplifying the equation (2.20) and recognizing that $B_{ij} = B_{ji}$,

$$\frac{\partial P_L}{\partial P_i}=\sum_{j=1}^{NG}2B_{ij}P_j \tag{2.32}$$

Assuming quadratic plant cost curves as given in equation (2.26), incremental cost is obtained as,

$$\frac{dC_i}{dP_i} = 2a_i P_i + b_i \tag{2.33}$$

Substituting $\frac{\partial P_L}{\partial P_i}$ and $\frac{dC_i}{dP_i}$ from above in the coordination equation (2.27),

$$2a_i P_i + b_i + \lambda \sum_{j=1}^{NG} 2B_{ij} P_j = \lambda \tag{2.34}$$

Collecting all terms of P_i and solving for P_i,

$$(2a_i + 2\lambda B_{ii})P_i = -\lambda \sum_{\substack{j=1 \\ j\neq i}}^{NG} 2B_{ij} P_j - b_i + \lambda \tag{2.35}$$

or

$$P_i = \frac{1 - \frac{b_i}{\lambda} - \sum\limits_{\substack{j=1 \\ j\neq i}}^{NG} 2B_{ij} P_j}{\frac{2a_i}{\lambda} + 2B_{ii}} \qquad for \quad i = 1, 2, ...NG \tag{2.36}$$

For any particular value of λ, above equation can be solved iteratively by assuming initial values of P_i's. Iterations are stopped when P_i's converge within specified accuracy. Above equation along with power balance equation (2.24) for a particular load demand P_D are solved iteratively according to the algorithm given below. Following this is given a flow chart of the method used to solve this problem.

2.3.2.1 Algorithm

Following steps presents the algorithm:

1. Input the value of load demand, P_D and the values of cost coefficients, a_i, b_i, c_i where i=1, 2…NG
2. Input the values of B-coefficients of equation (2.20).
3. Initially choose $\lambda = \lambda_0$.
4. Assume $P_i = 0$ for i = 1, 2… NG.
5. Solve equation (2.36) iteratively for P_i's.
6. Calculate P_L according to equation (2.20).

7. Check if power balance equation (2.24) is satisfied, i.e., $|\sum_{i=1}^{NG} P_i - P_D - P_L| < \in$, where $\in$ is a specified value. If yes, stop. Otherwise, go to next step.
8. Increase λ by Δλ which is an appropriate step size, if $\left(\sum_{i=1}^{NG} P_i - P_D - P_L\right) < 0$ or decrease λ by Δλ, if $\left(\sum_{i=1}^{NG} P_i - P_D - P_L\right) > 0$, go to step 5.

The above steps are shown in the flow chart given below as fig. 2.2.

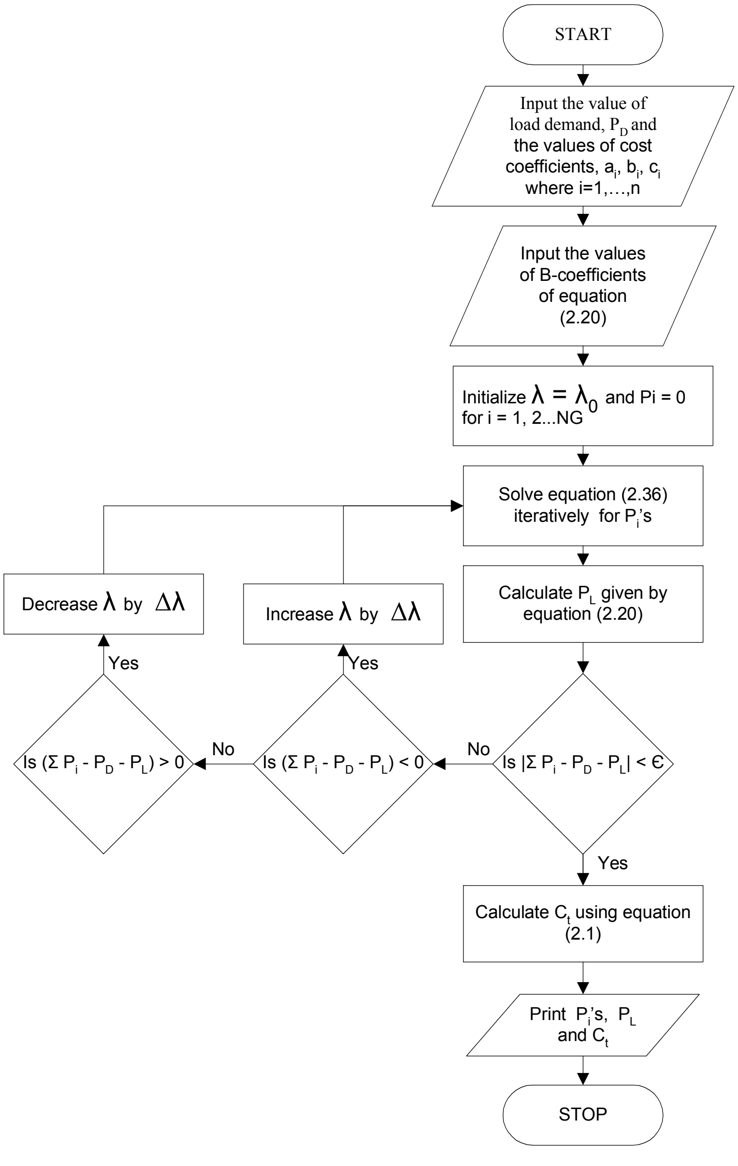

Fig. 2.2 Economic Load Dispatch considering losses using Lagrange Multiplier method

CHAPTER-3

ELD USING HOPFIELD NEURAL NETWORK

This chapter discusses the salient features of Hopfield Neural Network in brief and describes the mapping of Economic Dispatch Problem to Hopfield Neural Network.

3.1 HOPFIELD NEURAL NETWORK

The benefits of using neural network are that it is computationally powerful. It maps the unknown non-linear relationships between the given inputs and outputs. They are universal approximators and are highly parallel systems. Neural net learn by example as compared to the conventional methods where programming is done with the help of instructions. Conventional methods are sequential and synchronous in nature while ANN are parallel and asynchronous in structure. During learning neural net self organize themselves but other methods are software dependent and their knowledge is replaceable as it is stored in address memory location. In ANN knowledge is adaptable as the information is stored in the interconnection between neurons. They are fault tolerant because they are redundant and have distributed representation. But other conventional methods are non fault tolerant. Neurons are the basic elements of Artificial Neural Network. Fig. 3.1 depicts its model.

The neuron is fired if the net input exceeds a threshold. The output of a neuron is decided by an activation function. The various activation functions are Linear, Hard Limiter, Sigmoid etc. Depending on the type of activation function a neuron produces different types of outputs.

In Hopfield Neural Network (HNN), each neuron is connected to each other neuron and there exists parallel input and parallel output channels. A typical structure of HNN is shown in the figure 3.2.

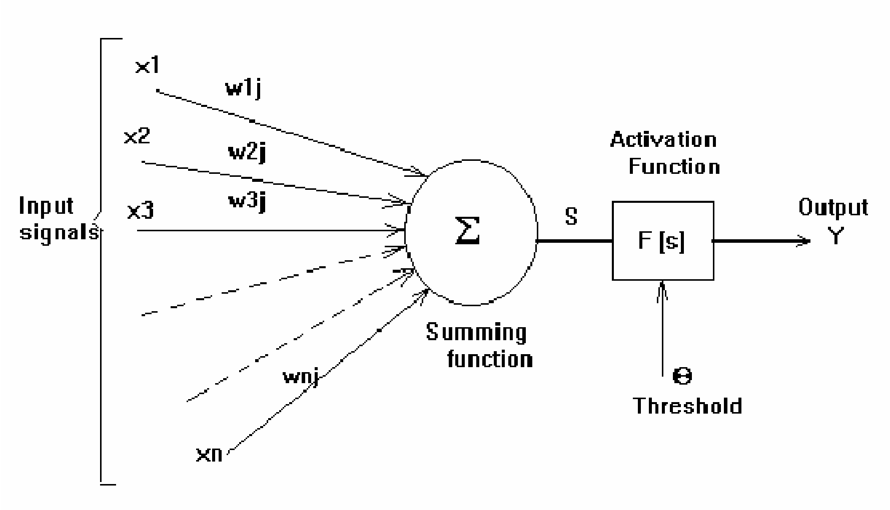

Fig. 3.1 The Model of a single neuron

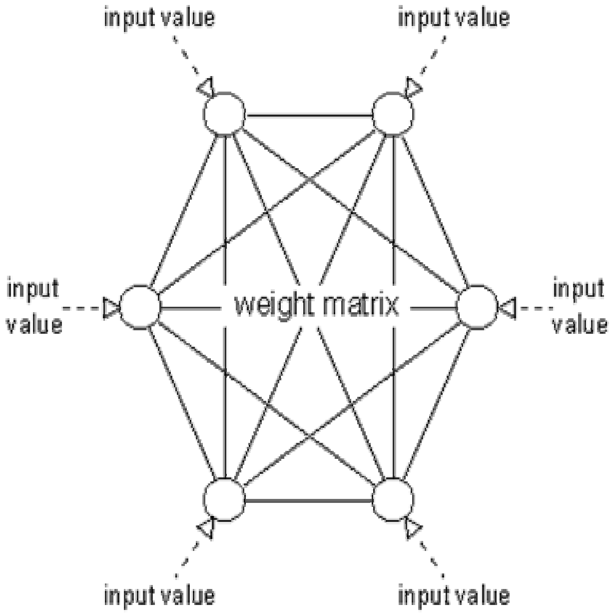

Fig.3.2 Structure of Hopfield Neural Network

This network has a single neuron layer. Its input value is binary and activation function can be sigmoid or hard limiter function. Unsupervised learning is used with simulated annealing learning algorithm and it does not require the training examples or training data. Here guidelines are taken for forming group or features. The simulated annealing algorithm is analogous to annealing process where the process is started at high temperature and then the temperature is lowered slowly whole maintaining thermal equilibrium. Instead of searching the local neighborhood of the feasible solution space only for improvements, simulated annealing allows to accept an increase in cost function in the hope of overcoming local minima problems. These properties are tabulated in Table 3.1.

Table 3.1 Properties of Hopfield Neural Network

Properties of Neural Network	**Hopfield Neural Network**
Learning	Unsupervised Learning
Algorithm	Annealing
Activation Function	Hard limiter, Sigmoid or Signum functions
Application	Pattern Recognition and Optimisation problems
Structure	Feedback structure
Input / Output layer	One (same)

Thus the hopfield neural network is mainly used in optimisation and pattern association applications. It is a feedback type neural network explained in fig.3.3.

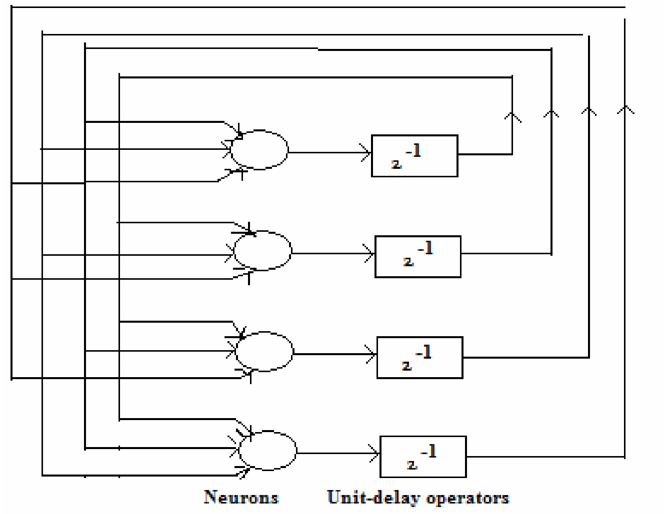

Fig. 3.3 Architectural graph of a Hopfield network consisting of N = 4 neurons

As already stated the Hopfield model consists of a set of neurons and a corresponding set of unit delays [108], forming a multiple-loop feedback system illustrated in fig. 3.3. The number of feedback loops is equal to the number of neurons. Basically, the output of each neuron is fed back, via a unit delay element, to each of the other neurons in the network. The feedback type Neural network can represent that each neuron has an infinite fading memory. This concept is explained with the help of a typical single loop feedback system depicted in the fig. 3.4.

