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A Constrained Satisfaction Model for Cost Minimization of Power System Generation

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Abstract- Constraint satisfaction is an Artificial Intelligence technique with wide applications in solving optimization problems. In this study, the concept of constraint satisfaction was used in the optimization of power system generation. The study adopted a qualitative research methodology. The data was gathered through secondary data collection method. Focus was on developing a model to provide an effective load distribution for optimal power generation with minimal fuel cost and satisfaction of the system constraints using deep belief network (DBN) with Relu Activation Function. Results obtained from the model show the optimal distribution of load as against equal distribution of load. The developed model recorded an accuracy level of 98%. The high level of accuracy shows the efficiency of deep belief network in the optimization of electricity generation in the power industry. The approach was validated using the Lagrangian Multiplier Method. The model was developed to assist operators in thermal power plants in the adequate planning and utilization of the various generating unit in order to generate power economically.

Keywords: Constraint Satisfaction, Artificial Intelligence, Optimization, Cost Minimization power generation, Deep Belief Network

INTRODUCTION

Constraint satisfaction has become a key concept in artificial intelligence and operations research. It is a versatile and widely used framework for defining and solving search problems. Constraint satisfaction is a problem-solving technique in which the solution value satisfies the problem's constraints. Addressing a constraint satisfaction problem entails giving suitable values to problem

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variables from the variables' domain in order to satisfy all of the constraints.

Most of the well-known problems in Artificial intelligence are regarded as constraint satisfaction problems. Some of these problems include; crossword, n-queen problem, Latin square problem, cryptarithmetic problem, planning and scheduling, optimization, resource allocation, computer vision and natural language processing. Several machine learning techniques have been adopted by many researchers for solving these problems. Among which are support vector machines, regression, decision tree learning, clustering, k-nearest neighbors, and so on.. It was observed that these methods depend on handcrafted features which will require a dedicated research to find the suitable features due to the various application domains and task involved in CSPs. Hence, the optimal features of CSPs need to be carefully selected by humans accordingly. [19], [30], [7], [1], [2], [9], [16], [31], [14].

However, other AI techniques such as Metaheuristic algorithms including evolutionary and swarm intelligence algorithms such as Particle swamp optimization [17, 21], Ant Colony Optimization Algorithm [29], Genetic Algorithm [31, 22] have shown successful results when solving constrained problems [28, 7] etc. This explains the growing interest of many researchers in the application of AI techniques in solving optimal power flow problems in the power sector.

Previously, traditional methods such as Lagrange relaxation method, Linear and Non-linear programming, Quadratic programming etc., have been adopted to solve the problem of power flow problems but these methods failed to solve these problems due to the fact that traditional approaches converge slowly to most iterations. Also, these methods have discontinuous and differentiable functions, and have trouble detecting infeasibility, which is susceptible to mistake. However, Artificial Intelligent optimization approaches for power system optimization have been proposed. Genetic Algorithm [22] Artificial Neural Network [3], Artificial bee colony [4], Dance bee colony [11], Backtracking Search Optimization [5], Particle Swamp Optimization [20], Ant Swarm Optimization [6], Evolutionary Programming [18] are based on heuristics and operations research which have global optimal solution. Even though these optimization approaches are successful in locating the global optimal solution, they would take a long time to compute in a large-scale real-world system.

This research work is focused on using deep learning analytical methods to solve the problem of optimal power generation with the aim of minimizing cost and satisfy the system constraints. This study will aid operators in thermal power plants with the task of planning generation in the most cost-effective manner in order to provide sufficient electricity supply to meet demand and improve the nation's socio-economic development. This study will also help to resolve Nigeria's most demanding challenge, which is the country's

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ongoing power outage due to inadequate use of generation planning, capacity, and finances to properly allocate customer load demands among the available thermal power generating units in a cost-effective, secure, and efficient manner.

2. Related Works

Both traditional and AI methods have been adopted to solve the problem of power system optimization as mentioned earlier. However, due to the exponential cost of systematical method, researchers have been looking for new algorithms for solving CSPs. Below are some researches which adopted various artificial intelligence techniques in the optimization of power system.

Anireh et al. [3] created model to produce the optimum load allocation at the lowest cost of fuel using artificial neural networks, (ANN). The study aimed at developing a system that would determine the best load distribution for optimum generation. The Lagrangian multiplier model was employed to validate the method used in this study. The result obtained from the system showed the daily cost savings resulting from optimum load allocation against equal load allocation.

