COMPARATIVE STUDY OF ECONOMIC LOAD DISPATCH (ELD) USING MODIFIED HOPFIELD NEURAL NETWORK

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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 has been solved by various methods like Lagrange method, Newton's method etc.This paper presents the Hopfield Neural Network (HNN) to solve the Economic Environmental Dispatch (EED) problem. The equality constraints of power balance and the inequality generator capacity constraints are considered. The EED problem is a biobjective non linear optimization problem since it is obtained by considering both the economy and emission objectives. This biobjectives problem is converted into a single objective function using a price penalty factor approach. In this paper HNN are tested on six generators system and the results are compared. The solutions are quite encouraging and useful in the EED.
Index Terms - Hopfield Neural Network, optimization problem, transmission line loss, emission and economic dispatch.

1. INTRODUCTION

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. Different techniques have been reported in the literature pertaining to combined environmental economic dispatch (EED) problem. The EED problem has been reduced to a single objective problem by introducing price penalty factor. In this paper Hopfield Neural Network (HNN) is implemented to Economic Environmental Dispatch (EED) problem.

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

Minimise $C_t = \sum_{i=1}^{ng} C_i$ (2.1)

where NG is the set of dispatchable generating units.

Subjected to, $\sum_{i=1}^{ng} Pi = P_d + P_l$ (2.2)

$P_i^{min} \leq P\ i \leq P_i^{max}$ i= 1,……………. NG (2.3)

The cost of generating unit Ci is expressed as

$C_{i=}\ a_i\ P2 + b_i\ P_i + c_i$ (2.4)

Where

i i i a ,b ,c are cost coefficients for unit i,

Ct = total cost of generation

PD = load demand

PL = total system transmission loss

Pi = generation of ith plant and

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

2.1 OPTIMUM LOAD DISPATCH

The optimum load dispatch problem involves the solution of two different problems. The first of these is the **unit commitment** or pre dispatch problem wherein it is required to select optimally out of the available generating sources to operate to meet the expected load and provide a specified margin of operating reserve over a specified period time .The second aspect of economic dispatch is the **on line economic dispatch** whereas it is required to distribute load among the generating units actually paralleled with the system in such manner as to minimize the total cost of supplying the minute to minute requirements of the system. The objective of this work is to find out the solution of non linear on line economic dispatch problem by using PSO algorithm.

2.2 COST FUNCTION

The Let Ci mean the cost, expressed for example in dollars per hour, of producing energy in the generator unit I. the total controllable system production cost therefore will be

$C=\Sigma^{N}_{i=1} C(i)\$/h$

The generated real power PGi accounts for the major influence on ci. The individual real generation are raised by increasing the prime mover torques ,and this requires an increased expenditure of fuel. The reactive generations QGi do not have any measurable influence on ci because they are controlled by controlling by field current. The individual production cost ci of generators unit I is therefore for all practical purposes a function only of PGi, and for the overall controllable production cost, we thus have

$C = \Sigma^{N}_{i=1} CiPG(i)$

When the cost function C can be written as a sum of terms where each term depends only upon one independent variable.

2.3 SYSTEM CONSTRAINTS

Broadly speaking there are two types of constraints

i) Equality constraints

ii) Inequality constraints

The inequality constraints are of two types (i) Hard type and, (ii) Soft type. The hard type are those which are definite and specific like the tapping range of an on-load tap changing transformer whereas soft type are those which have some flexibility associated with them like the nodal voltages and phase angles between the nodal voltages, etc. Soft inequality constraints have been very efficiently handled by penalty function methods.

2.4 The Lambda –Iteration Method

In Lambda iteration method lambda is the variable introduced in solving constraint optimization problem and is called Lagrange multiplier. It is important to note that lambda can be solved at hand by solving systems of equation. Since all the inequality constraints to be satisfied in each trial the equations are solved by the iterative method

i) Assume a suitable value of λ (0) this value should be more than the largest intercept of the incremental cost characteristic of the various generators.

ii) Compute the individual generations

iii) Check the equality

$Pd= \Sigma^{n}_{n=1}Pn$- - - - - - - - - - - - - - - - (2.1)

is satisfied.

iv) If not, make the second guess λ repeat above steps

2.4.1 Newton's Method:

Newton's method goes a step beyond the simple gradient method and tries to solve the economic dispatch by observing that the aim is to always drive

$$P\ \Psi_{x} = 0$$

Since this is a vector function, we can formulate the problem as one of finding the correction that exactly drives the gradient to zero (i.e. to a vector, all of whose elements are zero).Suppose we wish to drive the function g(x) to zero. The function g is a vector and the unknown, x are also vectors. Then to use Newton's method, we observe

$g(x+\Delta x)=g(x)+[g'(x)]\ \Delta x=0$ - - - - - - - - - - - - - - - - - - - (2.7)