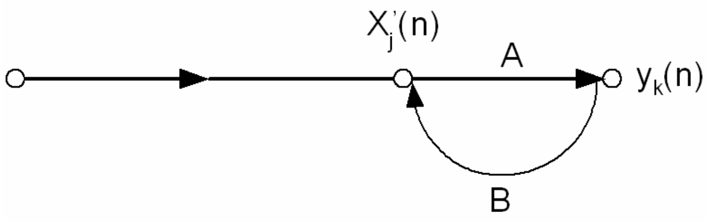

Fig 3.4 Single loop feedback system

Assuming A as the weight and B the unit delay operator z^{-1}, then the output of this system is calculated as follows:

$$\begin{aligned} y_k(n) &= \frac{A}{1-AB}[x_j(n)] \\ &= \frac{w}{1-wz^{-1}}[x_j(n)] \end{aligned}$$

Using the binomial expression, it can be written as

$$\begin{aligned} y_k(n) &= w\sum_{i=0}^{\infty} w^l z^{-l}[x_j(n)] \\ &= w\sum_{l=0}^{\infty} w^{l+1} x_j(n-l) \end{aligned}$$

where |w|<1 i.e., the system output is exponentially convergent as shown in fig. 3.5.
For |w|<1, the output depends upon the samples of input extending into infinite past i.e. it has infinite memory. The influence of past samples is reducing i.e. the memory is fading.

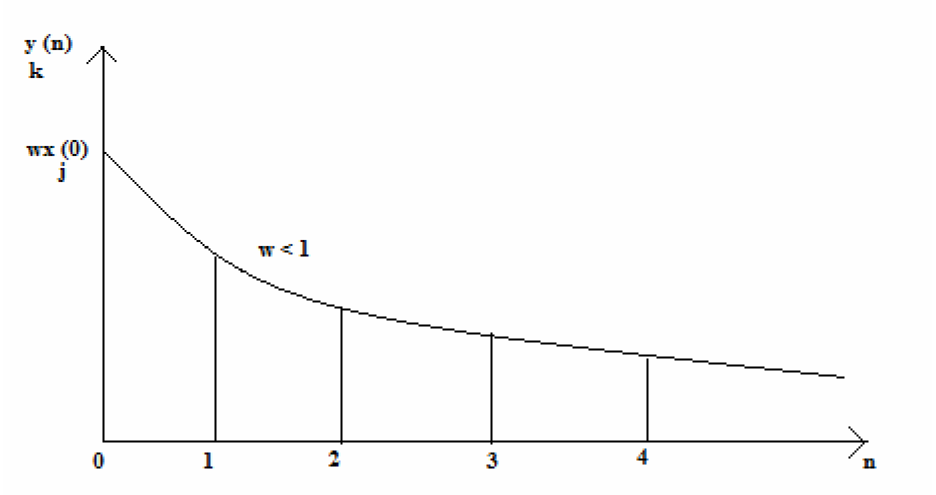

Fig. 3.5 Diagram showing exponentially converging system output

3.1.1 Dynamic Analysis of HNN

This model considers neural networks as a dynamical system, with a feedback mechanism, which can be defined as a set of differential equations.

3.1.1.1 Discrete Hopfield Neural Network

This network comprises a fully interconnected system of "n" neurons, each of which is considered to be a binary unit (0 or 1). Each interconnection has a weight, denoted by Wij from neuron j to i. Weight matrix is symmetric, i.e. Wij=Wji, and also no neuron has self feedback (Wii=0). At each moment, a binary state vector can represent the entire state of the network.

The firing rule of an arbitrary neuron i:

$$\begin{aligned} V_i &= 1 \quad if \sum W_{ij} V_j > U_i \\ &= 0 \quad if \sum W_{ij} V_j < U_i \end{aligned} \qquad (3.1)$$

where V_i denotes the output of neuron i and U_i is its threshold. Each network has an associated energy in a quadratic form:

$$E = -1/2\ (\sum \sum W_{ij} V_j V_i) + \sum V_i U_i$$

Each neuron randomly and asynchronously updates according to equation (3.1).

3.1.1.2 Continuous Hopfield Neural Network

Its activation function $g_i(u_i)$ is given by

$$V_i = g_i(u_i) = 1/2(1 + \tanh(u_i / T))$$

In the biological system, u_i lags behind the instantaneous outputs, V_j of the other neurons because of the input capacitance, C_i of the cell membrane, the trans-membrane resistance R_i, and the finite impedance R_{ij} equal to $|W_{ij}|^{-1}$ between the output V_j and the cell body of neuron i. The summing function is thus characterized by low input resistance unity current gain and high output resistance. This indicate the low pass nature of R_c circuit shown in fig. 3.6., which is justified as biological synapse is also a low pass filter to an excellent approximation [108]. The following resistance-capacitance differential equation determines the rate of change of u_i, and hence the time evolution of the continuous Hopfield network.

$$C_i(du_i / dt) = \sum W_{ij} V_j - (u_i / R_i) + i_i$$

$$du_i / dt = \sum W_{ij} V_j - (u_i / \tau) + i_i$$
$$where \quad u_i = g_i^{-1}(v) \quad and \quad \tau = RC$$

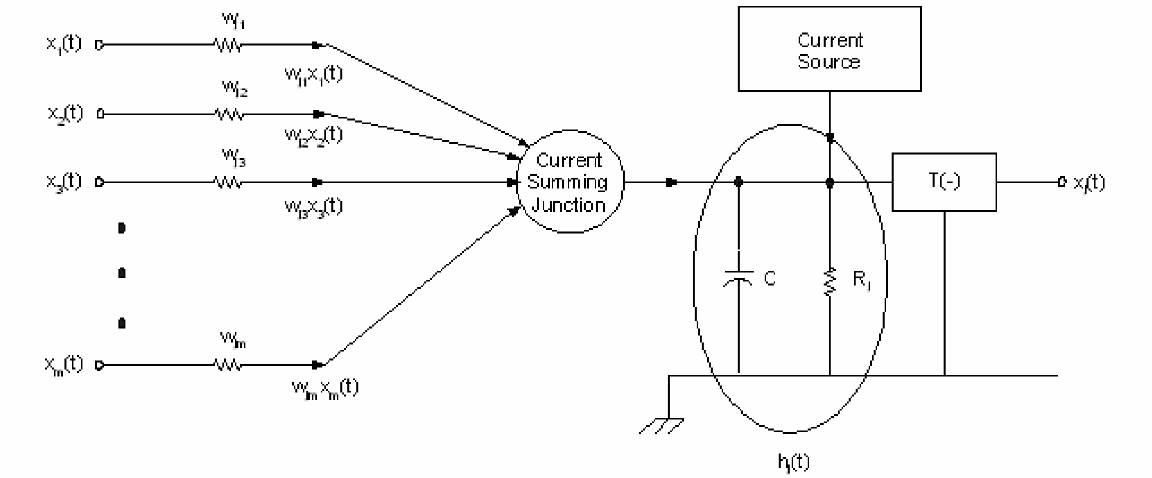

Fig. 3.6 Additive model of a neuron

The energy function for the continuous hopfield network is defined as

$$E = -1/2\sum_{i}\sum_{i} V_i W_{ii} V_i - \sum_{i} i_i V_i + \int V_i g_i^{-1}(V)\,dV$$

The time derivative of E is

$$\begin{aligned} dE/dt &= -\sum_{i} dV_i/dt\left(\sum_{i} W_{ii}V_i - u_i/\tau + i_i\right) \\ &= -\sum_{i} (dV_i/dt)(du_i/dt) \\ &= -\sum_{i} g_i^{-1}(V_i)(dV_i/dt)^2 \end{aligned}$$

As $g_i^{-1}(V_i)$ is a monotonically increasing function

$$\begin{aligned} &dE/dt \leq 0,\ and \\ &dE/dt = 0 \quad if\ \ dV_i/dt = 0 \quad \forall\ i \end{aligned}$$

The weights Wij, are the coefficients of the quadratic terms ViVj, and the external inputs, Ii are the coefficients of the linear terms Vi in the chosen energy function. The network can then be initialized by setting the activity level Vi of each neuron to a small random perturbation. From its initialized state, asynchronous updating of the network will then allow a minimum energy state to be attained, because the energy level never increases during state transitions.

The types of Combinatorial Optimization problems that can be solved through this model are unit commitment, economic dispatch, power system restoration, distribution system planning, traveling salesman problem, assignment, timetabling etc.

3.2 SOLVING OPTIMIZATION PROBLEMS USING HOPFIELD NEURAL NETWORK

For solving the above mentioned problems using the given model, the network energy function is made equivalent to the objective function of the optimization problem that needs to be minimized, while the constraints of the problem are included in the energy function as penalty terms.

In general if the problem is to minimise f(*v*),

$$\text{s.t.,}\quad \begin{array}{l} [A]_1\, v = b_1 \\ [A]_2\, v = b_2 \\ \dots\quad \dots\quad \dots \\ [A]_r\, v = b_r \end{array}$$

then the energy function for Hopfield network is defined as

$$E(v) = \alpha\ f(v) + \beta_1([A]_1 v - b_1)^2 + \beta_2([A]_2 v - b_2)^2 + \beta_3([A]_3 v - b_3)^2 + \dots\dots + \beta_m([A]_r v - b_r)^2$$

where

α, β_1, β_2 and β_3 are the penalty parameters which reflect the relative importance of each term in the energy function. The network parameters (weights and inputs) can be inferred by comparison with the standard energy function.

3.3 MAPPING ELD PROBLEM USING HNN

The Hopfield model [10, 89] is a single layer recursive neural network, where the output of each neuron is connected to the input of every other neuron. There is an external input to each neuron denoted by I_i. In a Hopfield network all connective weight values are calculated initially from system data. Then as patterns or input values are applied, the network goes through a series of iterations until it stabilizes on a final output. Thus, the values of neuron inputs U_i, and the outputs V_i, change with time and form a dynamic system [118]. It is important to ensure that the system will converge to a stable solution. This requires finding a bounded function (a Lyapunov or energy function) of the state variables such that all state changes result in a decrease in energy.

Park [10] used a Hopfield dynamic model described by:

$$\frac{dU_i}{dt} = \sum_j T_{ij} V_j + I_i \tag{3.2}$$

and an energy function described by,

$$E = -\frac{1}{2}\sum_{i}\sum_{j} T_{ij}V_iV_j - \sum_{i} I_iV_i \tag{3.3}$$

where,

T_{ij} = interconnection conductance from the output of neuron j to the input of neuron i.

T_{ii} = self connection conductance of neuron i

These modifications simplify network analysis and thus have been adopted for this work. The time derivative of the energy function [6] can be proven to be negative. Therefore, in the computational process the model state always moves in such a way that the energy function gradually reduces and converges to a minimum.

The objective of Economic Load Dispatch is to minimise the overall cost of generation, i.e.,

minimise $C_t = \sum_{i=1}^{NG} C_i$

where NG is the set of dispatchable generating units.

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,\ldots,NG$$

The cost of generating unit C_i is expressed as

$$C_i = a_iP_i^2 + b_iP_i + c_i$$

where

a_i, b_i, c_i are cost coefficients for unit i,

C_t = total cost of generation

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

$P_i^{\min}$, $P_i^{\max}$ = the minimum and maximum generating limits respectively for plant i.

When losses are considered, the Economic Dispatch model using Hopfield method has energy function which is defined as

$$E = (A/2)(P_D + P_L - \sum_i P_i)^2 + (B/2)\sum_i (a_i P_i^2 + b_i P_i + c_i) + (C/2)P_L \qquad (3.4)$$

where, A, B and C = Weighting factors

Now this energy function is composed of transmission losses, power mismatch and fuel cost. The positive weighting factors A and B and C introduce the relative importance for their respective associated terms. Term C is introduced for including losses in the equation.

