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DEEP LEARNING OPTIMISATION FOR DYNAMIC MULTI-AREA ECONOMICS DISPATCH ISSUES

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ABSTRACT
Determining generating methods that satisfy load needs and technical limits is vital in linked power systems, and thus, Multi-area Economic Dispatch (MAED) plays a crucial part in this process. The need to address MAED dynamically arises from hourly load changes, leading to the particular multi-area dynamic economic dispatch MADED problem. While judging ramp rate and other limitations, DED expands upon stable economic dispatch SED by optimizing the generating scheduling for committed units to fulfil anticipated load needs at the least cost. To tackle the DED problem in four domains, including 3-, 13-, and 40-unit systems, this study presents an improved Deep Recurrent Neural Network DRNN model that uses Long Short-Term Memory (LSTM) networks. Long short-term memory networks are an advanced form of recurrent neural network (RNN) developed to address the shortcomings of more conventional RNNs, particularly the vanishing gradient problem, making learning dependencies that span several time periods challenging. Combining memory cells with gating mechanisms makes LSTMs ideal for sequence modelling and time series prediction. Overall, the DRNN model with LSTM is used in the DED context to successfully capture the power-generating data's complex connections and temporal dependencies. This approach ensures that the generation schedule meets the balance and power distribution constraints and adheres to the generating limits, transmission line capacities, and overall power balance requirements. The proposed model improves performance in optimizing the generation schedule for multiple areas, thereby contributing to more efficient and cost-effective power system operations.

Keywords
Dynamic Economic Dispatch DED, Long Short-Term Memory LSTM, Deep Recurrent Neural Network DRNN, Transmission Losses, Multi-area Power Systems

1. INTRODUCTION

The electricity system is under a lot of strain due to the dramatic growth in energy consumption caused by the fast development of technology and science and improved living standards. Research on dynamic economic dispatch has recently exploded in popularity, both at home and abroad, to enhance the efficiency of power utilization and optimize power system scheduling [1]. Economic dispatch with constant change By breaking the day into phases and optimizing dispatches based on demand projections, the DED problem—introduced by Bechert and Kwanty in 1971—extends static economic dispatch SED. DED considers several thermal power unit limitations to make it more in line with how power systems work. Allocation of economic loads ELD is an essential optimization problem in DED that seeks to meet limitations while distributing power across units in the most cost-effective way possible. More conventional approaches were utilized for easier scheduling issues, such as gradient projection, dynamic programming, and prioritization [2]. Cost functions that are neither smooth nor convex are inapplicable to most conventional approaches. The DED problem has been tackled by employing several heuristic optimization approaches. A few examples of these techniques include the GA, SA, tabu search, FA, BA, CS, and GSA (gravitational search algorithm). The DED issue has been successfully solved using these methods with little constraints on the cost function curves. Algorithms take a starting set of feasible solutions and iteratively apply an assortment of operators to create a population of solutions.

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The literature describes several optimization strategies, from mathematical to metaheuristic, for solving the economic dispatch ED problem. The ED problem is addressed in [6] using a stochastic programming technique with a distributed resilient optimization algorithm by minimizing the cost of variable energy supplies. Considering the limitations of decision variables and DC power flows, it maximizes the output of conventional generators, energy storage, renewables curtailment, and deferrable loads. A Kho-Kho algorithm in [7] handles combined emission economic dispatch, which considers the valve point impact and imposes limitations on generating output limits and power balance. In order to make the environmental economic dispatch solution work better and converge faster, differential evolution-crossover quantum particle swarm optimisation, a modified PSO method, is used in [8]. This algorithm considers limitations such as load balancing, generation limits, and ramp rates. An accurate and simplified solution to the problem of combined heat and power economic dispatch is given using a deep reinforcement learning method [9]. A dynamic programming technique handles both convex and non-convex restricted socioeconomic dispatch, which requires rethinking limitations, power, heat load balance, and other restrictions into single unit banned zones and ramp rate constraints [10]. The eleventh Uses several case studies to provide new approaches to initial solution generation that speed up optimization, with a particular emphasis on forbidden zones, valve point effects, and different fuel types. The economic dispatch of heat and power as well as economic emissions are tackled in [12] through a multi-objective, multi-verse optimization strategy which also considers ramp rate constraints, practical operation zones, and valve point impacts. [13] Introduces a dynamic economic dispatch system that is security-constrained and ensures frequency restrictions in typical and crisis scenarios. It takes into account power generation limits and unit ramp rates. Considering network restrictions such as line flows and bus voltages, as well as ramp rate limits, generating capacity, and banned zones, the proposed dynamic economic emission dispatch considers these factors [14]. According to [15], a decomposition approach based on expert systems can be used in solving the nonlinear multi-area generation scheduling problem.

