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A Survey on Economic Load Dispatch (ELD) for Power Systems

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Abstract: It has remained a continuous effort of electrical engineers to minimize the operation cost per unit of electricity. With the advent of distributed power systems, an interconnection of power systems generating from different sources have come into consideration. However, all sources do not operate in the same manner and hence the generation cost for different sources varies significantly. Economic Load Dispatch (ELD) can be defined as a technique to schedule the power generator outputs with respect to the load demands, and to operate the power system in the most economical way.[7] This problem becomes challenging with system constraints and hence there is a need for effective optimization tolls for minimizing the cost to attain the condition of ELD. This paper presents the basics of economic load dispatch and the previous work in the domain along with its salient features. Moreover, the basics of using soft computing approaches such as fuzzy logic, neural networks and neuro fuzzy expert systems have also been introduces along with the previous work.

Keywords: Interconnected power systems, economic load dispatch, neural networks, fuzzy logic, neuro-fuzzy expert system.

I. Introduction:

The present day power systems are increasing in size due to increasing demands of power. With such an increase in size, the following associated challenges are being faced:[1]

1) Reducing system operating cost,

2) Reducing the magnitude of pollution.

3) Reducing transmission loss.

Economic Load Dispatch (ELD) can be thought of as an optimization technique that tries to optimize the generation of different sources so as to minimize operation cost.

The mathematical condition for attaining ELD is:

$$\frac{\partial C1}{\partial P1} = \frac{\partial C2}{\partial P2} = \cdots \frac{\partial Cn}{\partial Pn} = \beta \qquad (1)$$

Here,

$\frac{\partial Ci}{\partial Pi}$ stands for the increment cost generation for the generator.

The above condition is also known as the criterion of β distribution or incremental cost-loading principle.[11]

The optimization problem can be solved in several ways. One of the most promising ways is the use of neuro-fuzzy expert system. The subsequent section explains the concept.

II. Previous Work

A.Y. Abdelaziz et al. in [1] proposed that Economic Load Dispatch (ELD) is the process of allocating the required load between the available generation units such that the cost of operation is minimized. The ELD problem is formulated as a nonlinear constrained optimization problem with both equality and inequality constraints. The dual-objective Combined Economic Emission Dispatch (CEED) problem is considering the environmental impacts that accumulated from emission of gaseous pollutants of fossil-fueled power plants. In this paper, an implementation of Flower Pollination Algorithm (FPA) to solve ELD and CEED problems in power systems is discussed. A comparison of the simulated results using the proposed FPA is carried out to confirm its effectiveness against other swarm intelligent algorithms for six various power systems. The superiority of the proposed FPA compared with other algorithms is demonstrated even for large scale power system considering valve point loading effect.

Rasoul Azizipanah-Abarghooee et al. in [2] proposed that CHP (Combined heat and power) generation or cogeneration has been considered worldwide as the major alternative to traditional systems in terms of significant energy saving and environmental conservation. Furthermore, the wind power generators and photovoltaic units have vastly speared over the power systems due to their free inputs. However, there are many challenges for power system operators because of uncertain characteristics of renewable units and load demands. Therefore, a new multi-objective stochastic framework based on chance constrained programming is developed to handle combined heat and power economic load dispatch considering the stochastic characteristics of wind and photovoltaic power outputs, customer's electrical and heat load demands. The proposed technique makes use of a jointly distributed random variables method to calculate chance of meeting the electrical and heat load requirement using the target decision variables while maintaining the electrical energy cost below a scheduled value.

Sumit Banerjee et al. in [3] proposed a novel teaching learning based optimization (TLBO) technique to solve economic load dispatch (ELD) of the thermal unit without considering transmission losses. The proposed methodology can take care of ELD considering nonlinearity such as valve point loading. The objective of economic load dispatch is to determine the optimal power generation of the units to meet the load demand, such that the overall cost of generation is minimized, while satisfying different operational constraints. TLBO is a recently developed evolutionary algorithm based on two basic concepts of education namely teaching phase and learning phase. At first, learners improve their knowledge through the teaching methodology of teacher and finally learners increase their knowledge by interactions among themselves. The effectiveness of the proposed algorithm has been verified on three different test systems with equality and inequality constraints. Compared with the other existing techniques demonstrates the superiority of the proposed algorithm.

Jingrui Zhang et al. in [4] proposed the non-convex Economic Dispatch Problem (EDP) with power losses, prohibited operating zones, and generation cost functions modeling both valve-point loading effects and multiple fuel options. This constrained problem is stated as an unconstrained problem by using the augmented Lagrange formulation, while introducing Lagrange multipliers and penalty parameters. Then, a genetic algorithm (GA) relying on two iterative loops is described: the inner loop executes a GA with fixed penalty parameters and Lagrange multipliers, while the outer loop updates such parameters when required. The effects of four different mutation operators based on the Gaussian and Cauchy distributions are also investigated. Finally, the effectiveness of the proposed approach is shown by numerical simulations on two practical test systems.

