SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V11I7P122

Volume 11 Issue 7, 247-257, July 2024

Original Article

Multi-Area Economic Load Dispatch Using Deep Recurrent Model Expending Renewable Energy

A. Antony Charles[1*], R. Venkadesh[2]

[1,2]*Department of Electrical Engineering, FEAT, Annamalai University, Tamilnadu, India.*

[*]*Corresponding Author : antony8achar5@gmail.com*

Received: 10 May 2024 Revised: 13 June 2024 Accepted: 10 July 2024 Published: 26 July 2024

Abstract - *In minimizing the fuel cost through dispatch strategies by allocating power generation, Multi-Area Economic Load Dispatch (MAELD) poses a severe problem. The balance limitations must be met for the power distribution in economical load dispatch, and the generating limit, transmission line, and power balance limitations must be fulfilled. Traditional methods fail miserably when used to MAELD because of their complexity and non-linear issues. Many more metaheuristic algorithms have been used to solve the economic dispatch problems. In this research, an improvised version of the Deep Recurrent Neural Network model (DRNN) based on Long Short-Term Memory (LSTM) has been used to solve MAELD problems for four areas with a 3, 13 and 40-unit system. The LSTM algorithm combines the efficiency and diversity of heuristic search techniques with the subsistence of the most vital premise on or later evolutionary algorithms. This method eliminates the need on the way to comprehend the gradient of the optimization problem during the optimization search. The algorithm's performance was examined in various unit systems, and fine-tuning the parameters reveals its unique qualities and vulnerabilities in the most appropriate applications. Compared to the other metamorphic procedures, the recommended system minimizes cost, valve point loading, and emission. Multi-Area Economic Load Dispatch solved three separate test scenarios. Using LSTM optimization methods, the optimal demand sharing of power-generating units is assessed. The simulation findings, generated using the MATLAB/Simulink platform, show that LSTM delivers high-quality cost solutions without violating constraints.*

Keywords - *MAELD problem, Long Short-Term Memory, Evolutionary, Yield, Optimization.*

1. Introduction

The most critical issue or problem with system administration's optimization is 'Economic Dispatch (ED). In order to take into account the operational and physical constraints in a particular area, ED distributes load demand among the deployed generators in an extremely financially efficient manner. The generators are often separated and are interested in several generation regions that remain connected through tie lines. Economic dispatch has been expanded by Multi-Area Economic Load Dispatch (MAELD). The economic allocation of different generators remains termed system demand within the multi-area, considering all constraints [1].

Reducing emissions while minimizing fuel expenditures is the purpose of Economic Emission Dispatch (EED), a multiobjective optimization issue. MAELD determines production intensity and power exchange sandwiched among areas that lower the overall gasoline cost across the whole region while meeting power balance limits, generating limitations restrictions, and addressing tie-line capacity issues. Transmission constraints are routinely ignored when solving the economic dispatch problem.

Nevertheless, several scholars must consider the limitations of transmission capacity. Spinning Reserve Requirements (SRR) are considered nontrade. They take this into view by participating in the power pool electric market environment, which can further improve the system's economic and technological elements and the dependability performance of energy production. Combining EED with renewable energy sources, such as wind power, allows researchers to take advantage of the intermittent nature of renewable energy while still optimizing power system functioning. More efficient use of renewable energy sources, less dependence on fossil fuels, and progress towards energy sustainability and environmental objectives are all outcomes of this integration.

Therefore, the research gap solution of obtaining an effective and powerful optimization technique is essential for resolving the MADED problem. Several optimization techniques have addressed the ED problem, including mathematically-based and metaheuristic-based evolutionary algorithms. However, there are issues with the current algorithm-based MAELD. Hence, this research technique employs a fresh way of MAELD.

Multi-Area Economic Load Dispatch (MAELD) pleases multiple constraints simultaneously. In this research, the problem statement, the minimization of fuel cost in multi-area systems, has been considered when applying different unit systems. In this study, a new meta-heuristic method for power generation scheduling with transmission line constraints has indeed been proposed.

On the road to escape from local traps due to the fast emergence of the complexity of the problems in the economic load dispatch, high-speed real-time computations are evolved to attain accurate results. The other approaches in various algorithms that give a smaller computational time with a low participation factor were used to solve the preceding MAELD problems [1]. However, the computation effort to solve the problem is much more in these algorithms. There are many types of fast convergence search algorithms.

The classifications of nature-inspired are compared in many ways in previous literature papers, and comparative results have been proposed. Neural Search techniques and machine learning are commonly used due to recent technologies. Investigation of norm maximization with Linear Discriminant Analysis paved the way for the efficiency of nature-inspired algorithms [2].

The proposed deep recurrent neural network model constitutes a fast and evolving method that provides faster real-time computations. In this study, LSTM started addressing fuel-related issues with economic load dispatch and minimizing fuel costs using four generation units and four areas. It also allowed us to efficiently use systems with 3, 13, and 40 units.

DRNN algorithm search optimization is valuable to obtaining accurate results in ED challenges. Taking part in multi-area networks, it has also been shown to be the best algorithm for categorizing and maximizing the economy's generation scheduling. Towards solving every Economic and Emission Load Dispatch (EELD) challenge, current research suggested combining the robust and dependable algorithms of the DRNN algorithm.

The outcomes, compared to other intelligent methodologies, confirm the prospective presented algorithm's potential and efficacy. The goal function of the optimization issue is to reduce fuel expenses and emission rates to a minimum.