By changing the generation output of unit i from P_{i0} to P_i, the transmission losses change from P_{L0} to P_L, which is given as

$$\begin{aligned} P_L &= P_{L0} + \Delta P_L \\ &\cong P_{L0} + \sum_i I_{Li0}(P_i - P_{i0}) \end{aligned} \qquad (3.5)$$

where ΔP_L is the linearized power loss change and I_{Lio} is the incremental loss of unit i at power generation of P_{i0}.

The first term is squared to minimize the mismatch to zero; otherwise the solution produced may have insufficient generation. To obtain the connective conductances and the external inputs, energy function E can be expressed by substituting above equation in (3.4),

$$\begin{aligned} E &= (A/2)(P_D + P_L - \sum_i P_i)^2 + (B/2)\sum_i (a_i P_i^2 + b_i P_i + c_i) \\ &\quad + (C/2)(P_{L0} + \sum_i I_{Li0}(P_i - P_{i0})) \end{aligned} \qquad \text{or}$$

$$\begin{aligned} E &\cong (A/2)(P_D + P_{L0})^2 + (B/2)\sum_i c_i + (C/2)(P_{L0} - \sum_i I_{Li0}P_{i0}) - \\ &\sum_i [A(P_D + P_{L0}) - (Bb_i/2) - (C/2)I_{Li0}]P_i + \sum_i (A + Ba_i)P_i^2/2 + \sum_i \sum_{j \neq i} AP_iP_j/2 \\ &= CONST - \sum_i [A(P_D + P_{L0}) - (Bb_i/2) - (C/2)I_{Li0}]P_i + \sum_i (A + Ba_i)P_i^2/2 \\ &+ \sum_i \sum_{j \neq i} AP_iP_j/2 \end{aligned} \qquad (3.6)$$

where

$CONST = (A/2)(P_D + P_{L0})^2 + (B/2)\sum_i c_i + (C/2)(P_{L0} - \sum_i I_{Li0} P_{i0})$, is a constant.

By comparing equations (3.5) and (3.6) and letting the output of neuron i represent the power generation of unit i, the connective conductances and external input of neuron i for the Hopfield network is given as

$$\begin{aligned} T_{ii} &= -A - Ba_i \\ T_{ij} &= -A \\ I_i &= A(P_D + P_{L0}) - Bb_i/2 - CI_{Li0}/2 \end{aligned} \tag{3.7}$$

The neuron model chosen is a linear input-output model as shown in fig.3.7, instead of conventional sigmoidal model. In this model P_i can be expressed as

$P_i = h_i(U_i)$, where U_i is the input to the neuron i.

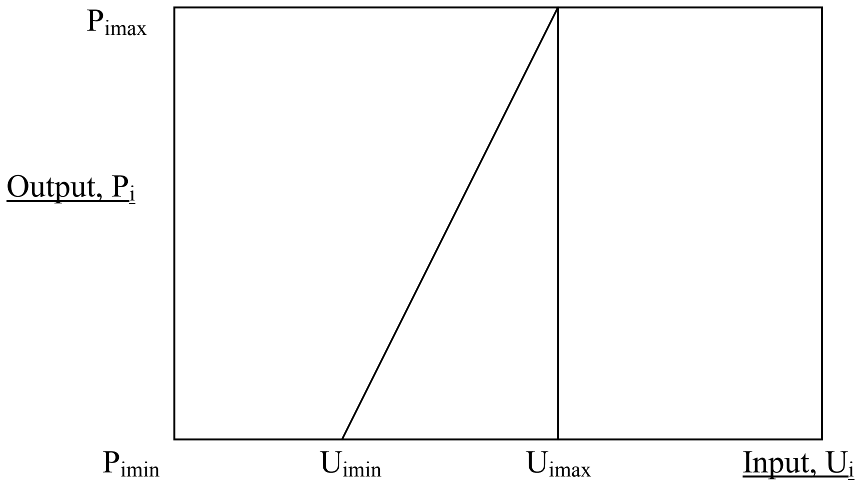

Fig.3.7 The input-output neuron model

The lower and upper limits of U_i are U_{imin} and U_{imax} respectively. Using straight line equation formula, P_i can be expressed as

$$\begin{aligned} &P_i = [(U_i - U_{i\min})/(U_{i\max} - U_{i\min})](P_{i\max} - P_{i\min}) + P_{i\min} \\ &or \\ &P_i = K_{1i}U_i + K_{2i} \qquad \forall\ U_{i\min} \le U_i \le U_{i\max} \end{aligned} \tag{3.8}$$

where both K_{1i} and K_{2i} are constants and are given as

$$
\begin{aligned}
&K_{1i} = (P_{i\max} - P_{i\min})/(U_{i\max} - U_{i\min}) \\
&and \\
&K_{2i} = -K_{1i}U_{i\min} + P_{i\min} && (3.9) \\
&P_i = h_i(U_i) = P_{i\max} \qquad \forall\, U_i \geq U_{i\max} \\
&P_i = h_i(U_i) = P_{i\min} \qquad \forall\, U_i \leq U_{i\min}
\end{aligned}
$$

Taking reference of equation (3.4), the dynamic equation of a neuron may be given as

$$\frac{dU_i}{dt} = \sum_j T_{ij}P_j + I_i \qquad (3.10)$$

Putting equation (3.7) into the above equation,

$$
\begin{aligned}
\frac{dU_i}{dt} &= A(P_D + P_{L0} - \sum_j P_j) - \frac{B}{2}(b_i + 2a_iP_i) - CI_{Li0}/2 \\
&= AP_m - \frac{B}{2}(b_i + 2a_iP_i) - CI_{Li0}/2
\end{aligned}
\qquad (3.11)
$$

where P$_m$ is the power mismatch, given by

$$P_m = P_D + P_{L0} - \sum_j P_j$$

Differentiating (3.8) and substituting above equation in it,

$$\frac{dP_i}{dt} = K_{1i}[AP_m - (\frac{B}{2})(b_i + 2a_iP_i) - CI_{Li0}/2] \qquad (3.12)$$

therefore,

$$P_i(t) = [P_i(0) - P_i(\infty)]e^{-(Ba_iK_{1i})t} + P_i(\infty) \qquad (3.13)$$

thus

$$P_i(\infty) = \frac{AP_m - (B/2)b_i - CI_{Li0}/2}{Ba_i} \qquad (3.14)$$

where P$_i$(∞) represents the optimal power generation of unit i, which is the solution of the problem. Here P$_i$(0) and P$_i$(∞) are the values of P$_i$(t) as t = 0 and t = ∞, respectively. The variable t is a meaningless variable and N is the number of units. Substituting the above equation into the equation defining P$_m$,

$$P_m = \frac{\left(P_D + P_{L0} + \sum_{i=1}^{N}\left[\left(Bb_i/2 + CI_{Li0}/2\right)/(Ba_i)\right]\right)}{1 + (A/B)\sum_{i=1}^{N}(1/a_i)} \qquad (3.15)$$

The weighting factor ‘A’ associated with power mismatch P_m is assigned highest priority over others. A is chosen very large, if A is too small then the solution may have a small fuel cost but a large mismatch.

Let the desired mismatch be less than P_m. To reach the optimal solution while meeting load requirements, the increase in energy due to the desired mismatch must be greater than or equal to the associated decrease in cost i.e.

$$A(P_m)^2 \geq B(\Delta F_T) \tag{3.16}$$

Where, ΔF_T is the change in total fuel cost.

Using above equation, ‘A’ can be determined for any value of B [8]. If B is kept equal to 1, the above equation reduces to

$$A \geq \frac{(\Delta F_T)}{(P_m)^2} \tag{3.17}$$

Therefore, the value of A can be set at the value obtained using above equation or greater than this. To determine the value of weighting factor C, incremental cost criteria is used for solution of Economic Dispatch problem, which says

$$PF_1(dF_1/dP_1) = PF_2(dF_2/dP_2) = \ldots = PF_n(dF_n/dP_n) \tag{3.18}$$

where PF_i is penalty factor of unit i equal to $1/(1-I_{Li0})$

Now,

$$\frac{dF_i}{dP_i} = b_i + 2a_iP_i$$

therefore,

$$\frac{dF_i}{dP_i} = b_i + 2a_iP_i = (2/B)(AP_m - CI_{Li0}/2) \tag{3.19}$$

According to equal incremental cost criteria equation,

$$\begin{aligned} &PF_1(2/B)(AP_m - CI_{L1o}/2) = PF_2(2/B)(AP_m - CI_{L2o}/2) = \ldots \\ &= PF_n(2/B)(AP_m - CI_{Lno}/2) \end{aligned} \tag{3.20}$$

Solving this

$$C = 2AP_m \tag{3.21}$$

3.3.1 Algorithm

The steps involved in the above described mapping is summarized below:

1. Input load demand P_D, loss coefficients B_{ij}, fuel cost coefficients a_i, b_i and c_i and neuron model parameters U_{max} and U_{min}.
2. Initialize power generation of each unit and set C=0 and iteration counter, k=0.
3. Calculate P_L from equation (2.20), incremental loss and P_m from equation (3.15), P_i from equation (3.14) and C from (3.21).
4. Check if |Power mismatch| < tolerance. If yes then check is $|P_{iold} - P_{inew}| <$ tolerance for all units otherwise go to step 3.
5. If $|P_{iold} - P_{inew}| <$ tolerance for all units then print the generations of each unit, losses and the total fuel cost using equation (2.1) otherwise increase the iteration.

The whole process of calculating the power generations and fuel cost using this model is shown in the flow chart as fig. 3.8:

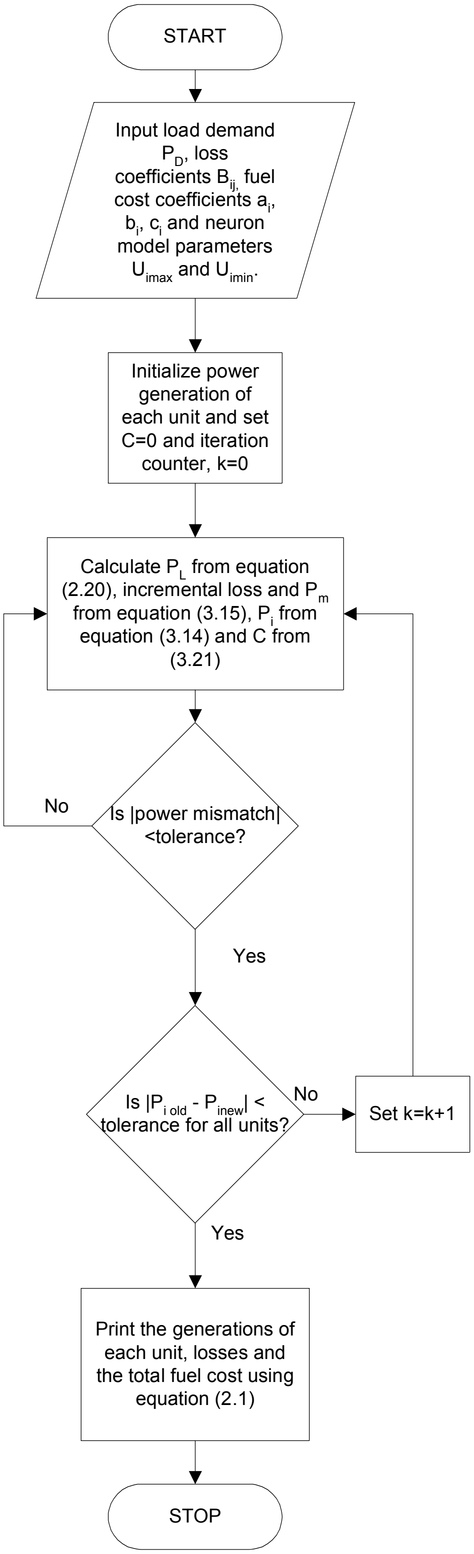

Fig. 3.8 Economic Load Dispatch with losses using Hopfield Neural Network

CHAPTER-4

ENVIRONMENTAL ELD USING MODIFIED HNN

In this chapter the modified Hopfield neural network is briefly reviewed. This formulation is applied to ELD, NOx optimization and SOx optimization and cost optimization with environmental constraints

4.1 THE MODIFIED HOPFIELD NETWORK

Hopfield networks are single-layer networks with feedback connections between nodes. In the standard case, the nodes are fully connected, i.e., every node is connected to all other nodes, including itself. The node equation for the continuous-time network is given by:

$$\dot{u}_i(t) = -\eta . u_i(t) + \sum_{j=1}^{n} T_{ij} . v_j(t) + i_b^i \qquad (4.1)$$

$$v_i(t) = g_i(u_i(t)) \qquad (4.2)$$

where

u_i (t) is the current state of the i-th neuron.

v_j (t) is the output of the j-th neuron.