Dipayan De et al. in [5] proposed a new improved optimization algorithm for economic Load dispatch (ELD) problem using self-adaptive real coded genetic algorithm. The ELD dilemma is formulated as a single-objective on-linear constrained optimization problem gratifying both equality and inequality constraints. The regeneration of population practice is integrated to the conventional real coded genetic algorithm (RCGA) in order to improve dodging the neighboring minimum solution by self-adaptation followed by polynomial mutation impact with arithmetic crossover. To test the outfitted performance and compatibility among genetic operators, a six unit's scheme is projected for a standard load model and the better simulation results produce improved solution by the proposed method

III. Fuzzy Logic

Fuzzy systems exhibit the following characteristics to meet the challenge of complex optimization problems, which are:

1) Parallel processing architecture
2) Learning and adapting capability i.e. continuously learning from previous data to reduce subsequent errors
3) Capability to handle non-exact boundaries i.e. fuzziness.

Fuzzy Logic (FL) is a method of reasoning that resembles human reasoning. The approach of FL imitates the way of decision making in humans that involves all intermediate possibilities between digital values YES and NO. The conventional logic block that a computer can understand takes precise input and produces a definite output as TRUE or FALSE, which is equivalent to human's YES or NO.The inventor of fuzzy logic, Lotfi Zadeh, observed that unlike computers, the human decision making includes a range of possibilities between YES and NO, such as:-

a. Certainly Yes
b. Possibly Yes
c. Can Not Say
d. Possibly No
e. Certainly No

The fuzzy logic works on the levels of possibilities of input to achieve the definite output.

Fuzzy Logic Systems Architecture

It has four main parts as shown −

Fuzzification Module − It transforms the system inputs, which are crisp numbers, into fuzzy sets. It splits the input signal into five steps such as −

LP x is Large Positive
MP x is Medium Positive
S x is Small
MN x is Medium Negative
LN x is Large Negative

Knowledge Base − It stores IF-THEN rules provided by experts.

Inference Engine − It simulates the human reasoning process by making fuzzy inference on the inputs and IF-THEN rules.

Defuzzification Module − It transforms the fuzzy set obtained by the inference engine into a crisp value.

Membership Function

Membership functions allow you to quantify linguistic term and represent a fuzzy set graphically. A membership function for a fuzzy *set A* on the universe of discourse X is defined as:

$$\mu_A : X \rightarrow [0,1] \qquad (2)$$

Here, each element of *X* is mapped to a value between 0 and 1. It is called membership value or degree of membership. It quantifies the degree of membership of the element in *X* to the fuzzy set *A*.

- x axis represents the universe of discourse.
- y axis represents the degrees of membership in the [0, 1] interval.

There can be multiple membership functions applicable to fuzzify a numerical value. Simple membership functions are used as use of complex functions does not add more precision in the output. –There can be several applications for the illustration of fuzzy systems. You can modify a FLS by just adding or deleting rules due to flexibility of fuzzy logic. A graphical illustration ensues wherein the membership functions are plotted against the voltage levels. All membership functions for LP, MP, S, MN, and LN are shown as below:-

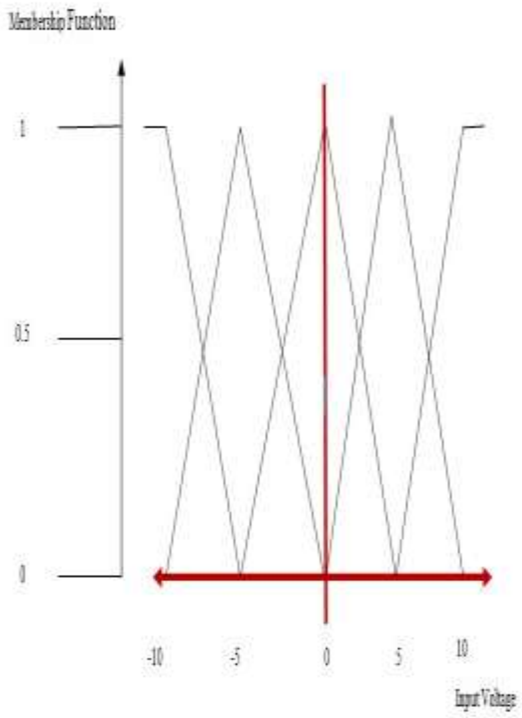

Fig. 1 Membership Function

IV. Neural Network

Artificial neural networks are a practical way of implementing artificial intelligence with an aim to solve fitting problems generally needing herculean efforts due to the data size and complexity. The artificial neural architecture tries to imitate the human thought process in the following ways:

- Process data as a parallel stream independently
- Identifying patterns and correlating them.