We look at five distinct approaches to evaluate LSTM's performance compared to other optimization techniques: Grasshopper Optimization (GO), Squirrel search Optimization (SO), Salp Swarm Optimization (SSO), and Firefly Optimization (FFO).

The following are the primary goals of the suggested approach:

- To develop and implement an improvised DRNN-based LSTM model for solving MAELD problems.
- In order to test the suggested LSTM model's efficacy on a range of unit systems.
- To evaluate the suggested LSTM model's cost-cutting capabilities in comparison to preexisting metaheuristic algorithms.
- To maximize accuracy and efficiency in MAELD applications by adjusting the LSTM model's parameters.

Continuing with the paper's structure, Section 2, literature review delves into previous Multi-Area Economic Load Dispatch (MAELD) studies, pointing out the shortcomings of traditional optimization methods and the merits of metaheuristic algorithms for dealing with non-linear complexity. Section 3, problem formulation, outlines the MAELD problem, focusing on fuel cost minimization and the associated constraints, including generating limits, transmission line constraints, and power balance requirements.

Section 4, proposed methodology, describes the procedural steps of the LSTM approach in addressing MAELD, detailing how the improvised DRNN-based LSTM model is applied to optimize power distribution. Section 5, LSTM implementation in MAELD, presents the implementation process, simulation findings, and analysis of results, showcasing the model's performance across various unit systems.

Section 6, conclusion, summarises the key research outcomes, implications of the findings, and potential future directions for further improving MAELD solutions using advanced neural network models.

2. Literature Review

Materials are harmed by it by increasing global warming and diminishing visibility. The emission-dispatching approach is preferable because it seeks to simultaneously decrease fuel costs and emissions [3–7]. The optimization of solutions to minimize fuel costs has been the most challenging aspect of economic load dispatch. Meta-heuristic-based hybrid approaches have recently demonstrated tremendous success in various applications [8]. They are iterative techniques that can adjust their various parameters to optimize the cost of fuel, which will then optimize the cost function. Among the most recent categories for nature-inspired algorithms include tangible, Chemical-based, Local Search Algorithms (LSA), Swarm Intelligence, Evolutionary Algorithms (EAs), and Human-based algorithms [9, 10].

This nature-inspired algorithm paved the way for optimization in different applications, especially in economic load dispatch problems. Numerous additional application-specific techniques, like feature extraction - GWO [11], covid-19-optimization [12], Jaya- machine learning [13], load dispatch -salp swarm [14], and mathematical optimization [15]. Machine learning and optimization use neural-based approaches also used in the new trends of optimizing dispatch problems [16].

Due to the explanation of global energy production and consumption, conventional load forecasting based on economic load dispatch was indicated during COVID-19 and was shared in the paper [17]. An antagonistic theory-based turbulent grasshopper algorithm was employed in hybridized wind-based power systems to maximize reliable economic dispatch. The accuracy and efficacy of the suggested technique were corroborated on 6-unit and 10-unit dynamic load problems instead of traditional wind-based systems [18].

This work reviews different evolutionary methods for Multi-Area Economic Load Dispatch and compares (MAELD). The study provides a thorough evaluation of the searchability and merging comportment of Classical Differential Evolution (DE) besides numerous techniques to solve MAELD issues for both test power systems, the traditional Particle Swarm Optimization (PSO) and an upgraded PSO through constraint computerization method featuring Time Varying Acceleration Coefficients (PSO TVAC) are both used [19].

An analysis of a 48-bus power system serving two areas is the subject of this paper's [20] examination of multi-area economic despatch using the Swarm intelligence technique. Unscented transformation is used in a parallel process of MAELD to account for the uncertainty effect and maintain independence in MAELD situations [21].

Although the standard PSO effectively tackles the ED problem, it has certain limitations. The parameters of a typical PSO significantly impact how well it performs, and it can get stuck in local optima and prematurely converge [22]. By integrating PSO with chaotic equations like the logistic equation, the Chaotic PSO (CPSO) method has been suggested to address the limitations of the standard PSO [22–24].

Researchers have also integrated it with GA and used this hybrid approach across other disciplines [25, 26]. A Multi-independent based on Squirrel Search Algorithm (MOSSA) was presented by the author within [27] to address the Multi-Area Economic/Environmental Dispatch (MAEED) issue.

The MAEED conundrum was also solved using the Exchange Market Algorithm, Artificial Bee Colony, and Squirrel Search Algorithm-based Weighted Sum Methodology using expense forfeit components. The suggested strategy's suitability was approved for 40 producing entities, including single combined with multiple field power systems. The paper [28] implemented a method called Multiobjective Particle Swarm Optimization to address load dispatch unruly between steam and wind turbines whilst contemplating ecological factors in multi-area power systems and utilizing a mean value with wind energy density, technologically sophisticated methodologies specified holding area and additional cost in the Economic Load Dispatch (ELD) problem's target function and several factors.

A Salp Swarm Algorithm (SSA) optimized approach was developed in the paper [29]. The study uses SSA to suggest a resolution to the challenging limited Multi-Area Economic Load Dispatch problem for mutually stochastic wind integration- and stochastic wind-free power systems. Four distinct constrained test cases with various dimensions and levels of complexity have been the subject of simulation investigation.

The publication [30] suggested a new optimization approach to resolve the problem. The Grasshopper Optimization Algorithm (GOA) was employed to solve the MAELD algorithm more efficiently. The swarming behaviour of grasshopper insects served as the basis for the recently developed swarm-based optimization method known as GOA.