T_{ij} is the weight connecting the j-th neuron to i-th neuron.

i_b^i is the offset bias of the i-th neuron.

$\eta . u_i(t)$ is a passive decay term.

$g_i(u_i(t))$ is a monotonically increasing threshold function that limits the output of each neuron to ensure that network output always lies in or within a hypercube.

Energy function associated with the network is minimized:

$$E(t) = -\frac{1}{2} v^T(t).T.v(t) - v^T(t).i^b \qquad (4.3)$$

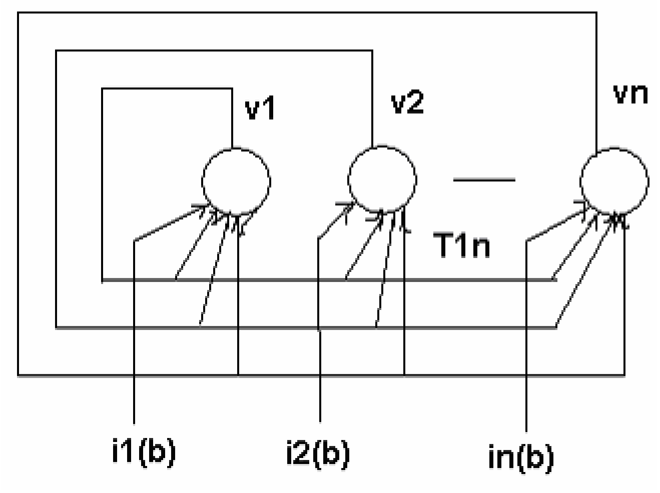

Fig.4.1 Conventional Hopfield Neural Network

A mapping of the economic load dispatch problem using a Hopfield network [7] consists of determining the weight matrix T and the bias vector i^b to obtain equilibrium points, which are the problem solution. A modified energy function E^m (t) is used here, described as follows:

$$E^m(t) = E^{conf}(t) + E^{op}(t) \qquad (4.4)$$

where E^{conf} (t) is a confinement term that groups the constraint and E^{op} (t) is an optimization term that conducts the network output to the equilibrium points. This method is in contrast to most neural approaches used in economic load dispatch problems, which become inefficient because they treat these terms as a single function of energy.

The minimization of E^m (t) of the modified Hopfield network [14] is conducted in two stages:

(i) minimization of the term E^{conf} (t):

$$E^{conf}(t) = -\frac{1}{2} v^T(t).T^{conf}.v(t) - v^T(t).i^{conf} \qquad (4.5)$$

This corresponds to confinement of v(t) in the valid subspace defined by constraint imposed by the problem.

(ii) minimization of the term $E^{op}(t)$:

$$E(t) = -\frac{1}{2} v^T(t).T^{op}.v(t) - v^T(t).i^{op} \tag{4.6}$$

This moves $v(t)$ towards an optimal solution defined by the cost function. The operation of the modified Hopfield network consists of three main steps, as in Fig. 4.2.

Step (I): Minimization of E^{conf}, corresponding to the projection of $v(t)$ in the valid subspace defined by

$$v(t+1) = T^{val}.v(t) + s \tag{4.7}$$

where T^{val} is a projection matrix ($T^{val}.T^{val} = T^{val}$) and the vector s is orthogonal to the subspace ($T^{val}.s = 0$). This operation corresponds to an indirect minimization of $E^{conf}(t)$, i.e., $T^{conf} = T^{val}$ and $i^{conf} = s$.

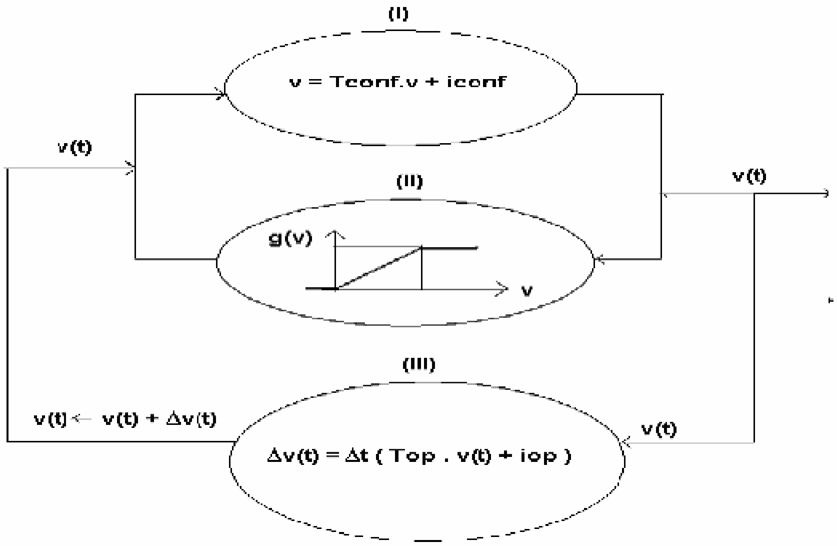

Fig.4.2 Modified Hopfield Neural Network

Step (II): Application of a nonlinear "symmetric ramp" activation function constraining $v(t)$ in a hypercube:

$$g_i(v_i) = \begin{cases} \lim_i^{\inf}, \lim_i^{\inf} < v_i \\ v_i, \lim_i^{\inf} \le v_i \le \lim_i^{\sup} \\ \lim_i^{\sup}, v_i < \lim_i^{\sup} \end{cases} \tag{4.8}$$

where $v_i(t) \in [\lim_i^{\inf}, \lim_i^{\sup}]$.

Step (III): Minimization of E^{op}, which involves updating of v(t) in direction of an optimal solution (defined by T^{op} and i^{op}) corresponding to network equilibrium points, which are the solutions for the economic load dispatch problem, by applying the gradient in relation to the energy term E^{op} :

$$\frac{dv(t)}{dt} = \dot{v} = -\frac{\partial E^{op}(t)}{\partial v} \qquad (4.9)$$
$$\Delta v = -\Delta t.\nabla E^{op}(v) = \Delta t.(T^{op}.v + i^{op})$$

Therefore, minimization of E^{op} consists of updating v(t) in the opposite direction of the gradient of E^{op} . These results are also valid when a ‘hyperbolic tangent’ activation function is used.

From fig. 4.2, each iteration has two distinct stages. First (from Step (III)), v is updated using the gradient of the term E^{op} alone. Second, after each updating, v is directly projected in the valid subspace. This is an iterative process, in which v is first orthogonally projected in the valid subspace defined in (4.7), and then thresholded so that its elements lie in the range [$\lim_i^{inf}$, $\lim_i^{sup}$].

4.2 MAPPING ELD PROBLEM BY MODIFIED HNN

An economic load dispatch problem is a problem of minimizing a cost function in presence of linear constraints of the inequality or equality type. Since equality constraints can be easily converted to inequality constraints, we use only inequality [26] constraints. Consider the following constrained optimization problem,

minimise $$C_t = \sum_{i=1}^{NG} C_i$$

where NG is the set of dispatchable generating units.

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,\ldots,NG$$

The cost of generating unit C_i is expressed as

$$C_i = a_i P_i^2 + b_i P_i + c_i$$

where

a_i, b_i, c_i are cost coefficients for unit i,

C_t = total cost of generation

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

P_i^{min}, P_i^{max} = the minimum and maximum generating limits respectively for plant i.

Now mapping this problem in Hopfield Neural Network,

Minimize

$$E^{op}(v) = C_t \tag{4.10}$$

subjected to,

$$E^{conf}(v) : [A]'[v] = [b] \tag{4.11}$$

$$z^{\min} \le v_i \le z^{\max} \qquad i \in \{1, ..., n\} \tag{4.12}$$

$$0 \le v_i \le z^{\max} \qquad i \in \{n+1 ... N\} \tag{4.13}$$

where n = number of variables, m = constraints and N = n + m and vector *v* corresponds to the variables P_i in (2.17).

If rows of A are linearly independent, solution for (4.11) is given by

$$v = A.(A^T.A)^{-1}.b \tag{4.14}$$

and the expression of the valid subspace in (4.7) must take into account this solution, i.e.,

$$i^{conf} = A\ .(A^T.A\ )^{-1}.b \tag{4.15}$$

From (4.15), the parameter T^{conf} is derived as follows:

$$\begin{aligned} v &= T^{conf}.v + i^{conf} \\ &= T^{conf}.v + A(A^T.A)^{-1}.b \end{aligned} \tag{4.16}$$

Inserting the value of (4.11) in (4.16), the expression for T^{conf} is given by:

$$T^{conf} = I - A(A^T.A)^{-1}.A^T \tag{4.17}$$

where I is identity matrix.

The parameters T^{op} and i^{op} in this case are such that the vector *v* is updated in the opposite gradient direction that of the energy function E^{op}. Since conditions given by (4.11), (4.12) and (4.13) define a bounded convex polyhedron, the objective function

(4.10) has a unique global minimum ($|T^{op} = 0|$). Thus, using (4.6) and (4.9), the equilibrium points of the network can be calculated by assuming the following values to T^{op} and i^{op}:

$$i^{op} = -\left[\frac{\partial f(v)}{\partial v_1} \frac{\partial f(v)}{\partial v_2} .... \frac{\partial f(v)}{\partial v_N} \right] \tag{4.18}$$

for updating the values, correction factor is given as

$$\Delta v = \Delta T[i^{op}]' \tag{4.19}$$

therefore new value is given as

$$v = v + \Delta v \tag{4.20}$$

$$T^{op} = 0$$

and objective function,

$$f(v) = E^{op}(v)$$

4.2.1 Algorithm

The algorithm of performing Economic Load Dispatch using modified hopfield neural network is given below –

1. Initialise [v], $\Delta T = 0.01$
2. Calculate [A]’, $T^{conf} = I - [A].inv(A'A).A'$
3. Calculate $f_{old} = f(v)$.
4. Calculate new value of [v] as
   $[v] = T^{conf}[v] + A.inv(A'.A)[b]$
5. Check for the limit values of variables, otherwise force them to be within limits.
6. Calculate $i^{op} = -[\ \partial f(v)/\partial v_1 \quad \partial f(v)/\partial v_2 \quad \ldots\ldots\ldots]$
7. Calculate correction $\Delta v = \Delta T.[i^{op}]'$
8. Calculate new value of variable v,
   $v = v + \Delta v$
9. Calculate $f_{new} = f(v)$
10. If $|\ f_{new} - f_{old}| \leq 0.0001$, then convergence is obtained, otherwise goto step 3.
11. Stop.

The flow chart of performing Economic Load Dispatch with the help of modified hopfield network is given below in fig. 4.3.