Where g'(x) is the familiar Jacobian matrix. The adjustment at each step is then

$\Delta X = -[g'(x)]-1\ g(x)$ - - - - - - - - - - - - - - - - - - - (2.8)

The x ▫ ψ is a Jacobean matrix which has now second order derivatives is called Hessian matrix. Generally, Newton's method will solve for the correction that is much closer to the minimum generation cost in one cost in one step than would the gradient method

3.1. ARTIFICIAL NEURAL NETWORK AND PSO

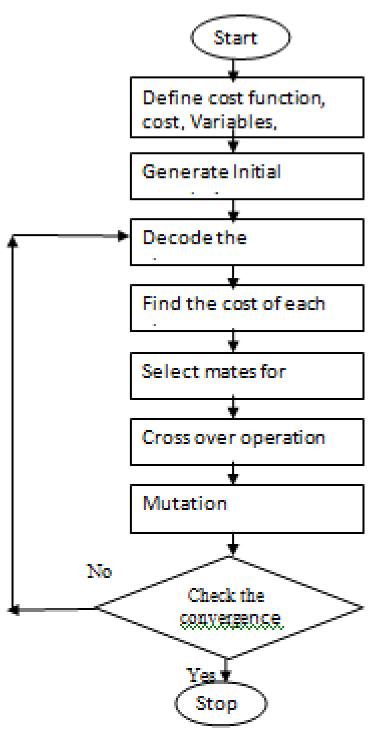
An artificial neural network (ANN) is an analysis paradigm that is a simple model of the brain and the back-propagation algorithm is the one of the most popular method to train the artificial neural network. Recently there have been significant research efforts to apply evolutionary computation (EC) techniques for the purposes of evolving one or more aspects of artificial neural networks. Evolutionary computation methodologies have been applied to three main attributes of neural networks: network connection weights, network architecture (network topology, transfer function), and network learning algorithms. Most of the work involving the evolution of ANN has focused on the network weights and topological structure. Usually the weights and/or topological structure are encoded as a chromosome in GA. The selection of fitness function depends on the research goals. For a classification problem, the rate of misclassified patterns can be viewed as the fitness value. The advantage of the EC is that EC can be used in cases with non-differentiable PE transfer functions and no gradient information available.

The disadvantages are:

1. The performance is not competitive in some problems.
2. Representation of the weights is difficult and the genetic operators have to be carefully selected or developed.

There are several papers reported using PSO to replace the back-propagation learning algorithm in ANN in the past several years. It showed PSO is a promising method to train ANN. It is faster and gets better results in most cases.

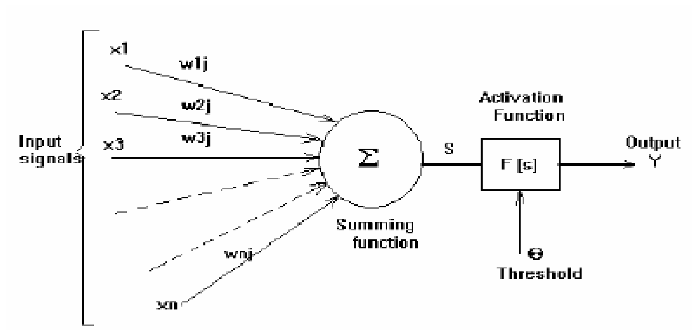
FLOW CHART OF GENETIC ALGORITHM



4. ELD USING HOPFIELD NEURAL NETWORK

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. 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.



The Model of a single neuron

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. These properties are tabulated in Table 6.1.

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)

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. 6.4.

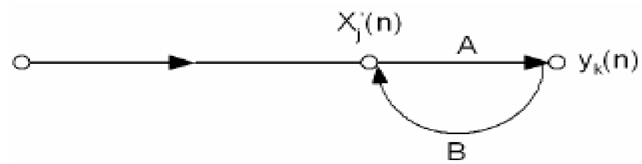


Fig 6.4 Single loop feedback system

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

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

Using the binomial expression, it can be written as

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

where |w|<1 i.e., the system output is exponentially convergent as shown in fig. 6.5.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.

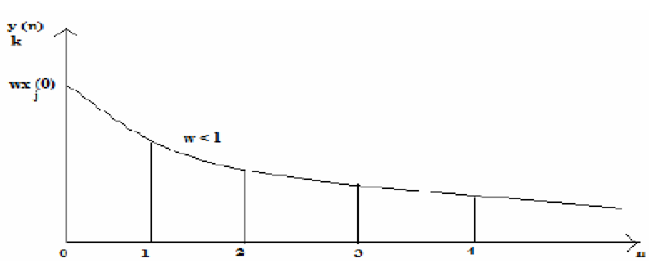


Fig. 6.5 Diagram showing exponentially converging system output

5. CONCLUSION

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

6. 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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