The method was tested using three distinct issue studies, and the outcomes were associated with various meta-heuristics to show that the system could successfully solve MAELD problems. A more advanced fireworks algorithm included two efficient cross-generation mutation strategies to solve multi-dimensional and multi-constraint MAELD issues [31].

A multiobjective load dispatch method using information mining technologies was presented and proved in [32] for applying significant coal plants. For energy-integrated systems, researchers have suggested an LSTM-based LF technique that uses multi-feature data and dynamic, similar-day meteorological information. Feature engineering techniques are utilized in the construction process daily.

Grey correlation analysis with the Gaussian Mixture Model. To forecast multiple loads, Sis is also used to pick the features of the days that are most connected with each other to determine the weights for construction on comparable days [33]. Integrating the LSTM model used for load forecasting can achieve optimal outcomes in cost minimization within economic and emission dispatch problems.

The main novelty of this optimization approach in MAELD is minimizing multi-area economic fuel costs with the efficient improvised LSTM technique. The test system has been formulated to optimize the minimum cost of all generating units in MATLAB / Simulink. The LSTM's optimization flow optimization gives excellent advantages when applying MAEED problems.

3. Problem Formulation

3.1. Objective Function and Constraints

3.1.1. Fuel Cost Minimisation

The chief goal appropriate to the optimization method must be the road to cut the total cost of all generation areas while keeping emission costs low. The initial focus of the research was on minimizing the cost of gasoline while meeting various limitations.

The total fuel expenditures for all generating units make up the optimization problem F.

$$F_i(P_i) = a_i P_i^2 + b_i P_i + c_i + e_i \times \sin\left(f_i \times \left(P_i^{min} - P_i\right)\right) \quad (1)$$

Someplace a_i, b_i, c_i, d_i, e_i are cost curve constants of the i^{th} unit, P_{im} is the output power of i^{th} unit at time m, and $F_i(P_i)$ represents fuel cost of area I and P represents power generated by i^{th} area generator. N becomes the total quantity of generating units, M becomes the total number of hours around the time horizon, and P_i remains a lower production limit for the i^{th} unit.

$$F(P_{mi}) = \begin{cases} a_{mi1}P_{mi}^2 + b_{mi1}P_{mi} + C_{m11}, \dots, \text{ if } \dots P_{m(min)} \le P_{mi} \le P_{l1}, \text{ fuel..1} \\ a_{mi2}P_{mi}^2 + b_{mi2}P_{mi} + C_{mi2}, \dots \text{ if } \dots P_{l1} \le P_{mi} \le P_{l2}, \text{ fuel } \dots 2 \\ \dots \\ \dots \\ a_{mik}P_{mi}^2 - b_{mik}P_{mi} + C_{mik}, \dots \text{ if } \dots P_{mik-1} \le P_{mi} \le P_{mi(max)}, \text{ fuel..k} \end{cases} \quad (2)$$

Where k is the available fuels and a_{mik}, b_{mik}, and cmik are the fuel cost coefficients of the i^{th} unit of the m^{th} region.

$$\text{Min } F_r = \sum_{i=1}^{N} F_i(P_i) + \sum_{j}^{M-1} f_i T_{j(M-1)} \quad (3)$$

The cost function for the tie line electricity stream from area j to the area is called Fi (M-1).

The generation cost function is built using the knowledge gained during high-temperature evaluation, where information about the operational zone's feedback is gathered. On big turbine generators, many fuel intake valves are frequently present and thus are opened one at a time when the unit needs to increase production.

The heat rate dramatically increases whenever a valve opens, instantly raising throttling losses. The nozzle effects, which also cause swirls around heart-rate curves, cause an objective function to be irregular and nonconvex and have several bare minimums.

3.1.2. Constraints

Power Stability Restrictions

The power stability constraints [36] designed in place of region m neglecting losses can be given as

$$\sum_{i=1}^{N} = P_{im} = \left(P_{Dm} + \sum_{j}^{M-1} T_{j(M-1)}\right) = 0 \quad (4)$$

Instead of m = 1, 2, 3,…..M (Areas). PD_m is the load demand in the m^{th} area and T_i is a symbol of tie line flows to the j^{th} area from the other areas.

Generating Maximum Restraints

A unit's capacity output should be distributed between its smaller and upper absolute power generation limits while specified with

$$P_i^{min} \le P_i \le P_i^{max} i = 1,2,\dots,N \quad (5)$$

Tie-Line Limit Constraints

The maximum and minimum tie line energy in area j should be utilized.

$$T_{j(M-1)}^{min} \le T_{j(M-1)} \le T_{j(M-1)}^{max} j = 1,2,\dots,M \quad (6)$$

Someplace T_j remains the power flow through the tie line.

4. Proposed Methodology

Members of the deep learning community have developed networks with Long Short-Term Memories (LSTMs). To circumvent the vanishing gradient issue and capture long-term dependencies in sequential data, the development of Recurrent Neural Networks (RNN) was the Long Short-Term Memory (LSTM) network. Although it cannot keep data long, RNN cannot deal with long-term dependencies. The architecture now incorporates the LSTM without modifying the training model, thanks to eliminating the vanishing gradient problem.

Figure 1 depicts the algorithm's training and testing flow diagram from the proposed methodology. To get the best possible initial values for the LSTM model's parameters, the model is trained first. Next, the data is used to test the trained model and make predictions. By iteratively refining the model, it is possible to attain satisfactory outcomes and a data flow chart of the LSTM model architecture to calculate the cost and valve point effect in the effective test system. The processed data is given for training with parameter initialization, which takes place in the model. This step involves processing data before feeding it into the algorithm. The raw historical data has been subjected to feature engineering to eliminate outliers, detect duplicate data, and fill in missing information. The training and testing data sets are separated to evaluate the suggested LSTM model's predicting capabilities.