In contrast, [16] proposes a multi-objective particle swarm optimization (MOPSO) solution for the multi-area economic dispatch problem. [17] Utilizes MAED's teaching-learning optimization approach and evaluates it compared to DE, RP, and evolutionary programming. Develops a penalty function-hybrid direct search technique for economic generation and reserve dispatch with wind power integration [18] and uses an evolutionary method to formulate and solve a multi-area unit commitment issue with ED [19]. [20] Introduces a refined Jaya method to produce practical Pareto-optimal answers to the bi-objective MAED issue. [21] Using a variety of case studies, a multi-area economic dispatch that considers valve point effects and restrictions related to different types of fuel is suggested.

Accurate load forecasting is essential for community microgrid supply-demand balance. Methods like SVM, ANN, SR, GM, DR, and EA are employed [22]. For instance, in [23], an SVM model predicts air conditioning load using modified simulated annealing optimization. Decision trees forecast building energy demand in [24], while [25] reduces power usage over the long run by optimizing gene expression programming. Even if they work for load forecasting [26], SR and GM have difficulty understanding internal relationships and must be more accurate. However, ANN needs more vital learning ability for complex relation modeling and neglects needs more tendencies. Thus, there's a need for deep neural network models considering both feature representation and time dependency [27,28]. In [29], a multi-objective load dispatch method employing information mining technologies is demonstrated for significant coal plants. An LSTM-based load forecasting technique is proposed for energy-integrated systems, utilizing multi-feature data and dynamic meteorological information. Feature engineering techniques are applied, including Grey correlation analysis with the Gaussian Mixture Model and Similarity-based Instance Selection SIS for selecting relevant features [30]. This LSTM model can optimize Economic and Emission dispatch problems by forecasting multiple loads and minimizing costs. This study focuses on multi-area economic fuel cost minimization using an improvised LSTM technique implemented in MATLAB/Simulink for optimizing generating unit costs. The LSTM optimization flow offers significant advantages in addressing multi-area economic dispatch problems. After that, the model that has been suggested is described in full, down to the derivation of the constraints and objective function. The subsequent section elaborates on implementing the DRNN with LSTM networks in solving the DED problem, highlighting their ability to capture temporal dependencies. Results from applying the proposed model are then presented, followed by a discussion on their implications and comparative performance analysis. Lastly, the study concludes by reviewing the main points and suggesting where the research may go.

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2. PROPOSED MODEL

The purpose of the Dynamic Economic Dispatch (DED) problem is to find the optimal power generation levels for all online units throughout a particular scheduling period (e.g., 24 hours per day) in order to minimise fuel expenditures. This must be achieved while adhering to various equality and inequality constraints and considering factors such as the valve point effect (VPE) and network losses. This is the exact mathematical description of the issue:

2.1 Objective function

A smooth quadratic function may be used to estimate the gasoline cost goal function, taking into consideration the valve point effect:

$$minF(P) = \sum_{t=1}^{T} \sum_{i=1}^{N} \left\{ a_i + b_i p_{t,i} + c_i p_{t,i}^2 + \left| d_i \sin\left[e_i \left(p_i^{min} - p_{t,i} \right) \right] \right| \right\} \tag{1}$$

In equation (1), the following variables are defined: FP, which stands for the total amount of fuel cost of the thermal energy generating units; P, for all online units' output power; T, for the entire 24-hour dispatch cycle; N, for the total number of system generators; and ai, bi, ci, di, ei, for this ith generator's fuel consumption coefficients. The ith thermal generating unit's output power at time t is represented by p{t, i}, and the lowest active output of the unit is pimin. The influence at the valve point is considered by the part of the equation that uses absolute value.

2.2 Constraints and limits

Generation capacity restrictions, unit ramp rates, power balancing needs, transmission loss concerns, and other equality and inequality constraints are all part of this dynamic economic dispatch problem.

