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Multi-Area Load Dispatch with Emission and Fuel Cost Constraints Using Deep Recurrent Lstm Under Stochastic Pv and Wind Power Integration



Abstract: - An interconnected power system must employ multi-area economic load dispatch (MAELD) to keep generation dispatch efficient, satisfy load demands, and stay within technological limits. The goal of MAELD's operational constraints is to reduce fuel costs and emissions from multi-area power production facilities. Consequently, optimization solutions that successfully tackle MAELD problems are highly sought after. By merging an alternative model with the Deep Recurrent Neural Network (DRNN) one, this paper suggests a fresh approach to addressing MAELD problems. This paper provides a detailed account of the various optimization methodologies used to address the issue of load dispatch when non-conventional energy sources are present. Four domains utilizing 3-, 13-, and 40-unit systems were used to test the suggested DRNN and LSTM approach. Comparing this method to various optimization algorithms as firefly, Salp Swarm, Squirrel search, Particle Swarm, and Gross Hopper, results produced from the MATLAB/Simulink environment show that it delivers superior trade-off solutions without breaching limitations.

Keywords: Multi-area economic load dispatch, generation dispatch strategy, fuel cost, emissions, Long short term memory, renewable energy sources.

1. INTRODUCTION

As society and the economy continue to grow rapidly, there is a corresponding increase in the demand for electric energy. However, the electric power industry must comply with new laws that mandate it save energy and reduce emissions. In this case, optimizing power system operation is critical, notably by effectively planning generator outputs according to expected load demands. This optimization seeks to lower both fuel expenses and pollutant emissions [1]. As a result of its practicality and compatibility with short-term load demands in real-world circumstances, the topic of cost-effective emission dispatch has received substantial awareness. The purpose of economic emission dispatch (EED) is to minimise both fuel costs and emissions, making it a multi-objective optimisation problem. Various practical restrictions, akin equally power balance constraints, ramp rate limits, output power constraints, and spinning reserve constraints, must be considered in order to achieve this. Electric car charging and discharging behaviours, as well as the inherent vagueness of wind power generation, are all included in EED model, making it not only effective for swiftly transmitting generator outputs based on shifting load demands within a specified interlude, but also more realistic. As a result, recent research investigations show an increasing interest in merging EED with renewable energy sources. Researchers want to maximize power system operation while embracing the fluctuating nature of renewable energy sources by merging EED with renewable energy, such as wind power. This integration allows for more effective utilization of renewable energy, reduces reliance on fossil fuels, and contributes to overall energy sustainability and environmental goals. The combination of EED and renewable energy represents an important research area, as it addresses the need for optimizing power system operations ensuing the fluctuation in undeletable energy sources. Every promise of a more sustainable and ecologically friendly power system can be realized through the combining of EED and renewable energy. Investigators in various fields have shown a marked surge in interest in bio-inspired optimization strategies over the past decade. This rise in popularity can be attributed to the growing complication and size of real-world optimization problems. Stochastic optimization methods, like those drawn from biology, use chance to find improvements. Given this ambiguity, gradient-free search techniques can be expanded, which is helpful when attempting to solve difficult optimization problems. These optimization techniques draw inspiration from biological phenomena, and they can be broadly categorized grounded on evolutionary principles, mutual behaviour (swarm-based), ecological singularities, or physical sciences. One of the key advantages of bio-inspired optimization approaches is their ability to handle real-world optimization problems effectively. Engineering, finance, healthcare, and logistics are just a few of the fields where these algorithms have shown their worth. These strategies provide resilient and adaptable optimisation methods that can adjust to changing and complex problem spaces by modelling them after natural processes. Furthermore, bio-inspired optimization approaches provide alternative solutions to traditional optimization methods, which often rely on mathematical formulations and assumptions. The stochastic nature of these algorithms allows for exploration of a broader search space and the potential discovery of novel and more optimal solutions. Overall, bio-inspired optimization techniques have proven their

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efficacy and potential in addressing real-world optimization problems. Their ability to leverage randomness, emulate natural phenomena, and provide robust search mechanisms makes them valuable tools for researchers and practitioners in various fields.

