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Analysis of Economic Load Dispatch in Power Systems using Scaled Conjugate Gradient Approach in Machine Learning

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***Abstract*—The escalating size of power systems has heightened the need to minimize operational costs, pollution, and transmission losses. This study tackles the Economic Load Dispatch (ELD) problem, a crucial optimization challenge in power systems, aiming to allocate generations optimally among available units to achieve minimum generation costs. Three load demand scenarios – low, normal, and high – are considered, with incremental cost serving as a key system performance metric. Fuzzy Logic is employed to implement ELD constraints, formulating an optimization problem. Due to the complexity of solving ELD problems amidst numerous system constraints, Fuzzy Logic proves to be an efficient tool. This research utilizes the Fuzzy Logic toolbox, incorporating constraints such as generating limits, power balance, minimum uptime, minimum downtime, and spinning reserve to develop requisite rules and membership functions. A case study involving three generating units demonstrates the effectiveness of the proposed approach in solving unit commitment problems.**

***Index Terms*—Economic Load Dispatch, Fuzzy Logic, Optimization, Power System, Unit Commitment.**

I. INTRODUCTION

In electrical power systems, managing operational costs is crucial due to fluctuating power demands from diverse sources. The primary objective is to minimize costs while meeting load requirements. Economic Load Dispatch (ELD) enables power systems to operate economically by optimizing power allocation from various sources. In reality, power plants are often located far from demand centers, and fuel costs vary among generators. Consequently, power systems must prioritize economical operation, making optimized performance a key concern. Power generation companies strive to meet efficient demand while conserving fuel and maximizing efficiency. Efficient scheduling of unit outputs can significantly reduce costs. However, power generators must comply with system constraints, and traditional optimization methods are ineffective due to the nonlinear input-output characteristics of generators.

Optimizing power generation is crucial to minimize costs and maximize economic efficiency. This necessitates the development of an Economic Load Dispatch (ELD) model that leverages advanced methodologies to determine the optimal power generation strategy. By identifying the most cost-effective combination of power sources, ELD can significantly reduce generation costs, ultimately benefiting the power systems sector and enhancing overall efficiency.

The generation of electrical power is a fundamental aspect of modern life, underpinning the operation of countless electrical and electronic devices worldwide. Power plants, equipped with large-scale generators, play a critical role in meeting global energy demands. These generators harness energy from diverse sources, categorized into renewable and non-renewable segments, to produce the electricity that powers our daily lives.

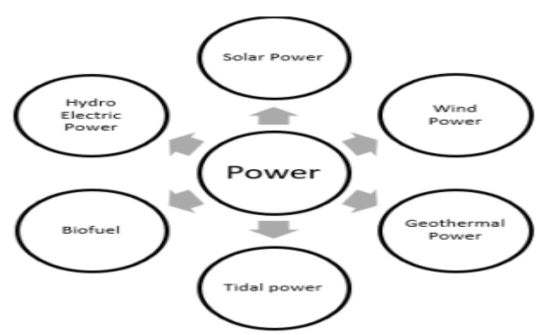

Fig.1 Diagram of major renewable sources of power generation

II. PROBLEM FORMULATION

A. Factors governing cost of generation- The Economic Load Dispatch (ELD) problem revolves around optimizing the output of various generators to achieve the lowest possible total generation cost. This intricate problem involves allocating power generation among different sources to minimize overall expenses, as visualized in the generator cost curve, which serves as a fundamental illustration of the challenge at hand.

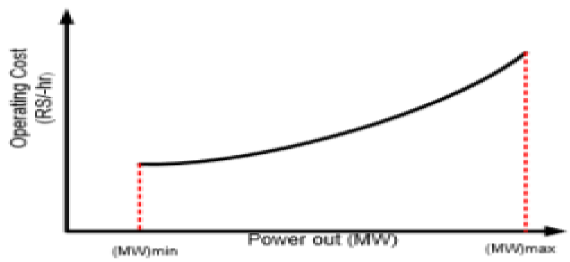

Fig. 1 The variation of operational cost w.r.t. Output Power

The generation cost of power plants is directly tied to their output levels. As generators approach their maximum capacity, their operating costs tend to escalate, exhibiting a nonlinear relationship between output and expenditure.