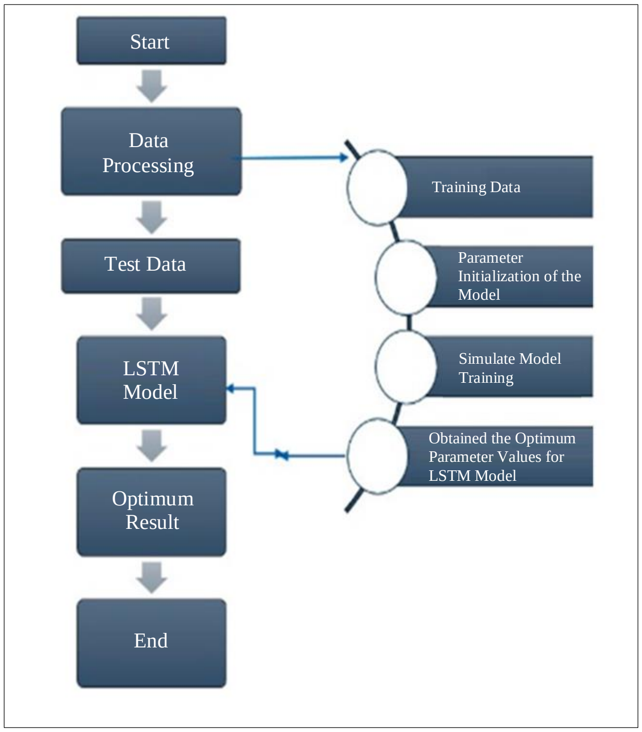

Fig. 1 Flow chart of the proposed methodology with the LSTM model

Figure 2 represents the LSTM architecture that is useful for cost dispatch problems. The data are simulated in the LSTM training model according to the architecture: hidden state (new), h_{t-1} is a hidden state (previous), C_t is new cell state, C_{t-1} is previous cell state, and X_t is input data.

This paradigm is also functional when dealing with continuous values and noise. Eliminating the requirement to maintain a fixed set of states is one of the many advantages LSTMs offer over Hidden Markov Models (HMMs). Learning rates, input biases, and output biases are only a few of the many customizable factors available to LSTMs, in contrast to HMMs with a fixed number of states. The network can adapt and perform better since these parameters give control and flexibility while learning.

4.1. Procedural Steps in the LSTM to MAELD

Economic Dispatch (ED) often mainly addresses cost reduction, but with pollution reduction becoming a legal necessity for environmental protection, depreciation of emission content has also emerged as a crucial issue. A complex Multiobjective Optimization (MOO) issue with competing objectives is Environmental Economic Dispatch (EED) [34, 35]. Many optimization algorithms are proposed for EED, but challenges remain. To solve that problem, this research methodology proposed a novel long-short-term memory algorithm for MAELD.

4.2. Renewable Energy Framework -MAELD

Figure 3 displays the block diagram for integrating Renewable energy with the proposed method in multi-area load dispatch. The block diagram above shows how to incorporate sources of renewable energy and demands into the recommended optimization method. To meet the needs of the various unit systems under consideration, the generating units have received wind and solar power. Firstly, the research methodology derived problem formulation (i.e., objective function) of the proposed methodology; this research methodology considers the multiobjective functions.

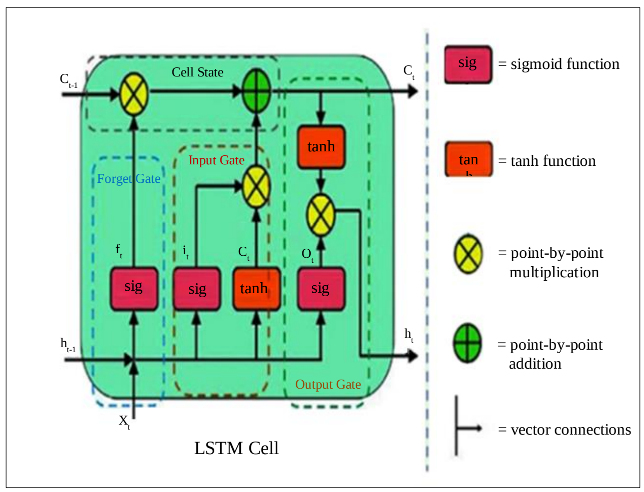

Fig. 2 Multi-Area Economic Load Dispatch LSTM framework

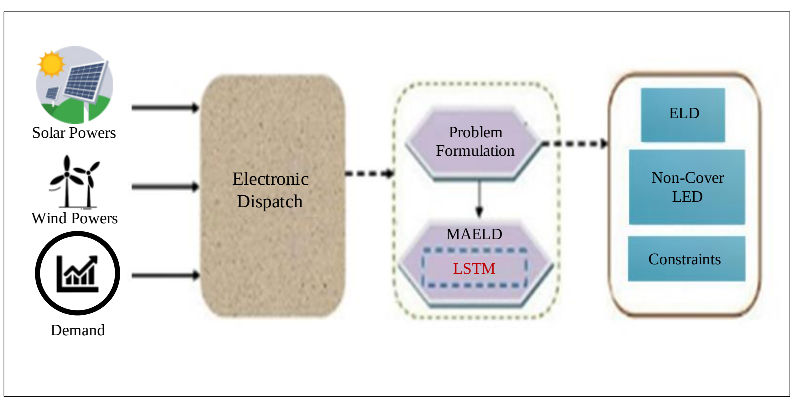

Fig. 3 Renewable energy integration framework

As a first step, the ELD unruly objective function is derived, followed by the biased function for the Nonconvex ELD problem and the constraints for the ELD problem, including transfer, forbidden operational zones, valve-point loading, multiple fuel sources, tie-line transmission line capacity restrictions, ramp rate caps, and Prohibited Operating Zones (POZ). After that, power generation parameters are optimized using the LSTM algorithm for the multiobjective function.