The Crowd intelligence-created optimization methods, aforesaid as Particle Swarm Optimization [2], Artificial Bee Colony optimization [3], Whale Optimization Algorithm [4], Grasshopper Optimization Algorithm [5], Spider Monkey Optimization [6], Grey Wolf Optimizer [7], and Teaching-Learning-Based Optimization [8], remain popular and efficient approaches. These algorithms mimic the self-organizing and task-driven behaviour observed in natural systems like fish schooling, bird flocking, honeybee foraging, humpback whale behaviour, spider monkey social structure, grey wolf hunting, and classroom learning. Another category of bio-inspired optimization methods draws inspiration from physical sciences. Simulated Annealing [9] emulates the annealing process in metals, Harmony Search [10] is based on jazz improvisation and the search for perfect harmony, Gravitation Search Algorithm [11] utilizes Newton's law of gravitation, Chemical Reaction Optimization [12] simulates molecular interactions, Stochastic Fractal Search Algorithm [13] employs random fractals for optimization, Water Cycle Algorithm [14] mimics the hydrologic cycle, Invasive Weed Optimization [15] replicates weed colonization, Biogeography-based Optimization [16] models species migration among habitats, and Flower Pollination Algorithm (FPA) [17] simulates the cross-fertilisation process of flowering plants. Various algorithms represent a diverse range of ecological and physical processes that have inspired efficient optimization methods. The Red deer algorithm (RDA) is being demonstrated to be a quick and efficient approach for performing real-time computations. [18] used RDA headed aimed at solving the Coordinated Quay Crane Scheduling & Assignment Difficulty and demonstrated its superior performance using numerical examples of varied sizes. The Modified RDA was proposed by the authors of another paper [19] to optimize thresholds in grayscale photographs. While examined on publicly available benchmark pictures, MRDA outperformed both RDA and standard Particle Swarm Optimization. [20] used real-world grayscale photos to evaluate MRDA, RDA, and the Classical Genetic Algorithm (CGA). Using statistical testing, MRDA outperformed the other algorithms and produced competitive results. [21] DHOA, a similar meta-heuristic algorithm that shares similarities with RDA, was introduced. [22] Presented a hybrid optimization model called Red Deer Adopted Wolf Algorithm (RDAWA) for assessing potential movement of stock values in financial exchanges. RDAWA combines RDA and Grey Wolf Optimization (GWO) to achieve improved optimization performance. Furthermore, an Improved RDA (IRDA) was employed by [23] for the engineering design of a Direct Current (DC) brushless motor.

Wind energy has emerged as a critical renewable energy source in efforts to decrease reliance on conventional thermal power generation, reduce fossil fuel use, and reduce pollutant emissions [24-26]. Several studies have been conducted by researchers to address how to integrate of wind power into electricity dispatching systems. [27] created a load allocation simulation that considers compactor of wind power on pollution management. [28] suggested possibility distribution model, based on "universal distribution," to estimate wind power failures in economic dispatch situations. With the liberalisation of the energy market, [29] zeroed down on integration of wind power furthermore vigorous economic emission dispatch (DEED). To account representing the sporadic character of load demand, a stochastic programming framework built on scenarios stay proposed [30]. The grey wolf optimizer algorithm was developed by [31] to address the challenges provided by wind power's unpredictability and the related economic-emission restriction problem in integrated systems. In addition, to account for the ambiguity of wind power generation, [32] suggested a limited multi-objective population extreme value optimization technique. [33] Managed the interchange market algorithm to deal with the DEED issue with wind farms. [34,35] Considered circumstances in which available wind power is exaggerated or miscalculated, coupled with presented an EED model to meet these scenarios. An energy integrated system is suggested to use an LSTM-based LF technique that incorporates multi-features and dynamic similar-day meteorological data [36]. These studies highlight the versatility and effectiveness of various variants and hybrids of the proposed RNN and LSTM in solving different optimization problems across diverse domains.

The goal of these research is to maximize power dispatching although taking into consideration of vagueness of wind power generation. This includes addressing challenges of excess wind power, which can result in wastage, as well as insufficient wind power, which requires additional spinning reserves and incurs extra costs [37]. By developing models and utilizing optimization algorithms, researchers aim to minimize the additional costs and enhance integration of wind power into power dispatching arrangements, leading to more efficient and sustainable energy utilization. since Feedforward neural network is deficient in processing the correlation information between loads, the prediction model developed by the author was studied as CNN [38, 39].