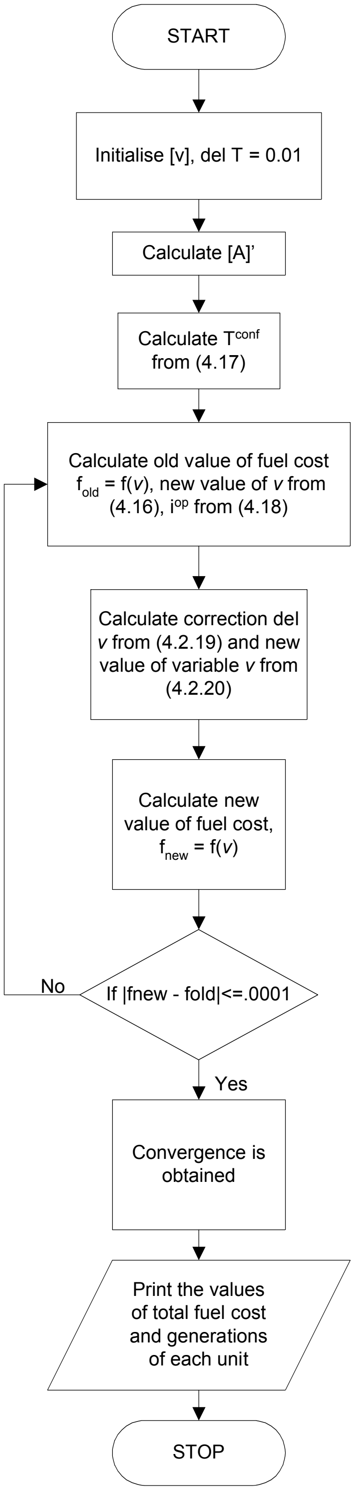

Fig. 4.3 Economic Load Dispatch using Modified Hopfield Neural Network

4.3 MAPPING ENVIRONMENTAL ELD PROBLEM BY MODIFIED HNN

For solving this problem Modified Hopfield Neural Network is used. This formulation covers three sections. Firstly formulation for optimizing NOx emissions with load balance constraint is presented then on similar lines SOx emissions are optimized and finally operating cost is minimized taking emissions as constraint considering losses.

4.3.1 NOx Optimisation Using MHNN

For performing NOx optimisation, the NOx objective function E_{Nt} is to be minimized i.e.,

Minimise $E_{Nt} = \sum_{i=1}^{NG} e_{iN}$

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,\dots, NG$$

where

$$e_{iN} = a_{iN} P_i^2 + b_{iN} P_i + c_{iN} \qquad for\ i = 1,2\dots NG$$

E_{Nt} = Total NOx emissions of the generating units

e_{iN} = NOx emissions of generator i, for i = 1, 2 ……NG

a_{iN}, b_{iN} and c_{iN} = emission coefficients of the objective function

P_D = load demand

P_L = total system transmission loss

P_i = generation of i^th^ plant and

$P_i^{\min}$, $P_i^{\max}$ = the minimum and maximum generating limits respectively for plant i.

Now considering its mapping in Modified Hopfield Neural Network,

minimize $E^{op}(v) = E_{Nt}$ (4.21)

subjected to

$$E^{conf}(v) : [A]'[v] = [b] \tag{4.22}$$

$$z^{\min} \le v_i \le z^{\max} \qquad i \in \{1,...,n\} \tag{4.23}$$

$$0 \le v_i \le z^{\max} \qquad i \in \{n+1...N\} \tag{4.24}$$

n = number of variables, m = constraints and N = n + m and vector *v* corresponds to the variables P_i in (2.17).

If rows of A are linearly independent, solution for (4.22) is given by

$$v = A.(A^T.A)^{-1}.b \tag{4.25}$$

and the expression of the valid subspace in (4.7) must take into account this solution, i.e.,

$$i^{conf} = A\ .(A^T.A\ )^{-1}.b \tag{4.26}$$

From (4.26), the parameter T^{conf} is derived as follows:

$$\begin{aligned} v &= T^{conf}.v + i^{conf} \\ &= T^{conf}.v + A(A^T.A)^{-1}.b \end{aligned} \tag{4.27}$$

Inserting the value of (4.22) in (4.27), the expression for T^{conf} is given by:

$$T^{conf} = I - A(A^T.A)^{-1}.A^T \tag{4.28}$$

where I is identity matrix.

The parameters T^{op} and i^{op} in this case are such that the vector *v* is updated in the opposite gradient direction that of the energy function E^{op}. Since conditions given by (4.22), (4.23) and (4.24) define a bounded convex polyhedron, the objective function (4.21) has a unique global minimum ($|T^{op} = 0|$). Thus, using (4.6) and (4.9), the equilibrium points of the network can be calculated by assuming the following values to T^{op} and i^{op}:

$$i^{op} = -\left[\frac{\partial e_N(v)}{\partial v_1} \quad \frac{\partial e_N(v)}{\partial v_2} \quad .... \quad \frac{\partial e_N(v)}{\partial v_N} \right] \tag{4.29}$$

for updating the values, correction factor is given as

$$\Delta v = \Delta T[i^{op}]' \tag{4.30}$$

therefore new value is given as

$$v = v + \Delta v \tag{4.31}$$

$$T^{op} = 0$$

and objective function,

$$e_N(v) = E^{op}(v)$$

The steps involved in this mapping are shown in the algorithm and the whole process is also depicted in the flow chart.

4.3.1.1 Algorithm

The steps involved are:

1. Initialise [v], delta T = 0.01
2. Calculate [A]’, T^{conf} = I – [A].inv(A’A).A’
3. Calculate $e_{Nold} = e_N(v)$.
4. Calculate new value of [v] as

   [v] = T^{conf}[v] + A.inv(A’.A)[b]
5. Check for the limit values of variables, otherwise force them to be within limits.
6. Calculate $i^{op} = -[\ \partial e_N(v)/\partial v_1 \quad \partial e_N(v)/\partial v_2 \quad \ldots\ldots\ldots]$
7. Calculate correction $\Delta v = \Delta T.[i^{op}]'$
8. Calculate new value of variable v,

   $v = v + \Delta v$
9. Calculate $e_{Nnew} = e_N(v)$
10. If $|\ e_{Nnew} - e_{Nold}| \leq \varepsilon$, ($\varepsilon$ is the tolerance value) then convergence is obtained, otherwise go to step 3.
11. Stop.

The Flow chart showing method of optimizing NOx emission with Load Balance constraint using Modified Hopfield Neural Network is shown in fig. 4.4.

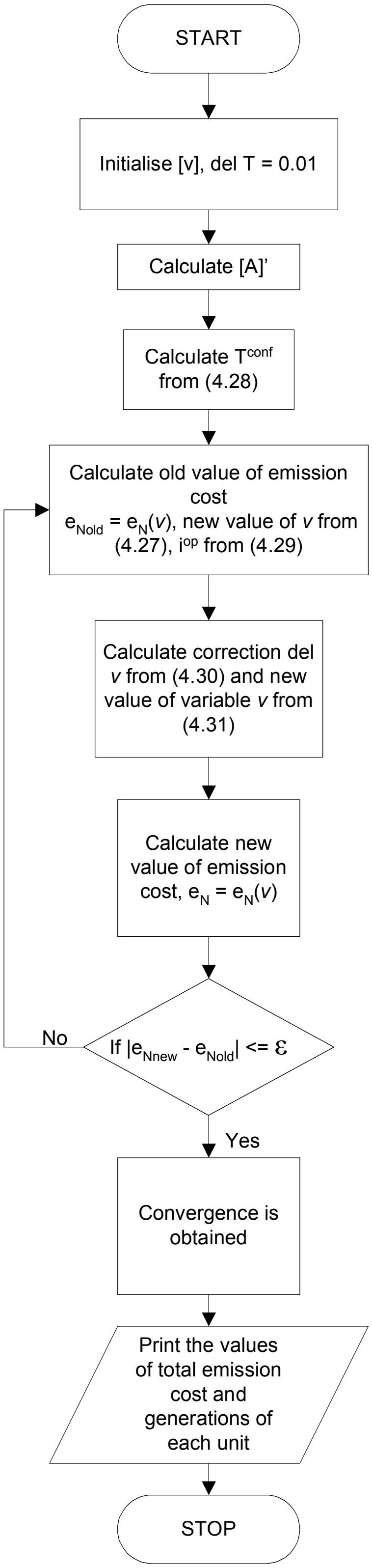

Fig. 4.4 Optimisation of NOx emission using Modified Hopfield Neural Network

4.3.2 SOx Optimisation Using MHNN

For performing SOx optimisation, the SOx objective function E_{St} is to be minimized i.e.,

Minimise $E_{St} = \sum_{i=1}^{NG} e_{iS}$

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \le P_i \le P_i^{\max} \qquad i = 1,...,NG$$

where

$$e_{iS} = a_{iS} P_i^2 + b_{iS} P_i + c_{iS} \quad for\ i = 1,\ 2 \ldots NG$$

a_{iS}, b_{iS} and c_{iS} = emission coefficients of the objective function

E_{St} = Total SOx emissions of the generating units

e_{iS} = SOx emissions of generator i, for i = 1, 2 ……NG

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

$P_i^{\min}$, $P_i^{\max}$ = the minimum and maximum generating limits respectively for plant i.

Now considering its mapping in Modified Hopfield Neural Network,

Minimize

$$E^{op}(v) = E_{St} \tag{4.32}$$

subjected to,

$$E^{conf}(v) : [A]'[v] = [b] \tag{4.33}$$

$$z^{\min} \le v_i \le z^{\max} \qquad i \in \{1,...,n\} \tag{4.34}$$

$$0 \le v_i \le z^{\max} \qquad i \in \{n+1...N\} \tag{4.35}$$

n = number of variables, m = constraints and N = n + m and and vector *v* corresponds to the variables P_i in (2.17).

If rows of A are linearly independent, solution for (4.33) is given by

$$v = A.(A^T.A)^{-1}.b \tag{4.36}$$

and the expression of the valid subspace in (4.7) must take into account this solution, i.e.,

$$i^{conf} = A\ .(A^T.A\ )^{-1}.b \tag{4.37}$$

From (4.37), the parameter T^{conf} is derived as follows:

$$\begin{aligned} v &= T^{conf}.v + i^{conf} \\ &= T^{conf}.v + A(A^T.A)^{-1}.b \end{aligned} \tag{4.38}$$

Inserting the value of (4.33) in (4.38), the expression for T^{conf} is given by:

$$T^{conf} = I - A(A^T.A)^{-1}.A^T \tag{4.39}$$

where I is identity matrix.

The parameters T^{op} and i^{op} in this case are such that the vector *v* is updated in the opposite gradient direction that of the energy function E^{op}. Since conditions given by (4.33), (4.34) and (4.35) define a bounded convex polyhedron, the objective function (4.32) has a unique global minimum ($|T^{op} = 0|$). Thus, using (4.6) and (4.9), the equilibrium points of the network can be calculated by assuming the following values to T^{op} and i^{op}:

$$i^{op} = -\begin{bmatrix} \frac{\partial e_S(v)}{\partial v_1} & \frac{\partial e_S(v)}{\partial v_2} & \ldots\ldots. & \frac{\partial e_S(v)}{\partial v_N} \end{bmatrix} \tag{4.40}$$

for updating the values, correction factor is given as

$$\Delta v = \Delta T[i^{op}]' \tag{4.41}$$

therefore new value is given as

$$v = v + \Delta v \tag{4.42}$$

$$T^{op} = 0$$

and objective function,

$$e_S(v) = E^{op}(v)$$

The steps involved in this mapping are shown in the algorithm and the whole process is also depicted in the flow chart as Fig. 4.5..

4.3.2.1 Algorithm

The steps involved are:

1. Initialise [v], delta T = 0.01
2. Calculate [A]’, $T^{conf} = I - [A].inv(A'A).A'$
3. Calculate $e_{Sold} = e_S(v)$.
4. Calculate new value of [v] as
   $[v] = T^{conf}[v] + A.inv(A'.A)[b]$
5. Check for the limit values of variables, otherwise force them to be within limits.
6. Calculate $i^{op} = -[\ \partial e_S(v)/\partial v_1 \quad \partial e_S(v)/\partial v_2 \quad \ldots\ldots\ldots]$
7. Calculate correction $\Delta v = \Delta T.[i^{op}]'$
8. Calculate new value of variable v,
   $v = v + \Delta v$
9. Calculate $e_{Snew} = e_S(v)$
10. If $|\, e_{Snew} - e_{Sold}| \leq \varepsilon$, ($\varepsilon$ is the tolerance value) then convergence is obtained, otherwise go to step 3.
11. Stop.