During optimum dispatch, generation capacity constraint (an inequality constraint) keeps the generation of each unit within certain limitations. Here is how it is stated: $p_i^{min} \leq p_{t,i} \leq p_i^{max}$

(2)

In this equation, pi^{max} and p_i^{min} are the maximum and minimum values that may describe each generator unit's active output

.

A ramp rate constraint is imposed to prolong the thermal power units' service life due to their large inertia. This constraint ensures that the unit's output can't be significantly regulated in a short period of time. It be present expressed by Formula (3).

$$\begin{cases} p_{t,i} - p_{t-1,i} \leq UR_i \\ p_{t-1,i} - p_{t,i} \leq DR_i \end{cases} \tag{3}$$

In this equation, UR_i and DR_i indicate the maximum allowable increase and decrease rates for the i-th generation unit. These rates characterize the thermal power unit's generation inertia.

At its core, the DED issue revolves around the complex power-balancing constraint. This constraint ensures that, in each time period, all generators' total active output p_i,t equals sum of the total load demand $p_{D,t}$, and the network active loss $p_{L,t}$ for that period. This constraint is expressed as Formula (4).

$$\sum_{t=1}^{T} p_{i,t} - p_{D,t} - p_{L,t} = 0 \tag{4}$$

It is common practice to simplify the mathematical formula regarding calculating complex transmission loss pL,t in the previous equation, as seen in Formula (5).

$$P_{L,t} = \sum_{i=1}^{T} \sum_{j=1}^{N} P_{t,i} B_{ij} P_{t,j} \tag{5}$$

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

$$T_{j(M-1)}^{\min} \leq T_{j(M-1)} \leq T_{j(M-1)}^{\max} \quad j = 1, 2, \ldots, M \tag{6}$$

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Someplace Tj remains power flow through the tie line.

3. DRNN-based LSTM implementation in DED

3.1 Recurrent neural network (RNN) and long short-term memory (LSTM)

A neural sequence model that excels at capturing temporal relationships within time series data is the Recurrent Neural Network (RNN). Its inherent ring structures enable the retention of information from previous time steps, empowering it to handle dynamic time series problems. An RNN's output at a given time step is affected by both the current input and the output from previous time steps, as represented in (7). RNNs have significant use in different fields, such as language modeling, handwriting recognition, and speech recognition. However, training RNNs using back-propagation often consumes considerable time. Learning long-term dependencies is complicated since gradients disappear or erupt over lengthy periods. A result-Term Memory (LSTM) network has been developed to address these concerns. LSTM u and replaces conventional RNN neurons it possesses the ability to dynamically scale input and output values, as well as to remember or forget cell state values. This adaptability is facilitated through input, forget, and output gates, as illustrated in Figure 1.

$$y^{(t)} = f\left(\omega_1 x^{(t)} + \omega_2 h^{(t-1)} + \theta\right) \tag{7}$$

Upon receiving the input X_t, the LSTM unit processes it through an activation function denoted as s, yielding an output represented as f_t.

$$f_t = \sigma\left(\omega_f \cdot [y_{t-1}, X_t] + \theta_f\right) \tag{8}$$

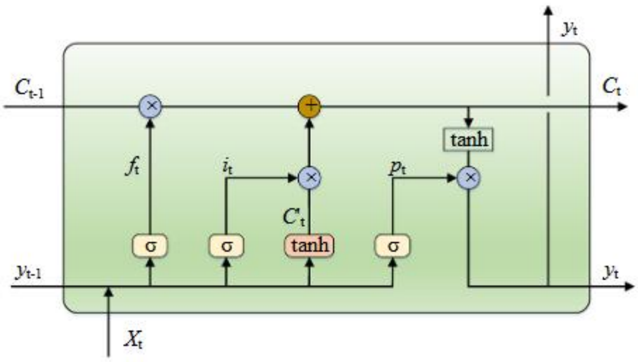

Figure 1 Schematic diagram of LSTM

Equation (8) introduces u_f as the weight parameter and q_f as the bias parameter. y^{t-1} stands for the result of the LSTM unit that came before it. After that, the input gate finds fresh information and adds it to the cell state using the following operations, while the forget gate removes redundant data from the temporary cell state.