This paper introduces the DRNN and LSTM as a potential solution for solving MAELD problems. The research aims to provide a comprehensive exploration of different optimization algorithms in addressing the economic load dispatch problem when renewable energy sources are incorporated. By employing the hybrid mode, the paper seeks to enhance the understanding of the algorithm's applicability and effectiveness in optimizing power dispatching with the integration appropriate to renewable energy sources. The following is the outline of the paper: Independent functions such as economic load dispatch, discharge dispatch, and mixed fiscal

and emission dispatch are presented in Section 2 lengthwise with the problem formulation. The limitations, existing methods, and application stay also covered. In Chapter 3, you'll find a case study. The results will be addressed in Section 4. Section 5 of the report discusses potential future research directions.

2. METHODOLOGIES

2.1 Delinquent interpretation

Identical to it comes to operational constraints such power balancing, producing or operating limits, and tie line capacity, the MAED approach aims for the absolute minimum achievable while yet meeting all of them.

2.1.1. Objective Functions

Economic Load dispatch

Power system management and planning should include consideration of economic load dispatching. As part of this procedure, generating units' fuel costs and emission rates will be lowered while still meeting the requirements of numerous regulations. Common practise has fuel cost curves represented as quadratic functions of active power production commencing the producing units. Therefore, ELD issue can be formulated as the subsequent optimisation problem,

Minimize

$$C_{ti}(OP_{gi}) = \sum_{M=i}^M \sum_{N=i}^N \left[A_i + B_i P_{im}^2 + \left| D_i \sin \left\{ E_i (OP_i^{\min} - OP_i) \right\} \right| \right] \quad (1)$$

Where

- The coefficients Ai, Bi, Ci, Di, and Ei on the ith genset's price curve.
- Pim is power output at instant m from the ith unit.
- The ith generation's minimum allowed production, denoted by min_iP.
- The number of generators is denoted by N.
- The temporal horizon has a length of M hours.

Emission Dispatch

By determining the ideal power generation levels of different units in a power system, the economic dispatch issue seeks to minimise the total fuel cost. However, this problem needs to consider the emissions released during power generation. These emissions have harmful effects on human health, other organisms, and the environment, including material damage and contributions to global warming. These impacts can be viewed as costs since they degrade the environment in various ways. The emission dispatch problem seeks to address this issue by minimising pollution released because of meeting electricity demand through the combustion of fuels. Emissions of various kinds, including nitrogen oxides, sulphur dioxide, particles, and heat, and the expenses associated with each are added up in the emission function. The goal of the emission dispatch problem is to determine the best schedule for generating electricity so as to limit emissions pollution and fuel costs. To find a middle ground between monetary efficiency and environmental sustainability in power system operation and planning, the emission dispatch factors in the cost of environmental deterioration into the optimisation problem. Emission dispatch problems be capable described as the optimization problem shown below.

$$C_{2i}(OP_{gi}) = \sum_{M=i}^M \sum_{N=i}^N \left[a_i + b_i P_{im} + c_i P_{im}^2 + d_i \exp(d_i P_{im}) \right] \quad (2)$$

The emission function incorporates the emission curve coefficients, represented by ai, bi, ci, di, associated with each generator. These coefficients capture relationship between the generator's power output and the emission level for specific pollutants.

Mutual Economic and Emission Dispatch (CEED)

The objectives and resources invested in fiscal dispatch and emission dispatch are different. Whereas fuel expenditures per chance reduced by economical dispatch, additional NOx emissions are generally the result. Emission dispatch, on the other hand, prioritises reducing system-wide emissions even if doing so increases operational expenses. A CEED strategy is used to establish a balance between cost & emission. The CEED issue is stated as follows:

Minimize the objective function f(C1i(OPgi), C2i(OPgi)) subject to power balance, generating or operating limits, and tie line capacity constraints. Here, C1i(OPgi) represents fuel cost of the ith generator's operating point (OPgi), and C2i(OPgi) represents the corresponding emissions.

It is argued that a price penalty factor (pf) be able to be managed to simplify multi equitable CEED issue into a single-objective optimisation problem. When we add up all the costs, we get:

$$\text{Minimize cost} = f(C1i(OP_{gi}) + pf(C2i(OP_{gi}))) \quad (3)$$

Price penalty factor in this formulation combines the pollution cost with the standard fuel expenses. By integrating the price penalty component, the system's overall operational cost include including cost of fuel as well as the implied cost of emissions. This method eliminates the requirement for separate economic and emission dispatch classes. The setting of the price penalty factor enables for fine-tuning the cost-emission balance. A larger penalty factor prioritizes emissions reduction at the expense of greater operating costs,

whereas a lower penalty factor prioritizes cost reduction at the expense of potentially higher emissions. In order to deal with both environmental and financial considerations in power system operation and planning, CEED issue might determine an ideal functioning argument that strikes a balance between cost and emission targets through adjusting the price penalty factor.