Oluwadare et al. [22] developed a genetic algorithm-based optimization model for solving economic dispatch problems. The model combined Lagrangian approach and Genettic Algorithm to promote cost minimization and satisfaction of the system constraints by scheduling generation among the committed units in an efficient manner. The model showed a degree of success over other existing ones. The result revealed that the model attained a good performance with average computational time. Patricia et al. [2002] provided a GA-based solution for the operational planning of hydro-thermal power plants. To overcome the shortcomings of non-linear programming-based techniques, The solution combined the theory with a real-world application for optimizing operation planning for a cascaded system of interconnected hydropower facilities.

Also, King et al. [15] developed an efficient algorithm using artificial neural network, decision trees and random forest classifier to determine the effective algorithm for optimal power flow. The result showed a favourable performance when compared using multi-label weighted learning. The algorithm minimized the number of overloaded branches within the network while lowering the number of generators.

3. Methodology

The Objective of the Model: The objective of the model is to minimize cost of production and satisfy certain constraints by scheduling generation among available generating units such that the Input Cost, C is minimal for the given power, P under the constraint that the sum of Px is equal to the Load demand, P_L (Load received). This can be mathematically expressed as;

$$\text{Min } C = \sum_{x=1} C_x P_x \qquad 3.1$$

Subject to the constraint;

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$$\sum_{x=1}^{N} P_x = P_L \qquad 3.2$$

$$\sum_{x=1}^{N} P_x - P_L = 0 \qquad 3.3$$

Where;

C = The total cost of power generatio
P = Output power
P_L = Total Power (Load received)
P_x = Power output for unit
C_x = Input cost of unit x
N = Total number of generating unit

The production (Input cost), C can be expressed mathematically as

$$C = a + bP + cP^2 + dP^3 \qquad 3.4$$

The equation (3.4) describes the relationship between the input the output of each generator where a, b, c, d to n are cost coefficients of the xth generator since the production cost is the major component of the operating cost of power generation.

In order to achieve the optimum allocation of load among the generating units, the principle of equal incremental cost of production must be applied. The incremental rate I_R, of the production component cost can be obtained by differentiating equation (4) to the third power with respect to p.

$\gamma = F(\alpha)$, F:[0;1]→[0;1], $F(0) = 0$, $F(1) = 1$ and F is strictly monotonic. Coefficient γ is calculated using different functions (polynomials, power functions, sine, cosine, tangent, cotangent, logarithm, exponent, arc sin, arc cos, arc tan or arc cot, also inverse functions) and choice of function is connected with initial requirements and curve specifications. Different values of coefficient γ are connected with applied functions $F(\alpha)$. These functions $\gamma = F(\alpha)$ represent the examples of probability distribution functions for random variable $\alpha \in [0;1]$ and real number $s > 0$:

$$I_R = \frac{dc}{dp} = b + 2cP + 3dP^2 \qquad 3.5$$

This shows that I_R increases with increase in P (Output). To minimize C;

$$\frac{dc}{dp_X} = 0 \qquad 3.6$$

then;

$$\frac{dc_1}{dp_1} = 0,$$
$$\frac{dc_2}{dp_2} = 0, \quad \frac{dc_3}{dp_3} = 0, \dots\dots\dots\dots\dots\dots\dots. \frac{dc_x}{dp_x} = 0$$

Hence;

$$\frac{dc_1}{dp_1} = \frac{dc_2}{dp_2} = \frac{dc_3}{dp_3} = \cdots \dots\dots\dots\dots. \frac{dc_x}{dp_x} \qquad 3.7$$

To obtain the incremental Cost, C the lagrangian multiplier, λ is applied where the function of the total power, f is equal to zero. That is;

F (P1, P2, P3 ……………… Px) = 0 or

$$\sum_{x=1}^{N} P_x - P_L = 0$$

Where C;

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C = $C_t - \lambda f$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \frac{d\lambda}{dp_2}F$$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \frac{d\lambda}{dp_2}\left[\sum_{x=1}^{N} P_x - P_L\right]$$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \lambda\,[1-0]$$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \lambda + 0$$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \lambda + 0$$

$$\frac{dc}{dP_x} = \frac{dc_t}{dp_x} - \lambda$$

Having stated in equation (3.6) that C is minimum when ;

$$\frac{dc}{dP_x} = 0$$

Then;

$$\frac{dc_t}{dp_x} - \lambda = 0$$

Hence;

$$\frac{dc_t}{dp_x} = \lambda \qquad 3.8$$

Comparing equations (3.5) and (3.8)