The LSTM technique combines the efficiency and richness of stochastic search techniques only with the persistence of the fittest premise from evolutionary algorithms. The algorithm's disadvantage is the addition of local operators to improve exploitation capabilities, which could lead to increased complexity and slower execution.

To solve that problem, this research methodology uses the secant formulation-based control parameter calculation. Because the range-based initial parameter setting makes more iteration, this research proposed an LSTM algorithm. In experimental analysis, the performance is analyzed based on fuel cost, emission, power loss, and other metrics.

5. Load Dispatch Deep Recurrent Implementation

Due to the additional tie-lines and restrictions on the area power balance, the MAELD challenge is far more complicated and accessible than the conventional ED problem. LSTM optimization for the given real-world MAELD problem is evaluated using test systems with distinct sizes and nonlinearities. Examine LSTM optimization for the specified real-world MAELD problem.

Test systems consist of about 3-unit, 13-unit and 40-unit system values, which remain considered for the optimization of actuator loading points and target values. The load demand P_D (in MW) for the 3 test unit systems are 850, 1800 and 10500, respectively. The fuel cost minimization objective function applied to the different unit systems can be given by the Equation (1).

Comparing the same problem and its outcomes using five different available optimization techniques, including

1. Firefly Optimization (FFO)
2. Salp Swarm Optimization (SSO)
3. Squirrel search Optimization (SO)
4. Particle Swarm Optimization (PSO)
5. Grasshopper Optimization (GO)

Most multi-area issues have been linked to the amount of system data units, the corresponding load demand, and the highest and lowest area values. The data are taken into consideration for the proposed LSTM with oil cost coefficients like a, b, and c for 3-unit 13 unit besides 40-unit systems, valve-point loading effects, besides nitrous oxide emission rate coefficients like alpha, beta, and gamma, Ramp rate limits B-coefficients and weightage factor considered for economy and emission.

One set of optimal solutions promoting the intensification phase involves planning the number of units necessary for implementing the suggested algorithm. The absolute power values are also considered with maximum and minimum values, and the system works accordingly with the optimization initialization.

The proposed algorithm's implementation is compatible with all nonconvex constraints that cause the immediate solution to MAELD problems. The data for the implementation are shown in the table below.

Table 1. Test system parameters

Constraints	Amount
Total Power Demand (MW)	10500
The Line Limit (MW)	200/100
Area Load Demand (%)	3/13/40
Population Size	100
w_{max}	0.9
w_{min}	0.1
c_{1b}	2
c_{1p}	0.5
μ_1	5
μ_2	3.9
η_t	2/3
k	4
itr_{min} / itr_{max}	1/1000

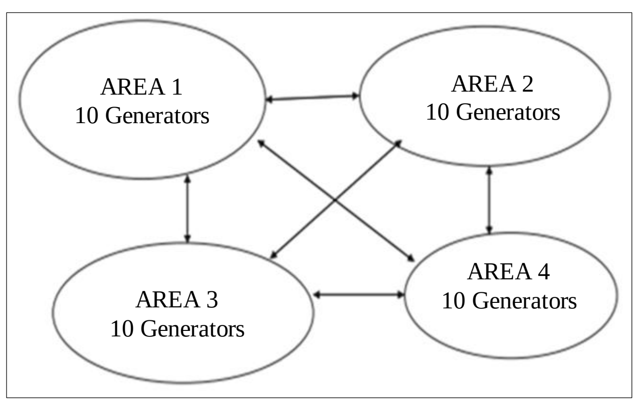

Fig. 4 Description of 4 areas, 40-unit system

The proposed algorithm reduces the generation cost in all unit systems and valve loading effect constraints. The proposed system was integrated with solar and wind sources to meet the load demands. When the algorithm identifies renewable sources, they will supplement the grid when the load demand goes over a certain threshold.The other important LSTM parameters are updated using an adaptive strategy to manage the search mechanism better. The equations mentioned above are regarded as the implementation's driving equations. The production cost function is estimated using "thermal run" measurements, which assess output and input data even as the device gradually travels through its active zone. As a result of wire drawing effects, the unit curve sways as each steaming entry gate in a turbine starts to open. As a first step towards accurately calculating the cost of each generating unit, we can state the effects of ripples in the cost equation that deals with the power sources' valve point loadings.

$$F_t = \Sigma_{i=1}^{N}\Sigma_{j=1}^{M_i}F_{ij}\left(P_{ij}\right) = \Sigma_{i=1}^{N}\Sigma_{j=1}^{M_i}a_{ij} + b_{ij}P_{ij} + c_{ij}P_{ij}^2 + \backslash d_{ij}x\sin\{e_{ij}\ x\ (P_{ij}^{min} - P_{ij})\} \quad (7)$$