4.3.3 Cost Optimisation with SOx and NOx Emissions as Constraints

Emissions of NOx and SOx should be well within limits i.e., it should be less than some specified value. This results in a non linear constraint on the operating cost and adds to the complexity of the problem and makes it more non linear. These constraints are to be converted to linear constraints for solving the problem. This is done by adding a slack variable. The main objective is to -

minimize $C_t = \sum_{i=1}^{NG} C_i$

where NG is the set of dispatchable generating units.

subjected to,

$$\sum_{i=1}^{NG} P_i = P_D + P_L$$

$$P_i^{\min} \leq P_i \leq P_i^{\max} \qquad i = 1,\ldots,NG$$

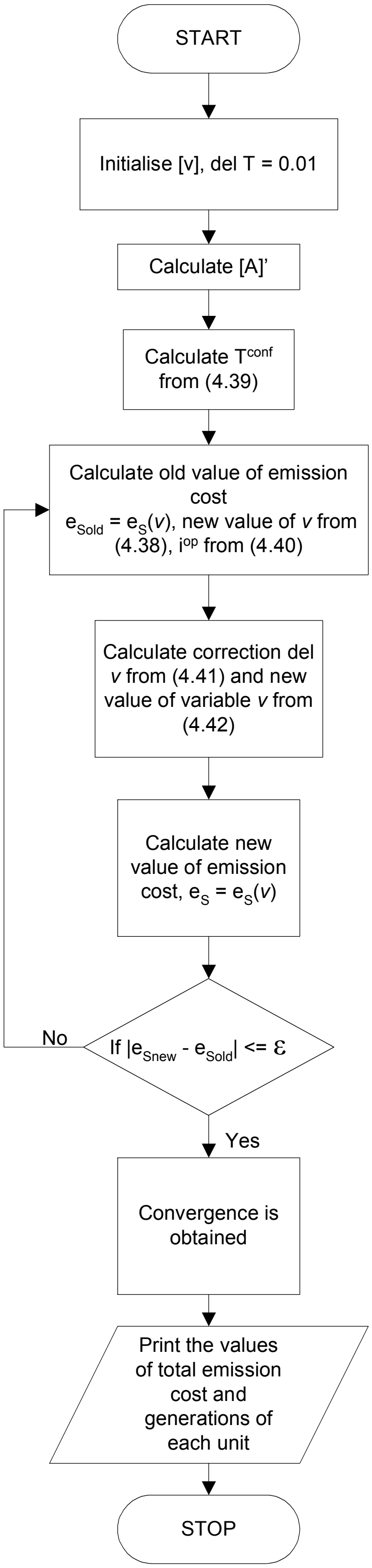

Fig. 4.5 Optimisation of SOx emission using Modified Hopfield Neural Network

The cost of generating unit C_i is expressed as

$$C_i = a_i P_i^2 + b_i P_i + c_i$$

where

a_i, b_i, c_i are cost coefficients for unit i,

C_t = total cost of generation

P_D = load demand

P_L = total system transmission loss

P_i = generation of ith plant and

P_i^{min}, P_i^{max} = the minimum and maximum generating limits respectively for plant i.

Considering the problem's mapping in MHNN, the objective function is to minimize

$$E^{op}(v) = C_t \tag{4.43}$$

subjected to,

$$E^{conf}(v) : [A]'[v] \le [b] \tag{4.44}$$

$$z^{\min} \le v_i \le z^{\max} \qquad i \in \{1,\ldots,n\} \tag{4.45}$$

The parameters T^{conf} and i^{conf} are calculated by transforming the inequality constraints into equality constraints by introducing slack variable w for each inequality constraint. After this transformation, the problem defined can be rewritten as

$$E^{op}(v) = C_t$$

subjected to,

$$E^{conf}(v) : [A^+]'[v^+] = [b^+] \tag{4.46}$$

$$z^{\min} \le v_i^+ \le z^{\max} \qquad i \in \{1,\ldots n\}$$

$$0 \le v_i^+ \le z^{\max} \qquad i \in \{n+1 \ldots N^+\} \tag{4.47}$$

where n = number of variables, m = constraints and $N^+ = n + m$, vector v corresponds to the variables P_i in (2.17) and $v^{+'} = [v' \;\; w']$ is a vector of extended variables.

If rows of A^+ are linearly independent, solution for (4.46) is given by

$$v^+ = A^+ . (A^{+T} . A^+)^{-1} . b^+ \tag{4.48}$$

and the expression of the valid subspace in (4.7) must take into account this solution, i.e.,

$$i^{conf} = A^{+}.(A^{+T}.A^{+})^{-1}.b^{+} \qquad (4.49)$$

From (4.49), the parameter T^{conf} is derived as follows:

$$\begin{aligned} v^{+} &= v^{+} - i^{conf} \\ &= v^{+} - A^{+}(A^{+T}.A^{+})^{-1}.b^{+} \end{aligned} \qquad (4.50)$$

Inserting the value of (4.46) in (4.50), the expression for T^{conf} is given by:

$$T^{conf} = I - A^{+}(A^{+T}.A^{+})^{-1}.A^{+T} \qquad (4.51)$$

where I is identity matrix.

The parameters T^{op} and i^{op} in this case are such that the vector v is updated in the opposite gradient direction that of the energy function E^{op}. Since conditions given by (4.44), (4.47) and (4.46) define a bounded convex polyhedron, the objective function (4.43) has a unique global minimum ($|T^{op} = 0|$). Thus, using (4.6) and (4.9), the equilibrium points of the network can be calculated by assuming the following values to T^{op} and i^{op}:

$$i^{op} = -\left[\frac{\partial f(v)}{\partial v_1}\frac{\partial f(v)}{\partial v_2}\cdots\cdots\frac{\partial f(v)}{\partial v_N}\right] \qquad (4.52)$$

for updating the values, correction factor is given as

$$\Delta v^{+} = \Delta T[i^{op}]' \qquad (4.53)$$

therefore new value is given as

$$v = v^{+} + \Delta v^{+} \qquad (4.54)$$

$$T^{op} = 0$$

and objective function,

$$f(v) = E^{op}(v)$$

4.3.3.1 Algorithm

The algorithm for performing cost optimization with SOx and NOx emissions as constraints using modified hopfield network is given below. These steps are shown in the flow chart in fig. 4.6.

1. Initialise [v], $\Delta T = 0.2$

2. Calculate $[A^+]'$, $T^{conf} = I - [A^+].inv(A^{+}{}'A^+).A^{+}{}'$

3. Calculate $f_{old} = f(v)$.

4. Calculate new value of [v] as

$[v^+] = [v^+] - A^+.inv(A^{+}{}'.A^+)[b^+]$

5. Check for the limit values of variables, otherwise force them to be within limits.

6. Calculate $i^{op} = -[\ \partial f(v)/\partial v_1 \quad \partial f(v)/\partial v_2 \quad \ldots\ldots\ldots]$

7. Calculate correction $\Delta v^+ = \Delta T.[i^{op}]'$

8. Calculate new value of variable v,

$v = v^+ + \Delta v^+$

9. Calculate $f_{new} = f(v)$

10. If $|\ f_{new} - f_{old}| \leq \varepsilon$ (tolerance value), then convergence is obtained, otherwise go to step 3.

11. Stop.

The flow chart of performing Economic Load Dispatch with the help of modified hopfield network is given below in fig. 4.6

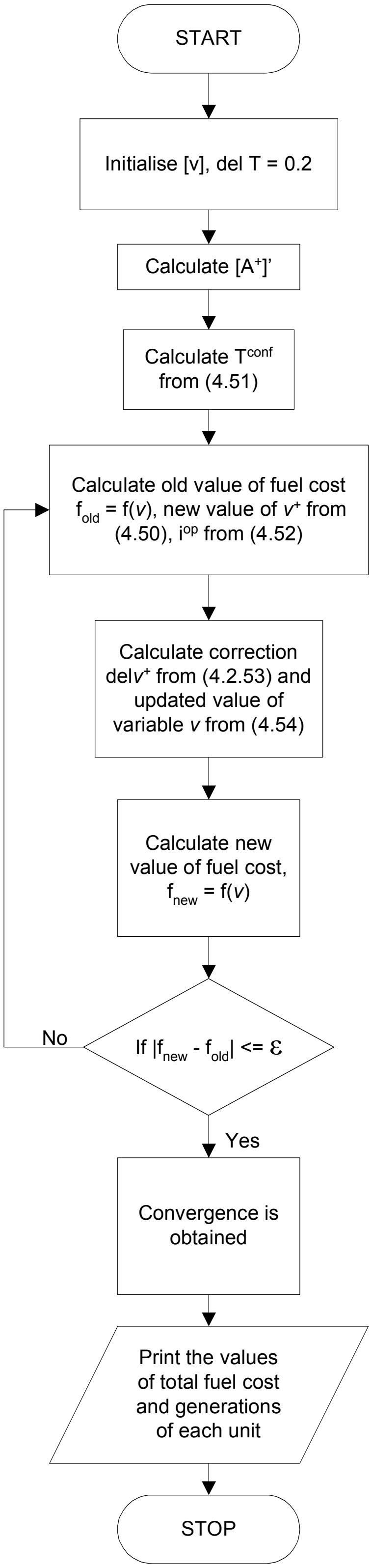

Fig. 4.6 Cost optimisation with SOx and NOx emissions as constraints using Modified Hopfield Neural Network

CHAPTER-5

RESULTS AND DISCUSSION

The results for a system of three generator [68] have been presented for cost optimisation, NOx optimisation, SOx optimisation with load balance constraint and cost optimisation with environmental constraints using Modified HNN. The cost optimisation is also attempted using Lagrange multiplier and conventional HNN for comparison. The programs are implemented in Matlab 6.5.The method's effectiveness has been tested while losses are considered and neglected. The system specifications are summarized as -

the cost of generations are -

$$C_1 = 561 + 7.92P_1 + 0.001562P_1^2$$
$$C_2 = 310 + 7.85P_2 + 0.00194P_2^2$$
$$C_3 = 78 + 7.97P_3 + 0.00482P_3^2$$

the operating limits are (5.1)

$$150 \le P_1 \le 600$$
$$400 \le P_2 \le 100$$
$$50 \le P_3 \le 200$$

the transmission losses are

$$P_L = 0.00003P_1^2 + 0.00009P_2^2 + 0.00012P_3^2 \quad MW \tag{5.2}$$

the NOx emission from generators are

$$\begin{aligned} e_{1N} &= (1.4721848e^{-7})P_1^2 + (-9.4868099e^{-5})P_1 + 0.04373254 \\ e_{2N} &= (3.0207577e^{-7})P_2^2 + (-9.7252878e^{-5})P_2 + 0.055821713 \\ e_{3N} &= (1.9338531e^{-6})P_3^2 + (-3.5373734e^{-4})P_3 + 0.027731524 \end{aligned} \tag{5.3}$$

the SOx emission from generators are

$$\begin{aligned} e_{1S} &= (1.6103e^{-6})P_1^2 + (0.00816466)P_1 + 0.5783298 \\ e_{2S} &= (5.4658e^{-6})P_2^2 + (0.00891174)P_2 + 0.3515338 \\ e_{3S} &= (5.4658e^{-6})P_3^2 + (0.00903782)P_3 + 0.0884504 \end{aligned} \tag{5.4}$$

the load demand P_D is 850 MW and

the environmental constraints are

$$\sum_{i=1}^{NG} e_{iN} \le e_{iN}^{\lim it} \quad \text{and} \tag{5.5}$$

$$\sum_{i=1}^{NG} e_{iS} \le e_{iS}^{\lim it} \tag{5.6}$$

The selection of these limits is discussed in Section 5.4.

The data is used for obtaining the optimum solutions for the following cases

A. Cost Optimisation
   (i) Without losses
   (ii) With losses
B. NOx emissions optimisation
   (i) Without losses
   (ii) With losses
C. SOx emissions optimisation
   (i) Without losses
   (ii) With losses
D. Cost Optimisation with environmental constraints
   (i) Without losses
   (ii) With losses

5.1 COST OPTIMISATION

The cost optimization with load balance is attempted while losses are neglected and losses are considered. The results are obtained using Lagrange Multiplier method, Conventional Hopfield and Modified Hopfield Neural Network. These are presented in Table 5.1 and Table 5.2 for neglecting the losses and considering the losses respectively.