$$i_t = \sigma(\omega_i \cdot [y_{t-1}, X_t] + \theta_i) \tag{9}$$

$$C'_t = \tanh(\omega_c \cdot [y_{t-1}, X_t] + \theta_c) \tag{10}$$

$$C_t = f_t \otimes C_{t-1} \oplus i_t \otimes C'_t \tag{11}$$

In the equation, u_i and u_c represent weight parameters, while q_i and q_c denote bias parameters. The vector determines which values will be updated: C_{0t} signifies new candidate vector,C_{t-1} denotes the cell state of the preceding LSTM unit, and Ct represents the updated cell state. Finally, y_t is produced through two activation functions within the output gate, and its expression can be formulated as

$$z_t = \sigma\left(\omega_p \cdot [y_{t-1}, X_t] + \theta_p\right) \tag{12}$$

$$y_t = z_t \otimes \tanh(C_t) \tag{13}$$

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In the equation, u_p signifies the weight parameter, while q_p represents the bias parameter. z_t denotes a component of the cell state that will be output.

4 Results and Discussion

The proposed LSTM method is evaluated using three separate test systems: a three-area system with thirteen units, a four-region system with forty components, plus a four-zone system containing three generating units. The LSTM method is applied to solve the MAELD and compared with recently published modern approaches to assess its suitability. Implemented in MATLAB (2023a) on an i5 processor with 8 GB of RAM, the LSTM technique is tested over 100 free runs for all systems. These case studies are compared against existing methods such as FFO, SSO, SO, PSO, and GO under identical constraints.

Based on the individual region load needs, the overall power demand throughout the system is 10,500 MW, with 3%, 13%, and 40% allocated to each area. The line limits for power transfer between regions exist set at 200 MW and 100 MW, ensuring that the power flow between interconnected regions does not exceed these thresholds. The population size for the optimization algorithm is 100, indicating the number of candidate solutions considered at each iteration. The inertia weight (w) parameters range from a maximum of 0.9 ($wmax$) to a minimum of 0.1 ($wmin$), influencing convergence speed and stability of optimization process. Cognitive coefficients (c1b and c1p) are set at 2 and 0.5, respectively, dictating the influence of individual and social learning components. The mutation coefficients (µ1 and µ2) are 5 and 3.9, and the learning rate (ηt) varies between 2 and 3, with k representing the number of clusters at 4. Finally, the iteration range is from a minimum of 1 (it min) to a maximum of 1000 (it max), defining the bounds for the optimization process iterations.

4.1 Test System 1: Four-Region System with 40 Components

A thorough and sophisticated configuration, the four-region system with 3, 13 & 40 generating units is intended to assess the efficacy of the suggested DRNN-based LSTM technique in challenging circumstances. Each of the four regions contains ten generating units, making 40 units across the system. These generating units include valve point loading effects, which add a layer of complexity to the optimization process due to the nonlinear characteristics of fuel cost curves associated with absolute power generation. The generating units are randomly allocated into two sections, with half of the units in each section. This division helps assess the robustness and adaptability of the DRNN-based LSTM technique in managing diverse configurations within the same system.

To reflect realistic scenario assumptions and generation, this system has a total load demand of 10,500 MW, which is spread unevenly throughout the four areas. In a specific scenario, Area 1 handles 15% of the total load, Area 2 takes on 20%, Area 3 bears the most significant share with 30%, and Area 4 manages 15%. This distribution ensures that each region has a substantial yet varying portion of the total demand, requiring efficient load management and power distribution strategies. The system is fully interconnected with tie-lines, allowing power transfer between regions. However, there are restrictions on the maximum allowable flow through these tie-lines: 200 MW connecting two Area combination, while other tie-lines have a 100 MW restriction. These constraints necessitate careful coordination to avoid overloading any single line while maintaining the overall system balance.

4.2 Test System 2: Three-Area System with 13 Units

The three-area system comprises 13 generating units distributed across three distinct areas, each interconnected by tie-lines. Area 1 includes four generating units (P1, P2, P3, and P4), Area 2 contains three units (P5, P6, and P7), and Area 3 comprises three units (P8, P9, and P10). This configuration tests the DRNN-based LSTM technique's effectiveness in managing a moderately complex system. Each region is accountable for a certain percentage of the system's overall load demand, which amounts to 2700 MW. The presence of load and generation in each area and tie-lines connecting each area to every other area create a realistic scenario for multi-area economic load dispatch (MAELD).