5.1. Findings and Conversations

Using computational simulations on three different test systems, including a four-region system in addition to 40 components, a three-area system through 13 units, and a two-zone system with three generating units, the effectiveness of the suggested LSTM technique is investigated in a multi-area concept. Additionally, the LSTM technique is used to solve the MAELD. It is contrasted with those of recently published contemporary approaches to evaluate the appropriateness of the proposed LSTM approach. Designed for 100 free runs across all test systems, the LSTM techniques are implemented using MATLAB (2023a) at an i5 processor through 8 GB of RAM and the proposed system. The three case studies that are included are thought about. The test systems are compared with the existing FFO, SSO, SO PSO and GO for the same constraints. The planned approach comprises three zones, ten generating units, and three fuel alternatives. In use across the system are 2700 MW. In Figure 1, the 13 production divisions are split into three. Area 1 includes the initial 4 types (P1, P2, P3, P4), following three (P5, P6, and P7) are in Area 2, and residual three (P8, P9, and P10) are in Area 3. (P8, P9, and P10). Each region has load and generation, and tie-lines connecting each place to every other site are shown. 50% of the required load is anticipated to be carried by Region 1. 25% and 25% of the overall load demands are placed on Areas 2 and 3, respectively.100 MW per tie-line is the maximum tie-line flow allowed. The LSTM-based test system with three units, 13 units, and 40 systems has a minimum cost of Rs. 34,161, which is manageable because the value satisfies area power balancing limitations. The same test system has been used in the real system and has been administered using several methods, producing satisfactory results for this system. The 40 generating units in this system have valve point loading effects. They were taken and randomly allocated into two portions, with half of the units in each section. The whole system load is 10,500MW. A comparison of the proposed system with all the other techniques is shown in the graphs given below, and simulations are carried out in MATLAB programming 2023a. The cost-effective implemented proposed system in different units is shown in Table 2, with the valve loading effect according to Equation (7).

Table 2. Cost-effective value with LSTM

Load Demand in MW	No. of Units	Cost (Rs.)	Valve Loading Effect (Rs.)
850	3	3075.8	3189.9
1800	13	10404.2	11390.5
10500	40	89005.1	94077.1

In Table 2, it has been demonstrated that the proposed system implemented in the multi-area system has been dynamically stable in all conditions of power demand with minimum cost and area split has been completed in the valve point loading effect. Renewable solar and wind energy resources will be used in the emergency islanding operation of the entire system. As noted in Section 5, the results produced from the LSTM-based system were compared with those of the other five methods. The data obtained, including the reduced cost and valve point loading impact, has been compared in all the 3 test unit systems. The comparison is indicated in Table 3.

Table 3. Comparison simulation table

Unit System	3 Unit		13 Unit		40 Unit	
Algorithm	**Cost**	**Loading Effect**	**Cost**	**Loading Effect**	**Cost**	**Loading Effect**
LSTM (Proposed)	3075.8	3189.9	10404.2	11390.5	89005.1	94077.1
Firefly	3938	4256.8	11058.8	12218.9	91699.4	96871.3
Salp Swarm Opt	4586.7	5053.9	11530.7	12205.6	95394.6	100649.9
Squriel Search Opt	5111.7	5596.4	10712.8	11811.6	96249	101290.4
PSO	4658.1	5261.8	12710.1	13856.6	106449.5	111437.6
Grasshopper Opt	3966.3	4386.3	11135.9	12422.9	93186.1	98264.6

The table mentioned above compares the suggested strategy to various approaches using the same unit systems, such as 3, 13, and 40 in, for both cost minimization and valve-point effects loading. The recommended method gives satisfactory reduced cost values for a multi-area system. When the system is interconnected with the Microgrid concept, LSTM rules out all the other techniques with its following advantages.

1. Fast convergence
2. Less stipulated time
3. Simple and easy to tweak than alternative algorithms,
4. It is simple to use interactions between the intensification and diversification phases.
5. High Performance
6. A solution to the cross-docking with product truck scheduling issues in real-world size
7. Fewer controlling parameters are needed.

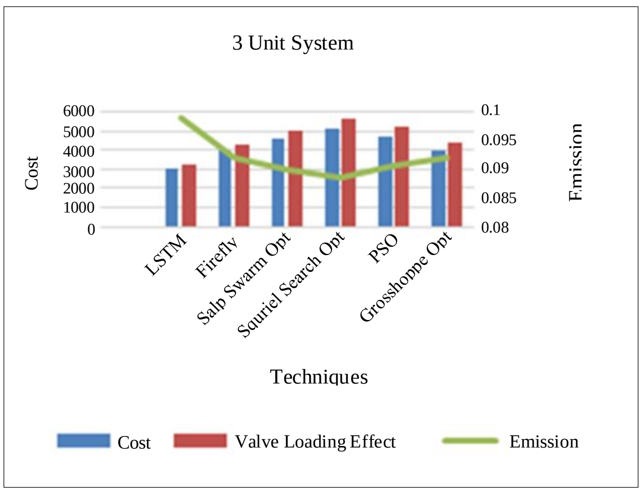

Fig. 5 Comparison graph – 3-unit system

Figures 5, 6, and 7 illustrate the results of comparing various methods in 3, 13, and 40-unit systems concerning cost, valve loading impact, and emission. All unit systems benefit significantly from the LSTM model's graph-based values, which result from the deep parameters that regulate them. The cost objective considers the valve loading effect and emissions and places a lower value on multi-area unit systems.