Evolving and updating the experiences (called weights) as per the changes in the data received. Neural networks work on training and testing mechanism. In this approach, the time series data is fed to a neural network resembling the working of the human based brain architecture with a self organizing memory technique.The general rule of the thumb is that 70% of the data is used for training and 30% is used for testing. The neural network can work on the fundamental properties or attributes of the human brain i.e. parallel structure and adaptive self organizing learning ability. Mathematically, the neural network is governed by the following expression:

$$\boldsymbol{Y} = \sum_{i=1}^{n} \mathbf{X_i} \,.\, \mathbf{W_i} \ + \ \boldsymbol{\theta_i} \qquad \textbf{(3)}$$

Here,

X_i represents the parallel data streams

W_i represents the weights

θ represents the bias or decision logic

It is mandatory to choose a model that can perform time effective real time data analysis. So the precise identification of the solar models is immensely necessary for accurate solar forecasting. There exist certain models for the same which can help in this regard.

V. Neuro-Fuzzy Expert Systems

Neuro Fuzzy Systems are a combination of:

1) Neural Networks
2) Fuzzy Logic

Neuro Fuzzy Systems generally are based on expert view or fuzzy logic for deciding the thresholds or boundaries. Subsequently the data is fed to neural network for training. After training the system is tested for accuracy. The concept is illustrated subsequently: Consider a signal s_1 travelling through a path p_1 from dendrites with weight w_1 to the neuron. Then the value of signal reaching the neuron will be $s_1 . w_1$.If there are "n" such signals travelling through n different paths with weights ranging from w_1 to w_n and the neuron has an internal firing threshold value of θ_n , then the total activation function of the neuron is given by:

$$\boldsymbol{y} = \sum_{i=1}^{n} \mathbf{X_i} \,.\, \mathbf{W_i} \ + \ \boldsymbol{\theta_i} \qquad \textbf{(4)}$$

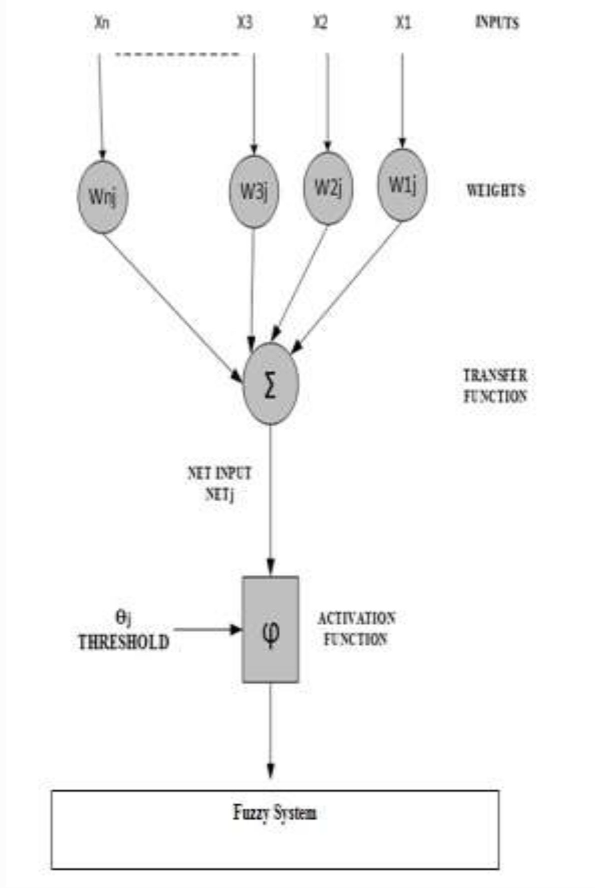

Fig.2 Block Diagram of a Neuro Fuzzy System

Where,

X_i represents the signals arriving through various paths,

W_i represents the weight corresponding to the various paths

and θ is the bias.

The entire mathematical model of the neuron or the neural network can be visualized pictorially or the pictorial model can be mathematically modelled. The design of the neural network can be modeled mathematically and the more complex the neural design more is the complexity of the tasks that can be accomplished by the neural network.

Conclusion: It can be concluded from the previous discussions, mathematical formulation that economic load dispatch is a complex optimization problem. Hence, in previous work, several optimization techniques have been used. The paper presents the different approaches put forth in contemporary works along with their salient points. Also the paper presents the basics of fuzzy logic and neural networks which are considered to be highly effective optimization techniques.

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