Mathematically,

$C = f\ (P_o, t)$

Here, C is cost of generation

P_o is the power output

t is time

f stands for a function of.

Typically,

$f = k1Pgi\ 2 + k2Pgi + k3$

Here,

Pgi is the Power corresponding to the ith generating source

K1, K2 and K3 are the constants depending on the fuel

The non-smooth fuel cost functions are depicted as:

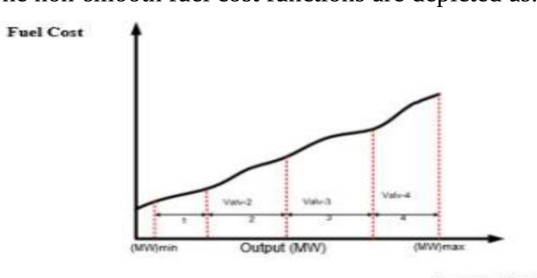

Fig. 3 The non-smooth fuel cost w.r.t. valve point effects

The illustration above demonstrates how valve effects can introduce non-smoothness in fuel costs. A critical consideration in economic load dispatch is accurately modeling the incremental cost curve (ICC) as a function of generator output power. Several approaches can be employed for this purpose:

1. Linear modeling, which assumes a linear relationship between output power and incremental cost.
2. Piecewise linear modeling, a widely preferred approach due to its ability to capture complex cost curves.
3. Non-linear modeling, which can accommodate more intricate relationships between output power and incremental cost.

A representative piecewise linear cost curve is shown in the figure below:

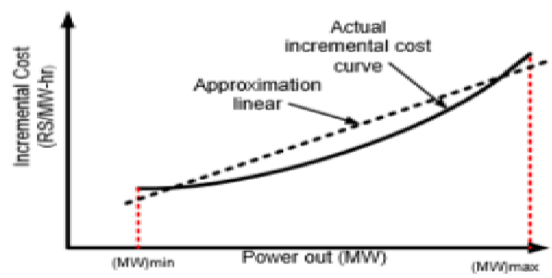

Fig. 4 Models for ICF

The incremental cost cure is generally modelled as:

Linear:

$ICC = k1P0 + k2$

Here,

Po is the generated power output

K1 and K2 are constants

ICC is the incremental cost curve

Non-Linear:

$ICF = k1PO\ m + k2PO\ m{-}1 \ldots \ldots \ldots kn{-}1PO + kn$

Here,

ICF is the incremental cost curve

$k1 \ldots.\ kn$ are the co-efficient values

Po is the cost of generation

Piecewise Linear

The piecewise linear model is mathematically governed as:

$ICC = k1PO + k2;\ PO1 < PO < PO3$

$ICC = k3PO + k4;\ P03 < PO < PO4$

$ICC = kn{-}1PO + kn;\ P0n{-}1 < PO < POn$

Here,

$k1$, k2……………… kn are the co-efficient

Po is the output generated power

$PO1$, $PO2$, ………………… POn, are the piece wise linear ranges for the incremental cost function (ICF) Finally, the incremental production cost curve (IPC) is depicted in the figure below:

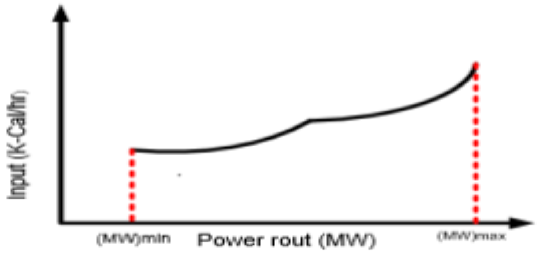

Fig. 5 Incremental Production Curve w.r.t. Output Power

The incremental production cost is an amalgamation of the incremental fuel cost (IFC) and Incremental Running Expenses (IRE) The incremental production cost is given mathematically as:

$IPC = IFC + IRE$

Here,

IPC is incremental production cost

IFC is incremental fuel cost

IRE is the incremental running expenses

The incremental costs of generation for different generators may be different and a typical situation is given below:

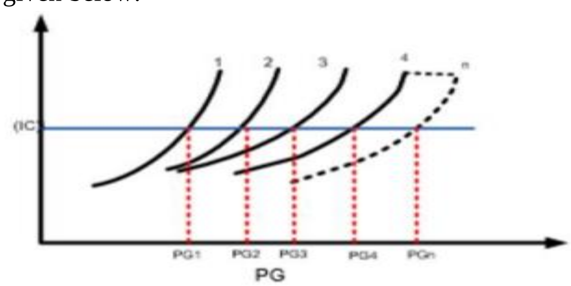

Fig. 6 Incremental Costs for different generators

The incremental cost curves for various generators are illustrated in the figure above. A notable observation is that the incremental costs fluctuate with changes in power output, yet the curves exhibit distinct profiles. This scenario typifies an interconnected power system where multiple generators collectively contribute to the overall power generation.

Consider a system comprising multiple generators, denoted as PG1, PG2, ..., PGn, each characterized by its respective incremental cost functions, ICF1, ICF2, ..., ICFn.

They may be leveraged by the interconnected power system as shown in the figure below:

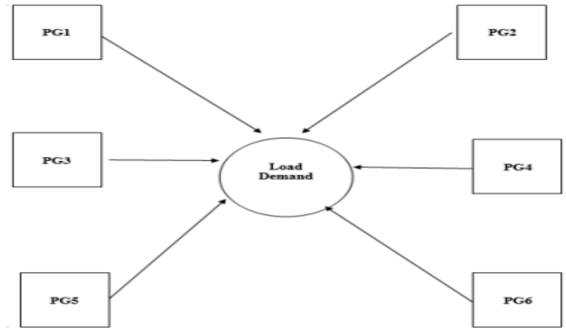

Fig. 6 Different Generators rendering fractional power in an interconnected power system

In an interconnected power system, multiple power generators with diverse generation costs can contribute to the overall power supply.

However, to ensure optimal operation, these contributions must adhere to the principles of Economic Load Dispatch (ELD), which are outlined in the subsequent section. This section elaborates on the ELD conditions and associated constraints that govern the allocation of power generation among various sources.

B. Problem Identification in ELD

While designing an Economic Load Dispatch mechanism, the following constraints are to be considered:

1. To ensure reliable operation, the capacity constraints of individual generators must be respected. Assuming a power system with 'n' generators, denoted as PG1, PG2, ..., PGn, each with respective capacities of C1, C2, ..., Cn, it is essential to prevent individual generator outputs from exceeding their designated limits. This constraint can be expressed mathematically as:

$LCGi \leq Cgi$

Here.

$LCGi$ is the load connected to Generator ‘i’

Cgi is the capacity of generator ‘i’.

This ensures that the total generation cost is minimized while adhering to the capacity limitations of each generator.

2. The optimal combination of loads connected to generators should result in the minimum overall cost of generation. To achieve this, the optimization process must focus on identifying the ideal combination that minimizes the cost function, representing the total cost of generation. This objective can be formulated mathematically as:

$\langle Jmin \rangle$ = min [$\sum LCGiCoGGi$] n i=1

Here,

J is the cost function which is the overall cost of generation

$LCGi$ is the load connected to Generator 'i' $CoGGi$ is the cost of generation of Generator 'i'

This mathematical representation aims to determine the optimal allocation of loads among generators, ensuring the lowest possible overall generation cost.

The approach should be able to optimize the parameters and minimize the cost function with low time complexity so as to make the approach feasible for time critical applications.

III. PROPOSED METHODOLOGY

Optimization a multivariate problem to attain the condition.

The Economic Load Dispatch (ELD) problem is a complex, multivariate optimization challenge that necessitates the application of sophisticated algorithms. These algorithms are designed to identify the optimal set of parameters that minimize the cost function. Several optimization techniques have been employed to solve the ELD problem, including:

1. Dynamic Programming, which breaks down the problem into manageable sub-problems.
2. Convex Optimization, a powerful method for solving linear and nonlinear optimization problems.
3. Particle Swarm Optimization, a population-based stochastic optimization technique inspired by flock behavior.
4. Bat Optimization, a bio-inspired algorithm that mimics the echolocation behavior of bats.
5. Ant-Colony Optimization, a metaheuristic approach that simulates the foraging behavior of ants.