$$\frac{dc_t}{dp_x} = I_R$$

and;

$$\frac{dc_t}{dp_x} = \lambda$$

The High Level Design

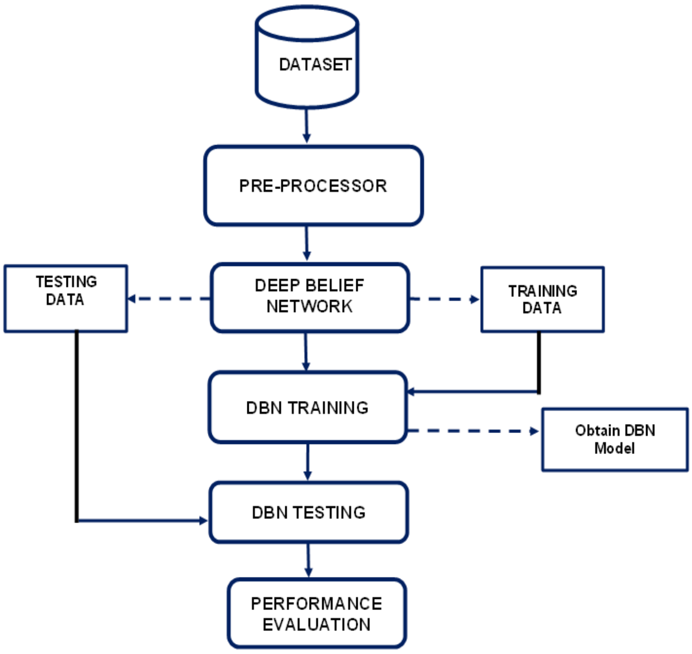

Fig 3.1. High Level Design of the New Model

The high-level design above shows the overall system design that describes the new model architecture and the relationship between the components of the system.

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Dataset

P1	P2	C1	C2	C3
16.60	16.60	528.245	442.108	328.149
22.30	22.30	709.631	593.916	440.826
22.70	22.70	722.359	604.569	448.734
16.70	16.70	531.427	444.771	330.126
29.93	29.93	952.539	797.214	591.722
29.97	29.97	953.599	798.102	592.381
17.50	17.50	556.885	466.078	345.940
17.70	17.70	563.249	471.404	349.894
25.70	25.70	817.825	684.468	508.038
22.70	22.70	722.359	604.569	448.734
26.10	26.10	830.554	695.121	515.945
17.27	17.27	549.460	459.863	341.327
17.30	17.30	550.521	460.751	341.986
16.67	16.67	530.367	443.883	329.467
29.03	29.03	923.899	773.245	573.931
20.13	20.13	640.683	536.211	397.996

The Deep Belief Network (DBN) is a deep learning technique adopted in this research for training the model. It produces results using probability and unsupervised learning. In other deep learning techniques like CNN, the early layers selects the basic features and the other layers assemble all the basic features selected by the previous layers for learning. This is not the case for DBN where each layer learns the full input. For this reason, DBN has produced tremendous results when applied in the area of optimization, fault diagnosis and prediction [27], Shao et al [25]; Shanthi et al [24]

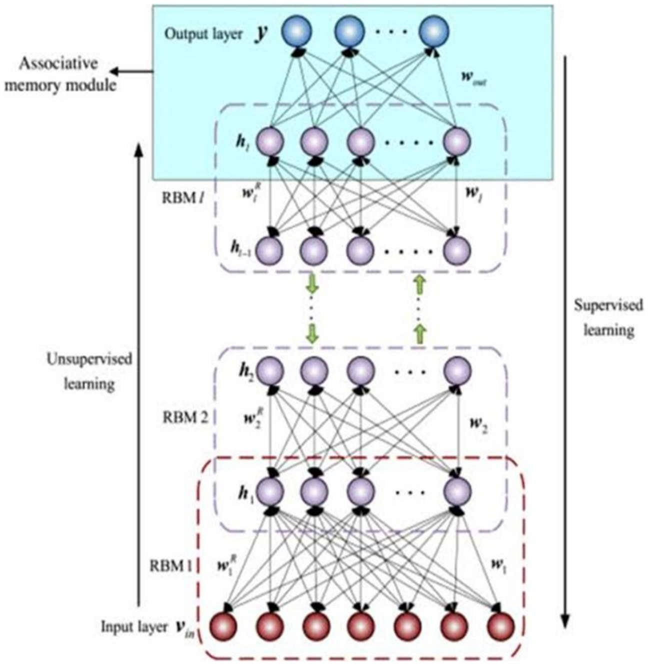

Fig 1. Deep Belief Network Architecture (Kaur & Singh [13])