Area 1 is expected to carry 50% of the total load in this setup, which amounts to 1350 MW. Areas 2 and 3 each handle 25% of the total load, equivalent to 675 MW each. This distribution reflects a situation where one area has a significantly higher demand, requiring efficient power generation and distribution to maintain balance across the system. The tie-lines have a maximum allowable flow of 100 MW, which adds a layer of complexity as power transfers need to be managed carefully to avoid overloading any single tie-line. This system tests the LSTM technique's ability to optimize power generation and distribution while adhering to these constraints and maintaining stability.

4.3 Test System 3: Two-Zone System with 3 Generating Units

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The two-zone system is the most basic of the three test systems, with two zones and three generating units overall. This configuration aims to assess the basic efficacy and performance characteristics of the DRNN-based LSTM method in a simplified setting. Each zone includes generating units that must meet the overall load demand while ensuring cost efficiency and system stability. The system provides a basic scenario to test the DRNN-based LSTM technique's core capabilities in managing power distribution and generation.

At 850 MW, this system's total load demand is smaller than the other two systems. The generating units must be managed to meet this demand while minimizing costs and maintaining system balance. This system's simplicity allows for a clear assessment of the DRNN-based LSTM technique's ability to handle basic power distribution challenges. Despite its simplicity, this test system provides valuable insights into the LSTM approach's effectiveness in ensuring stable and efficient power generation and distribution in a straightforward scenario.

5. Comparative performance analysis

The DRNN-based LSTM technique's performance is compared against several existing methods, including Firefly (FFO), Salp Swarm Optimization (SSO), Squirrel Search Optimization (SSO), Particle Swarm Optimization (PSO), and Grasshopper Optimization (GO). The comparisons are based on cost minimization and valve point loading effects across three test systems. The results indicate that the DRNN-based LSTM technique consistently achieves lower costs and satisfactory performance, demonstrating its effectiveness in various multi-area power systems. The detailed results, as shown in the provided tables, highlight the DRNN-based LSTM technique's advantages in cost and execution time compared to traditional and contemporary optimization methods.

Table 1 presents the load demand, number of generating units, the associated cost, and the valve loading effect for three different test systems

Table 1 Load Demand, Number of Units, Cost, and Valve Loading Effect

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

. Table 2 compares various algorithms' costs and valve loading effects, including the proposed DRNN-based LSTM technique, across unit systems with 3, 13, and 40 generating units.

Table 2: Comparison of Cost and Valve Loading Effect for Different Algorithms

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	3938.0	4256.8	11058.8	12218.9	91699.4	96871.3
Salp Swarm	4586.7	5053.9	11530.7	12205.6	95394.6	100649.9
Squirrel Search	5111.7	5596.4	10712.8	11811.6	96249.0	101290.4
Particle Swarm Optimization	4658.1	5261.8	12710.1	13856.6	106449.5	111437.6
Grasshopper	3966.3	4386.3	11135.9	12422.9	93186.1	98264.6

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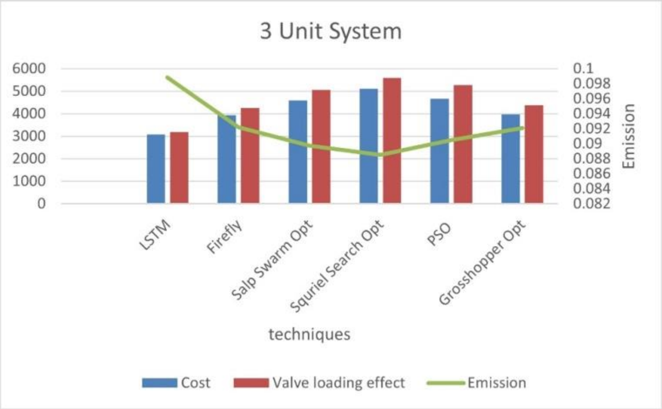