Considering equation (5.1), the results are obtained while neglecting losses and are shown in Table 5.1.

Table 5.1 Cost optimisation while neglecting the losses

	Lagrange Multiplier Method	Conventional Hopfield Method	Modified Hopfield Neural Network
P_1 (MW)	393.1698	392.9013	393.1308
P_2 (MW)	334.6038	334.3876	334.4629
P_3 (MW)	122.2264	122.1394	122.1318
Fuel Cost ($/hr)	8194.356121	8189.126299	8191.845489

The above results show that Fuel cost obtained through modified hopfield is lesser than Lagrange multiplier method.

The equations (5.1) and (5.2) are used for considering the losses and the results are summarized in Table 5.2

Table 5.2 Cost optimisation while considering losses

	Lagrange Multiplier Method	Conventional Hopfield Method	Modified Hopfield Neural Network
P_1 (MW)	435.198	435.197	447.368
P_2 (MW)	299.9690	299.9692	292.192
P_3 (MW)	130.660	130.661	125.754
Losses(MW)	15.829	15.82895	15.585
Fuel Cost ($/hr)	8344.590	8344.591	8342.607

As expected the operating cost for neglecting losses is lesser. The modified hopfield neural network is giving best results i.e. minimum operating cost while considering losses. The variation of fuel cost with number of iterations while losses are considered is shown in fig. 5.1.

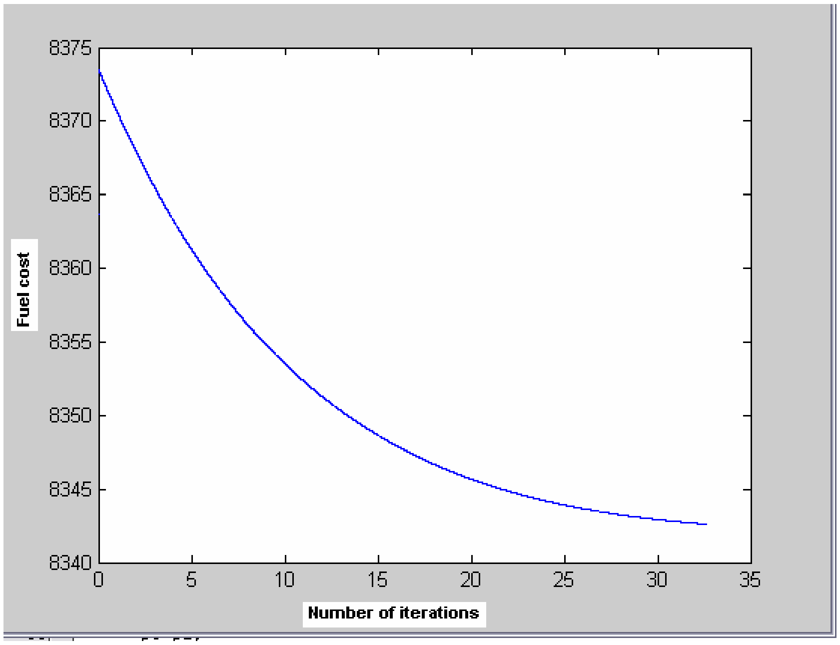

Fig. 5.1 Fuel cost Vs Number of iterations for cost optimisation

This graph ensures the convergence of fuel cost with load balance constraint considering losses as the iterations progresses, when Modified Hopfield Neural Network is used. The variation of Power outputs for the same problem while considering losses is shown in fig. 5.2.

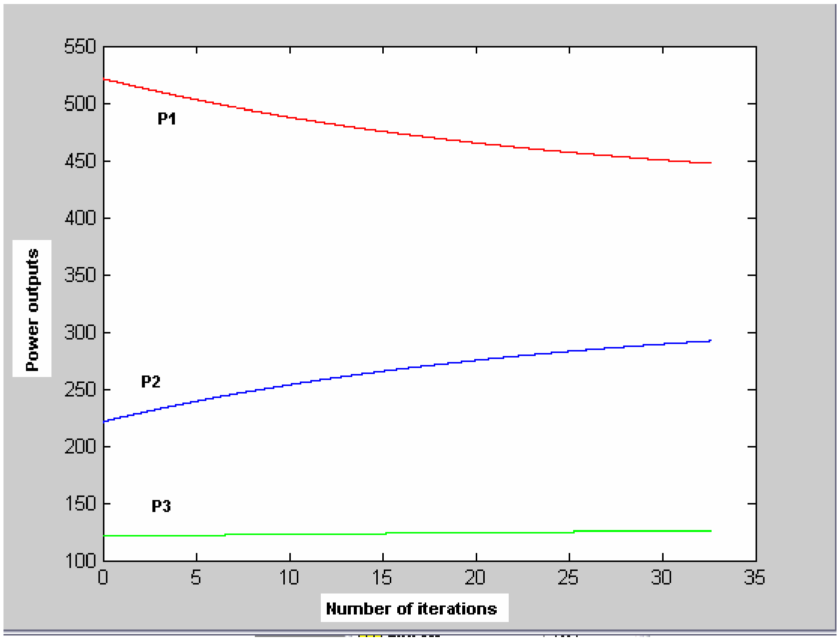

Fig. 5.2 Power outputs Vs Number of iterations for cost optimization

The Power outputs converge with increase in iterations with the use of Modified Hopfield Neural Network. As our work is primarily on Modified Hopfield Neural Network (MHNN), the results using MHNN are analysed in details.

5.2 NOx EMISSION OPTIMISATION

The results of NOx optimisation with load balance constraints using MHNN is carried out when losses are neglected and when losses are considered. Thus the problem is solved neglecting losses considering equations (5.1) and (5.3) and solved taking losses using equation (5.1), (5.2) and (5.3). The results are summarised in Table 5.3.

Table 5.3 NOx emission optimisation using Modified Hopfield Neural Network

	Without losses	With losses
P_1 (MW)	498.2725	508.1123
P_2 (MW)	246.7568	250.8762
P_3 (MW)	104.8150	105.5983
Losses (MW)	0	14.7480
Fuel Cost ($/hr.)	8226.620018	8363.368711
NOx emissions (ton/hr)	0.095130	0.095900
SOx emissions (ton/hr)	8.826668	8.960141

The results presented in the table 5.3 shows that the NOx emissions are lower when losses are neglected and similar is the case with the fuel cost. The minimisation of NOx emissions with the progressing iterations is shown in fig. 5.3.

Power Outputs converges in few iterations only. After some iterations these become almost constant.

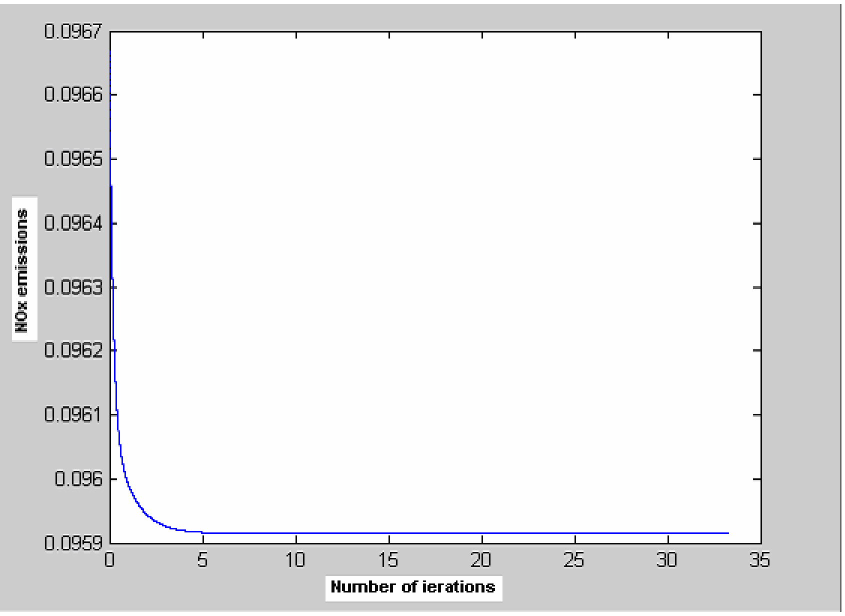

Fig. 5.3 Optimisation of NOx emissions Vs Number of iterations

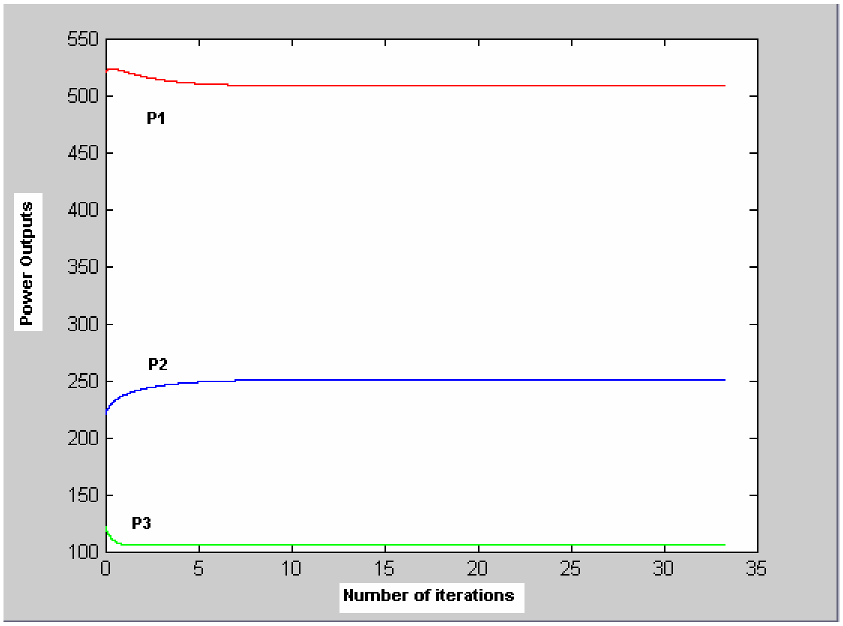

Fig. 5.4 Power outputs Vs Number of iterations for NOx optimisation

5.3 SOx EMISSION OPTIMISATION

The results of SOx optimisation with load balance constraints using MHNN is carried out when losses are neglected and when losses are considered. So this problem is solved in two ways. First case is done using equations (5.1) and (5.4), i.e., neglecting losses using Modified Hopfield Neural Network. In the next case, losses are included and are thus solved taking equations (5.1), (5.2) and (5.4) using Modified Hopfield Neural Network. Results for both cases are summarised in Table 5.4.

Table 5.4 SOx emission optimisation using Modified Hopfield Neural Network

	Without losses	With losses
P_1 (MW)	542.4701	520.9844
P_2 (MW)	227.3391	220.9197
P_3 (MW)	79.8934	121.0434
Losses (MW)	0	14.2934
Fuel Cost ($/hr.)	8257.412535	8363.399885
NOx emissions (ton/hr)	0.09673045779	0.09659
SOx emissions (ton/hr)	8.817902	8.959246

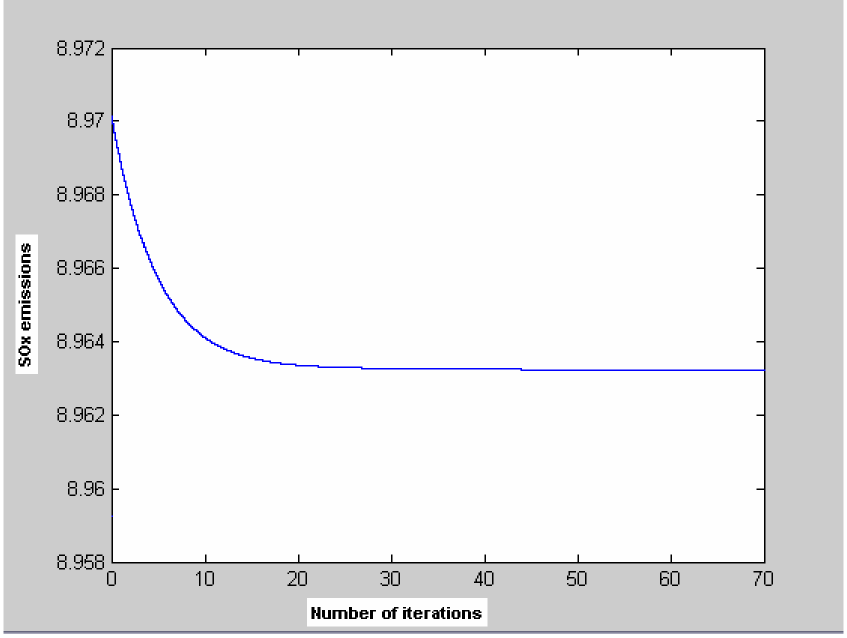

Fig. 5.5 SOx emissions Vs Number of iterations

Thus SOx emissions are lesser when losses are neglected Also fuel cost is least while neglecting losses. The minimisation of SOx emission with progressing iterations while considering losses using Modified hopfield neural network is clearly revealed through the exponential curve in fig. 5.5. The variations of power outputs in this case are shown in fig. 5.6.