The training process of DBN is categorized into both unsupervised and supervised learning. At the unsupervised learning stage, the DBN was pre-trained without target labels using Greedy learning algorithm to reconstruct its inputs. Greedy learning algorithm uses layer-by-layer approach for learning all the top-down approach and most important generative weights. Each layer of DBN acts as feature generator and converts the input to more abstract representation. In the supervised learning stage, the DBN is trained using target labels, the whole DBN is fine-tuned with standard back propagation algorithm. The adaptive moment estimation (ADAM) optimization algorithm was used to optimize the learning rate and iteration of

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the network algorithm for self-learning and better performance. The activation function employed was ReLU.

4. Implementation

The implementation of the constraint satisfaction model for cost minimization was implemented using Python Programming language. The model could determine the optimal cost of generating electricity that will meet the demand using any kind of input as far as the input parameters and dataset are relevant in this research area.

5. Results

Table 2. A Comparison between Cost for Equal Distribution and Cost for Optimal Distribution

COST FOR EQUAL LOAD ALLOCATION			
Load	**80MW**	**90MW**	**100MW**
Generator 1	795.2533	894.660	994.067
Generator 2	736.880	828.990	921.100
Generator 3	660.747	743.340	825.933
TotalCost (₦)	2192.880	2466.990	2741.100
COST FOR OPTIMAL LOAD ALLOCATION			
Load	**80MW**	**90MW**	**100MW**
Generator 1	427.0510	480.4320	533.8141
Generator 2	679.1087	763.9970	848.8858
Generator 3	1018.4750	1145.7840	1273.0940
Total Cost (₦)	**2124.6347**	**2390.2130**	**2655.7939**
OPTIMAL LOAD ALLOCATION			
Generator 1	14.321	16.121	17.901
Generator 2	24.576	27.648	30.722
Generator 3	41.104	46.245	51.380
Total Power	**80.021**	**90.014**	**100.002**

Fig The Table 2 above shows the result obtained from the cost minimization model for various load demand at equal and optimal load distribution.

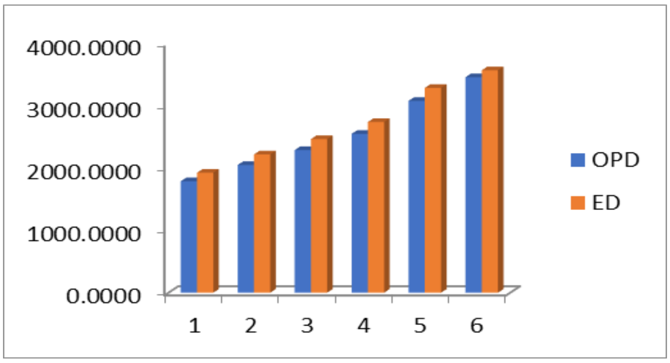

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Fig 2. A comparison on the cost of Equal Distribution as against Optimal Distribution

6. Discussion

This research work was focused on developing and implementing a constraint satisfaction model for cost minimization of power generation using Deep Belief Network. The model was implemented based on the dataset as shown in Table 1. The difference between the cost of operating the power station as against optimally is shown in Table 2. A comparison between the production cost of equal and optimal distribution of load is also shown in Fig 2. Based on the findings, it was observed that the cost of production was less when the three generators were operated optimally as shown on table 2. Hence, the optimum economy is achieved if all the three generators operate at the same incremental cost. This method was validated using lagrangian multiplier method. The result shows that DBN is an effective solution for power system optimization in terms of speed and accuracy.

7. Conclusion

A survey was conducted on the factors responsible for inadequate power generation in Nigeria. Data on power generation and cost of power generation was collected and analyzed. The data collected was preprocessed and spliited into training and testing data. The DBN was trained using the testing data in order to obtained the model. The model was designed to minimize cost of production and satisfy the given constraints by determining the effective way of allocating generation among the thermal unit. When compared with Langragian Multiplier Method, the model attained good performance with soft computing which give accurate and fast results.

8. Recommendation

This research work is recommended for operators in the thermal power plant for effective Generational Planning and Scheduling.

Researchers can also use this model with embedded internet of things to collect data from power plants from different locations in order to find the optimal operations of the real time power system.

9. Contribution to knowledge

This research work presents an analytical and effective methods for power system optimization that shows fast convergence, soft computing approach, low computational complexities and high performance accuracy when trained with huge amount of data.

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