Figure 2. Cost Comparison for 3-Unit System

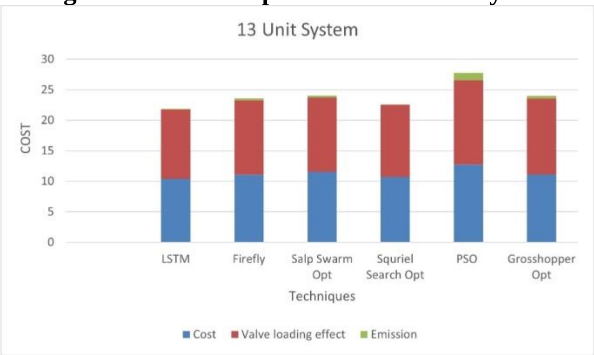

Figure 3. Cost Comparison for 13-Unit System

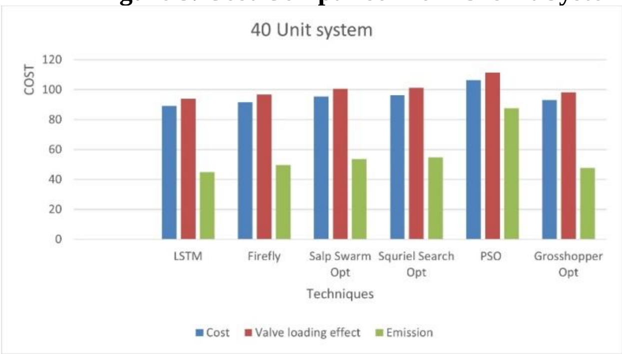

Figure 4. Cost Comparison for 40-Unit System

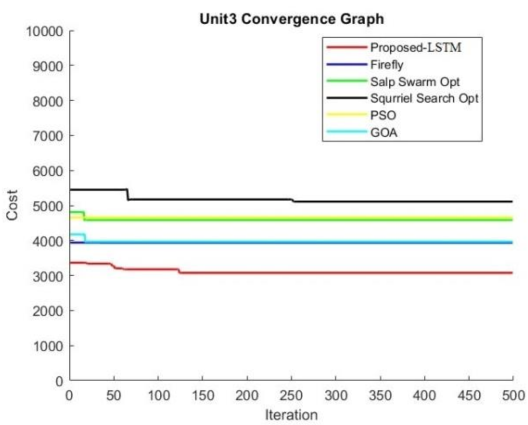

Figure 5. Convergence Graph for 3-Unit System (Cost)

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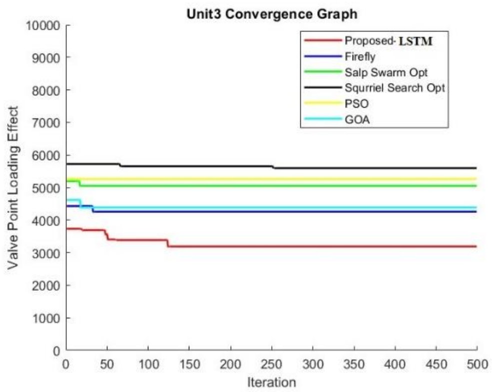

Figure 6. Convergence Graph for 3-Unit System (Valve Point Loading)

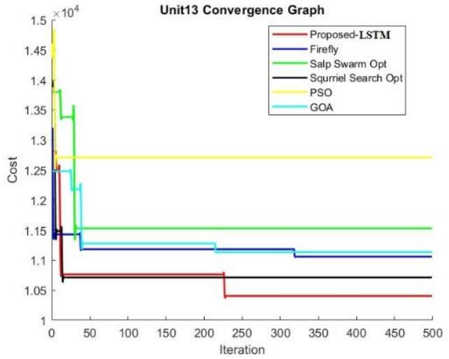

Figure 7. Convergence Graph for 13-Unit System (Cost)

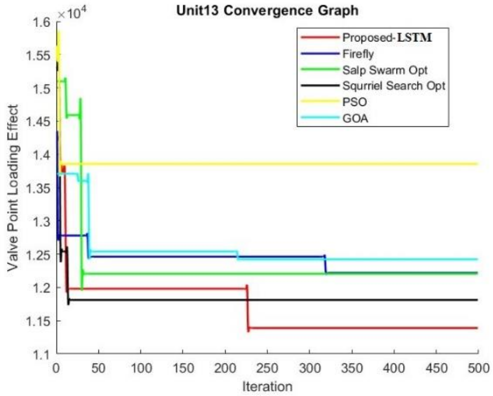

Figure 8. Convergence Graph for 13-Unit System (Valve Point Loading)