These optimization techniques, among others, have been successfully applied to solve the ELD problem and determine the most cost-effective allocation of power generation.

In recent years, artificial intelligence (AI) and machine learning (ML) techniques have emerged as powerful tools for solving intricate optimization problems. ML-based approaches have proven particularly effective in analyzing complex, large-scale datasets that defy conventional statistical analysis. Broadly, ML-based applications can be classified into three primary categories:

1. Supervised learning, where algorithms learn from labeled data to make predictions or classify new, unseen data.
2. Unsupervised learning, which involves discovering patterns, relationships, or groupings within unlabeled datasets.
3. Semi-supervised learning, a hybrid approach that combines labeled and unlabeled data to improve learning accuracy and efficiency.

These ML paradigms have far-reaching implications for solving complex optimization problems, including those encountered in economic load dispatch and other energy-related applications.

Artificial Intelligence (AI) and Machine Learning (ML) strive to replicate human problem-solving abilities within machines. To achieve this, various mathematical models are employed to mimic the human thought process, including:

1. Neural Networks, which simulate the interconnected structure of the human brain.
2. Fuzzy Logic, a methodology that deals with uncertainty and imprecision, similar to human reasoning.
3. Neuro-Fuzzy Systems, a hybrid approach combining neural networks and fuzzy logic.
4. Genetic Algorithms, inspired by the process of natural selection and genetics.
5. Deep Neural Networks, complex architectures that leverage multiple layers to learn and represent data.

These AI and ML models, among others, enable machines to learn from data, make decisions, and solve complex problems, bridging the gap between human intelligence and machine capabilities.

IV. MATHEMATICAL MODEL REPRESENTING THE NEURAL NETWORK

The biological model of the neural network translates into the mathematical model of the neural network as shown below:

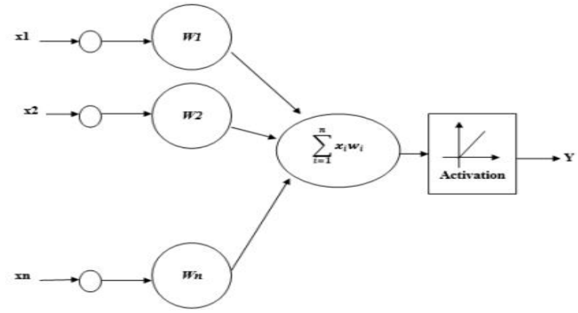

Fig. 7 Mathematical model of ANN

The mathematical model of the neural network is shown in the figure below which represents the parallel data processing, data analysis and pattern recognition ability of the neural network. The output of the neural network is given by:

$y = \sum XiWi + \Theta \; i{=}n \; i{=}1$

The mathematical descriptions can be understood with more clarity with the graphical counterparts shown below:

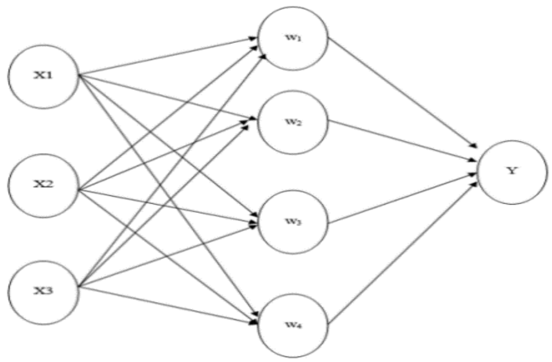

Fig. 8 Internal interpretation of neural structure

V. RESULTS AND DISCUSSIONS

The results are simulated on MATLAB 2018a. Two cases are simulated and analyzed:

1) The 3-unit system
2) The 6-unit system

A. Designed ANN

The designed neural network for the optimization purpose has been shown below.