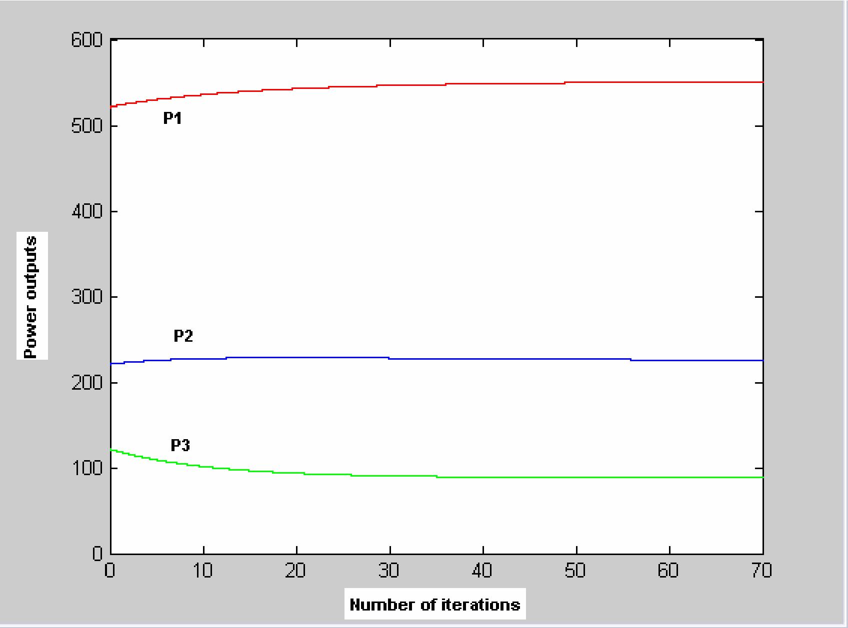

Fig. 5.6 Power outputs Vs Number of iterations for optimizing SOx emissions

5.4 COST OPTIMISATION WITH SO_X AND NO_X EMISSIONS AS CONSTRAINTS

The problem has been formulated as cost optimisation subjected to inequality constraints on NOx and SOx emissions. Two cases are considered for this purpose. First is Cost minimisation neglecting losses. Equations (5.1), (5.3) to (5.6) are considered for the problem. For second case equations (5.1) to (5.6) are used.

As the emission constraint data was not available it is considered as 1.1 times or ten percent higher than the respective optimum values obtained in section 5.2 and section 5.3. Therefore the limits for NOx and SOx emissions, i.e., e_{iN}^{lim} and e_{iS}^{lim} are set as 0.1045 and 9.8551706 respectively. This will give sufficient margin to have optimum solution while constraints are conflicting. Correspondingly the results are presented in

Table 5.5 while considering loses and neglecting losses. Correspondingly the variations in fuel cost and generation level with iterations are shown in fig. 5.7 and fig. 5.8 respectively. As the iteration progresses the fuel cost decreases in fig. 5.7.

Table 5.5 Cost optimisation with NOx and SOx constraints

	Without losses	With losses
P_1 (MW)	392.4797	434.846
P_2 (MW)	334.8901	299.926
P_3 (MW)	122.0813	130.509
Losses (MW)	0	15.812
Fuel Cost ($/hr.)	8189.335573	8339.542
NOx emissions (ton/hr)	0.0997	0.098
SOx emissions (ton/hr)	8.8868	9.016

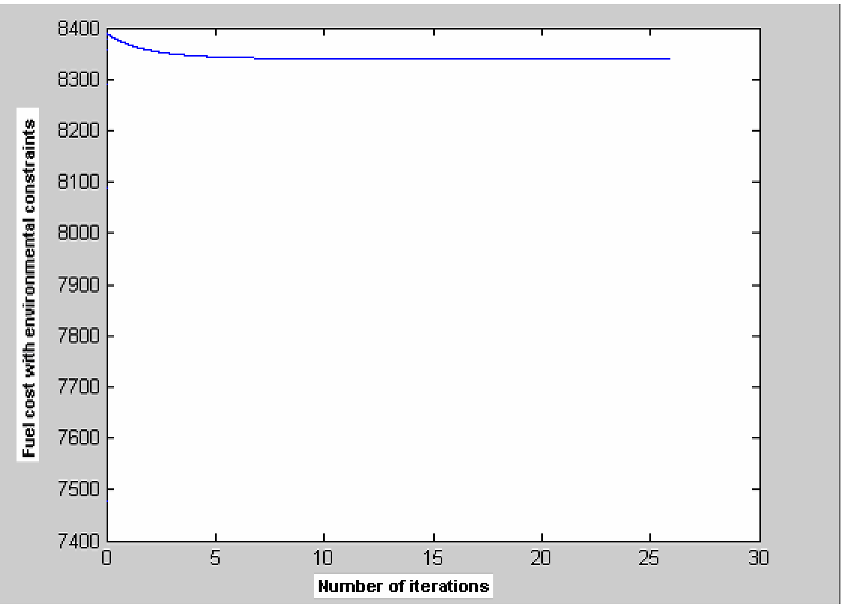

Fig. 5.7 Fuel cost with environmental constraints Vs Number of iterations

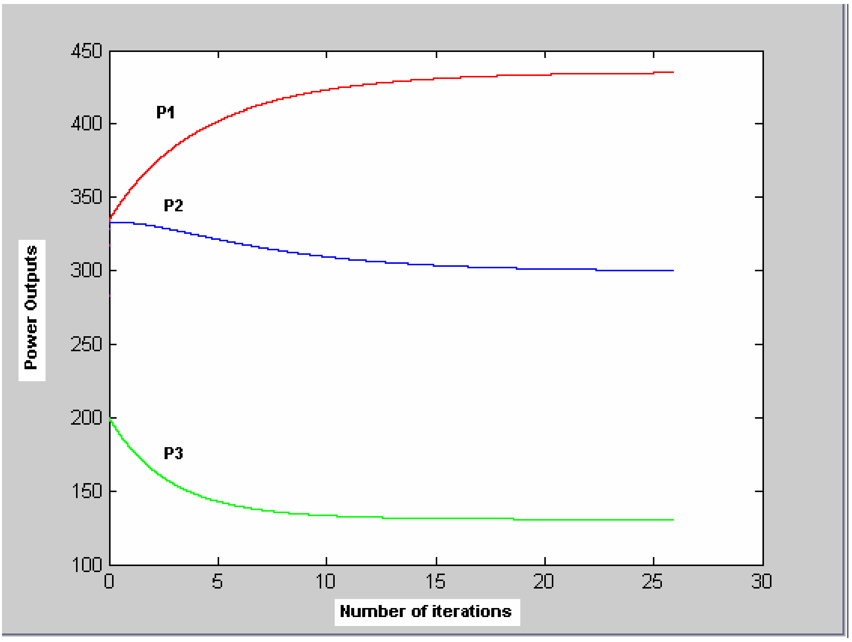

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Fig. 5.8 Power outputs Vs Number of iterations for cost optimisation with environmental constraints

The summary of the optimum results obtained for various cases using modified hopfield neural network are presented in Table 5.6 when losses are neglected and in Table 5.7 when losses are considered.

Table 5.6 Comparison of results (Modified HNN) without considering losses

	Cost optimisation	NOx optimisation	SOx optimisation	Cost optimisation with environmental constraints
P_1 (MW)	393.130	498.2725	542.470	392.479
P_2 (MW)	334.462	246.7568	227.339	334.890
P_3 (MW)	122.131	104.8150	79.893	122.081
Fuel cost ($/hr)	8191.845	8226.620	8257.412	8189.335
NOx emissions (ton/hr)	0.0996	0.0951	0.0967	0.0997
SOx emissions (ton/hr)	8.8890	8.8266	8.8179	8.8868

The above results reveal that optimizing NOx emissions results in least emissions as compared to other cases and similar is the case with SOx emissions. Fuel cost is least in case A where cost is optimised which is the required result.

Table 5.7 Comparison of results (Modified HNN) considering losses

	Cost optimisation	NOx optimisation	SOx optimisation	Cost optimisation with environmental constraints
P_1	447.368	508.112	550.425	434.846
P_2	292.192	250.876	225.785	299.926
P_3	125.754	105.598	88.104	130.509
P_L	15.585	14.748	14.608	15.812
Fuel cost	8342.607	8363.368	8392.523	8339.542
NOx emissions	0.097	0.095	0.096	0.098
SOx emissions	9.010	8.96	8.96	9.016

The results show that out of cost optimisation, NOx and SOx optimisation, fuel cost is minimum in case of cost optimisation which is on the expected lines. Similarly NOx and SOx emissions are least in case of NOx and SOx optimisations respectively.

The cost optimisation with emission constraints is giving slightly lower cost. This is mainly because of unavailability of e_{iN}^{lim} and e_{iS}^{lim} and because these limits are selected ten percent higher then the respective minimum values. Because of this the selected values of P_1, P_2 and P_3 are giving lower cost but slightly higher NOx and SOx emissions.

CHAPTER-6

CONCLUSIONS AND SCOPE FOR FUTURE WORK

6.1 CONCLUSIONS

The various aspects of environmental economic dispatch like cost optimisation, minimisation of emissions and the cost optimisation with environmental emission constraints are studied. An efficient and diversified approach using Modified Hopfield Neural Network is identified to solve the above optimisation problems.

The Modified Hopfield Neural Network works on the principle of minimizing the energy function and this property ensures convergence. There is flexibility of taking objective function and the constraints separately in this method. Also the results obtained are independent of initialization and weight selection. Its implementation is simple in computers. The internal parameters of neural networks are computed using valid subspace approach, which guarantee the convergence of solution at equilibrium points.

Here this method has been used for solving the Environmental Economic Load Dispatch problem. Various formulation of Environmental Economic Load Dispatch are solved by single mathematical formulation of Modified Hopfield Neural Network Firstly, cost optimisation is done with load balance constraints, then the NOx and SOx optimisation are done separately with load balance constraints and finally cost is minimized while considering SOx and NOx emissions as inequality constraints in addition to load balance constraint.

Case studies have been employed to illustrate the application of this method. The problem is solved considering and neglecting losses for each case with three generator data. The results of cost optimization are compared with Lagrange multiplier and conventional Hopfield Neural Network methods. The method employed has been found effective for all these cases and is found to be capable to support more realistic constraints or objective function.

6.2 SCOPE FOR FUTURE WORK

The scope of work after studying Environmental Economic Dispatch using Modified Hopfield Network is identified as:

- extend the problem for Optimal Power Flow while including various Facts devices.
- extend the problem for large number of units i.e., 30 or 90 or even higher units.
- extend the problem to include a more complex objective and constraints function like exponential function or an equation of higher order polynomial having more non linearity.
- extend it to include emissions other than NOx and SOx like Carbon dioxide emissions.

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