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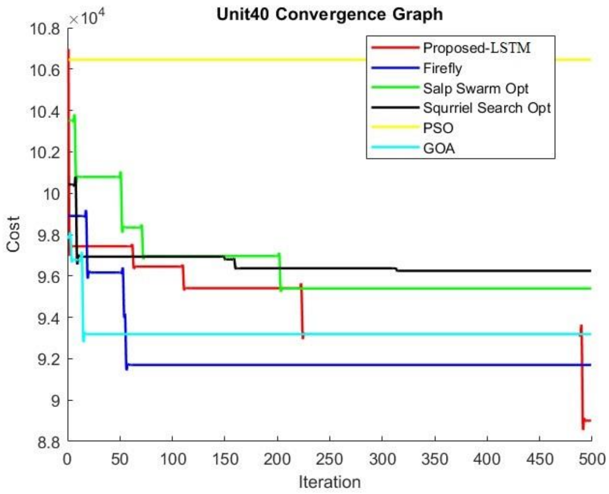

Figure 9. Convergence Graph for 40-Unit System (Cost)

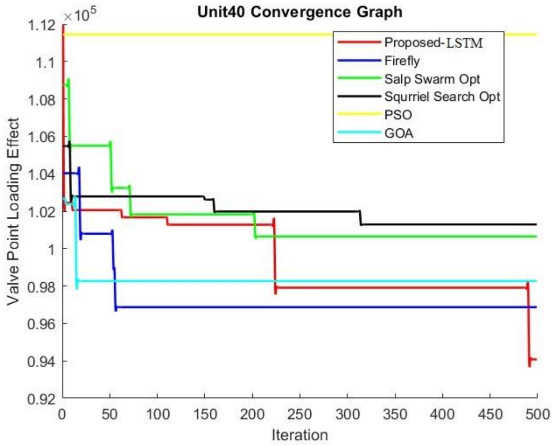

Figure 10. Convergence Graph for 40-Unit System (Valve Point Loading)

Figures 2, 3, and 4 compare the costs associated with different algorithms, including the proposed DRNN-based LSTM technique, for systems with 3, 13, and 40 generating units, respectively. Figure 5 shows the convergence behavior of the DRNN-based LSTM technique in terms of cost for the 3-unit system, demonstrating its swift and effective optimization. Figure 6 illustrates the algorithm's efficiency in minimizing valve point loading effects for the 3-unit system. Figure 7 highlights the DRNN-based LSTM algorithm's cost optimization performance for the 13-unit system, while Figure 8 shows its effectiveness in managing valve point effects for the same system. Figure 9 indicates how well the DRNN-based LSTM technique handles cost optimization in a more complex 40-unit system. Finally, Figure 10 underscores the algorithm's ability to efficiently manage intricate valve point loading effects in the 40-unit system. These figures collectively provide a comprehensive visual analysis of the DRNN-based LSTM technique's performance and convergence behavior across various system sizes and complexities.

6.CONCLUSIONS

This research successfully introduces and evaluates an enhanced Deep Recurrent Neural Network (DRNN) model, explicitly utilizing Long Short-Term Memory (LSTM) networks to address the Dynamic Economic Dispatch (DED) problem across multi-area power systems. The proposed DRNN-based LSTM technique significantly improves optimizing power generation schedules, effectively capturing temporal dependencies and complex relationships within the power generation data. The computational simulations conducted on three different test systems—a four-region system with 40 generating units, a three-area system with 13 units, and a two-zone system with three units—highlight the efficacy of the DRNN-based LSTM approach. The results consistently show that the proposed technique achieves lower costs and satisfactory performance

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compared to traditional and contemporary optimization methods, such as Firefly, Salp Swarm, Squirrel Search, PSO, and Grasshopper Optimization algorithms. The convergence graphs and cost comparison figures for the 3-unit, 13-unit, and 40-unit systems further underscore the DRNN-based LSTM's ability to optimize costs swiftly and effectively minimize valve point loading effects. This indicates its robustness and adaptability in managing diverse and complex power system configurations. Future research can extend the DRNN-based LSTM technique to integrate renewable energy sources, scale to larger systems, enable real-time implementation, develop hybrid optimization methods, incorporate advanced constraints, enhance feature engineering, and explore cross-domain applications for improved efficiency and sustainability.

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