Figures 8 and 9 show the convergence graph of the suggested system with the technique, and it incorporates two areas that use sharing methods. This system consists of three units. According to the research, the LSTM approach meets all requirements with lower costs, even in single-area systems. Figures 10 and 11 demonstrate that the convergence in the effect of valve loading is also considered when calculating the cost in the case of a 13-unit system. By comparing it to the current approaches, figures 12 (cost) and 13 (Valve point loading) reveal that the 40-unit system has converged. A considerable drop in the cost for a 40-unit system is achieved by the suggested LSTM, which, according to the statistics, optimizes minimum cost by means of the valve loading effect.

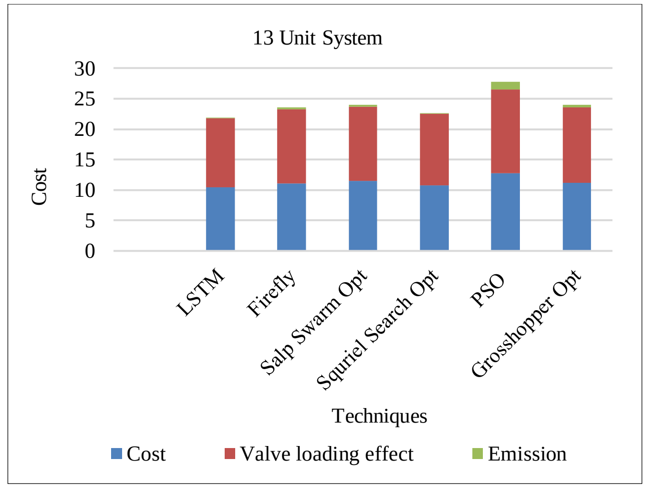

Fig. 6 Comparison graph - 13-unit system

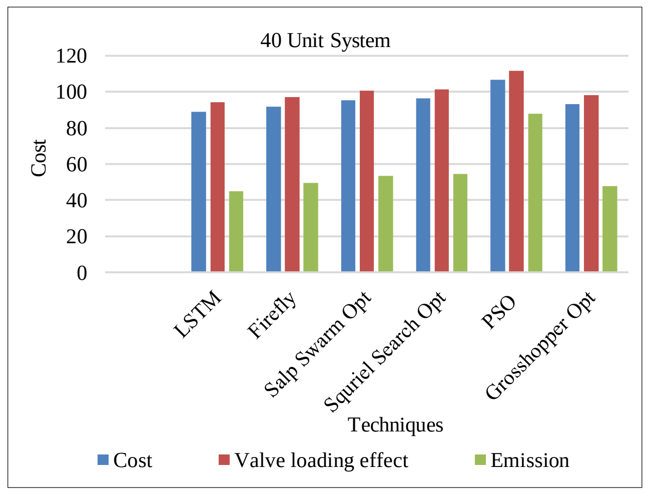

Fig. 7 Comparison graph - 40-unit system

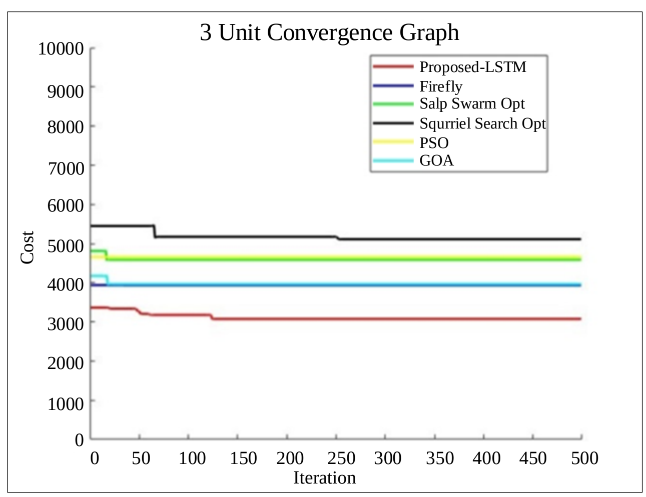

Fig. 8 Convergence graph 3 – unit system (cost)

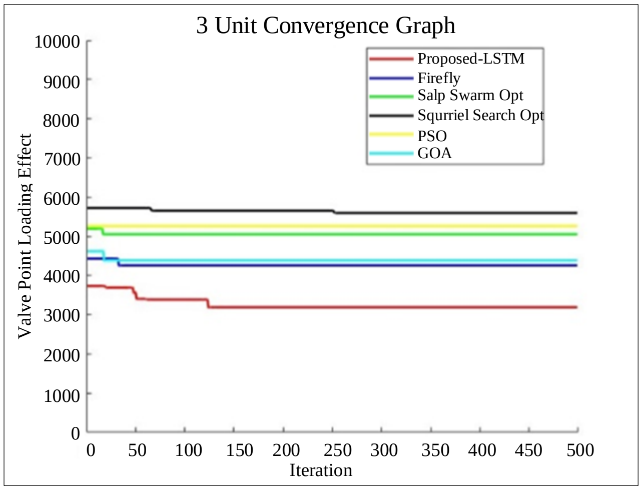

Fig. 9 Convergence graph 3 – unit (Valve point loading)

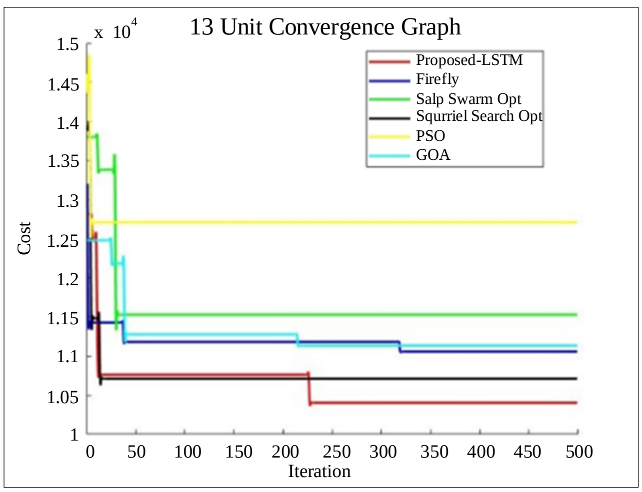

Fig. 10 Convergence graph 13 -unit system (cost)