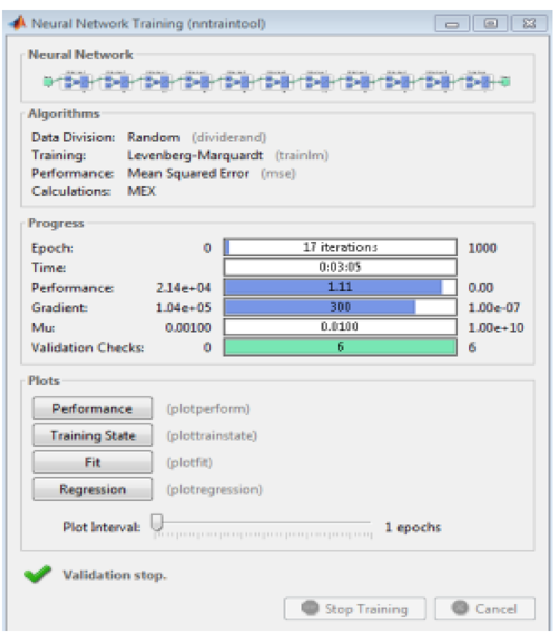

Fig. 9 ANN trained by Steepest Descent SCG approach

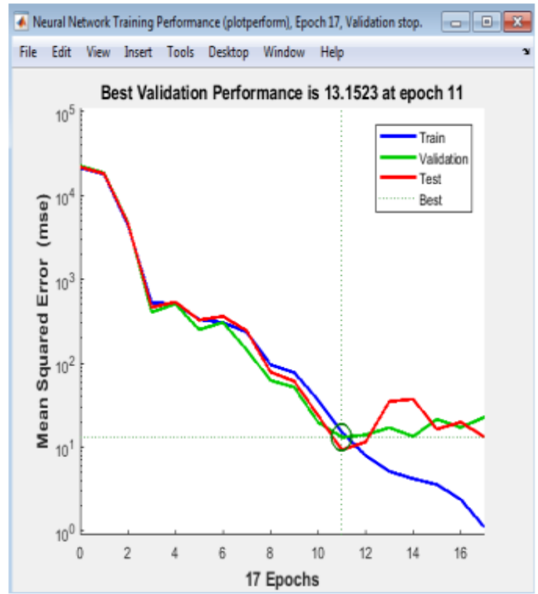

Fig. 10 Depiction of MSE variation in ANN w.r.t. epochs

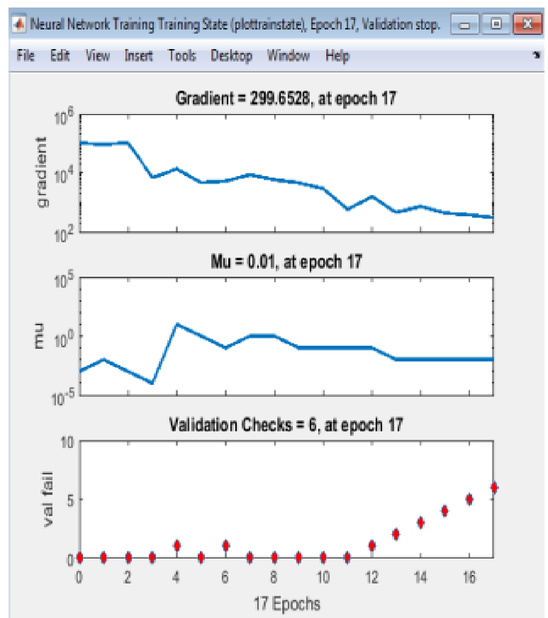

Fig. 11 Training States

The figure above depicts the variation of training states as a function of the iterations of training. The gradient, combination co-efficient and validation checks are depicted.

VI. CONCLUSION

The preceding discussions demonstrate that this research successfully implements an economic load dispatch (ELD) mechanism for interconnected power systems. The proposed work considers three distinct load demand scenarios: low, normal, and high. The optimization process utilizes incremental cost as a key variable for assessing system performance. Notably, Fuzzy Logic is employed to implement the proposed ELD constraint, effectively formulating it as an optimization problem.

Given the intricate nature of power systems, characterized by numerous constraints, solving the ELD problem poses significant complexity. Consequently, the development of efficient tools and methodologies is essential to address this challenge, ensuring optimal solutions for ELD problems in interconnected power systems.

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