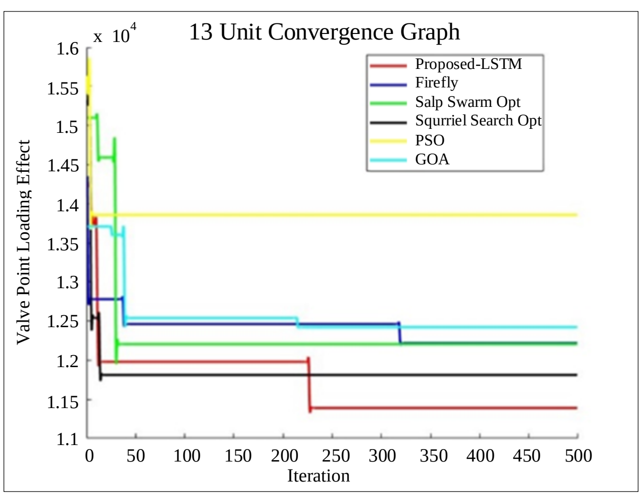

Fig. 11 Convergence graph 13- unit system (Valve point loading)

Production cost and execution time of the LSTM procedure have been less compared with other classical and non-classical techniques with a value of cost minimized, as shown in Table 3. Four zones, each with ten generator units, are considered for generation in this system. Valve point loading coefficients were incorporated in each producing unit. Power can move between any two locations because they are all interconnected. As illustrated in Figure 4, the system includes four sections, each containing ten generators and connected to the others by three tie lines. 10,500 MW becomes the total demand in this instance. Area 1, 2, 3, and 4 share 15 %, 20 %, 30 % and 15 % of the load demand in this case study. There is a 200 MW tie line restriction in the middle of areas 1 and 2, Areas 1 and 3, and Areas 2 and 3 or vice versa. Each tie line is assessed at 100 MW for all other tie lines.

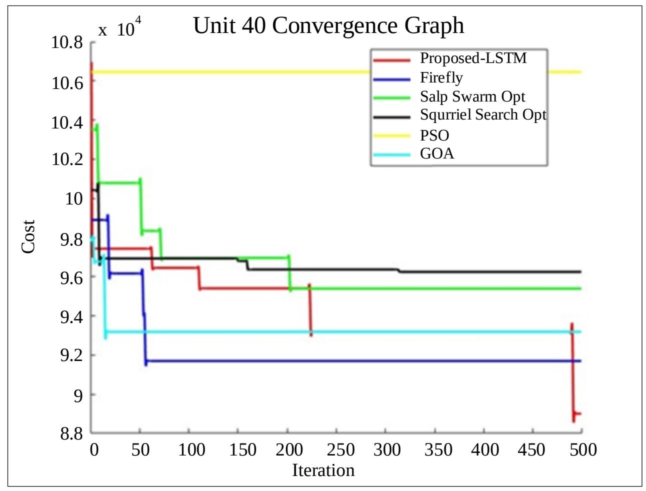

Fig. 12 Convergence graph 40 -unit system (cost)

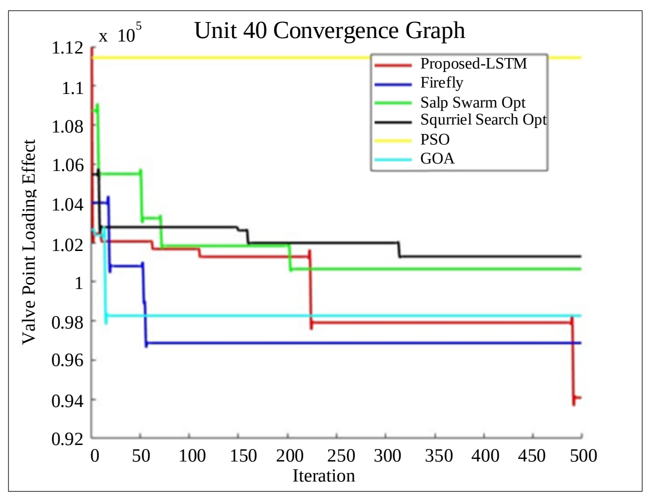

Fig. 13 Convergence graph 40- unit system (Valve point loading)

6. Conclusion

This research addresses MAELD problems for four areas with a 3, 13, and 40-unit system to employ a specially designed LSTM-based renewable energy system. LSTM incorporates the continued existence of the healthiest idea from evolutionary algorithms, with the same effectiveness as the depth of heuristic search approaches. The multiobjective functions for ELD and nonconvex ELD problems were derived and optimized using the best convergence technique. The values of data sets reveal the easiest convergence of all generating units, which can be successfully and economically done with the proposed methodology. Three different test cases were solved in multi-area economic load dispatch. The opportunity to introduce local operators to enhance exploration capabilities and add complexity has been lessened with faster execution. Using deep recurrent neural networks-based LSTM optimization methods, the optimal requirement allocation of power-generating units is assessed. The simulation findings, generated using the MATLAB platform, show that LSTM approaches deliver high-quality cost solutions without violating constraints.

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