The following processes are required to determine the penalty element current economic and emission dispatch together:

- **Step 1:** Define the impartial function: Determination of objective function that represents the trade-off between cost and emissions. In CEED, the objective function is typically defined as the sum of the fuel cost, the inferred cost of emissions, and the penalty factor. The importance of the goal function's emissions component is controlled by the penalty factor, denoted by h .
- **Step 2:** Set the penalty factor range: Define a range of possible values for the penalty factor. The range should cover a wide spectrum of trade-offs between cost and emissions. It is common to choose values between 0 and 1, where 0 represents a focus solely on cost minimization and 1 represents a focus solely on emissions reduction.
- **Step 3:** Generate penalty factor candidates: Divide the penalty factor range into a finite set of candidate values. Under various trade-off scenarios, the system performance will be assessed using these potential values.
- **Step 4:** Solve the optimization problem: For each penalty factor candidate, solve the CEED problem as a single actual optimization problem. Find the ideal dispatch plan that minimises the revised objective function (fuel cost plus implied cost of emissions) using an appropriate optimisation technique. This will give you the optimal operating point for each penalty factor candidate.
- **Step 5:** Evaluate the trade-offs: Analyze the solutions obtained from Step 4 for each penalty factor candidate. Assess the trade-offs between cost and emissions for different values of the penalty factor. This can be done by comparing the objective function values, emissions levels, and operating costs associated with each solution.
- **Step 6:** Choose the penalty factor: Based on the analysis of the trade-offs, choose the penalty factor that strikes a satisfactory balance between cost and emissions. The specific selection criteria may depend on the specific requirements and preferences of the system operator or decision-maker.

2.1.2 Constraints

Real Power Balance Constraints:

At every single interval over the scheduling horizon, whole real power generation must equalize expected power consumption plus real power losses in transmission networks.

$$\sum_{i=1}^N P_g - P_d - P_l = 0 \quad m \in M \quad (4)$$

Where:

- P_g generation represents total real power generated by all generating groups.
- P_d demand represents predicted power demand at each time interval.
- P_l losses represents the true power losses in the transmission lines.

The formula guarantees that the sum of all power produced by the generators, less all power demand, minus all power losses, equals zero. This restriction guarantees that the total real power generated is sufficient to maintain system power balance after losses and anticipated demand.

Real Power Operating Limits

$$P_{\min} \leq P_{\text{unit}} \leq P_{\max} \quad (5)$$

Where:

- The true electrical output of the generator is denoted by P_{unit} .
- P_{\min} represents lower operating limit or the minimum allowable real power output for the unit.
- P_{\max} represents the upper operating limit or the maximum allowable real power output for the unit.

This equation makes sure that generating unit's actual energy output stays within the set operational parameters. The generating unit's power output should not be less than the lower operating boundary (P_{\min}) or exceed the better operating limit (P_{\max}) to affirm safe and reliable operation of the unit.

Tie Line capacity Constraints

Tie line capacity constraints refer to the limitations on the maximum power flow between interconnected power systems or areas. These constraints ensure that the power flow on tie lines does not exceed their specified limits to maintain the reliability and stability of the interconnected systems.

The equation representing the tie line capacity constraint can be written as:

$$|P_{\text{tie_line}}| \leq P_{\max_tie_line} \quad (6)$$

Where:

- $|P_{\text{tie_line}}|$ represents the absolute value of the power flow on the tie line.

- $P_{max_tie_line}$ represents maximum allowable power flow limit for the tie line.

This equation ensures that the absolute value of the power flow on the tie line remains within the specified maximum limit. The constraint is applied to both the import and export directions of the tie line, considering the power flow as a scalar quantity. By enforcing these constraints, power system operators prevent excessive power flow on tie lines, which could lead to voltage instability, system oscillations, or even blackout conditions.

2.2 Hybrid model and its Implementation

Due to the valve point effect (VPE), however, EED issues are not convex objectives. Finding the optimal solution becomes more challenging due to the introduction of several local minimums, which reflect nonconvex features, to the objective problem caused by the VPE. Members in the deep learning community have developed networks with long short-term memories (LSTMs). An evolution of Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) networks were designed to capture long-term dependencies in sequential data and avoid the vanishing gradient problem. Because it can't keep data for a long time, RNN can't deal with long-term dependencies.

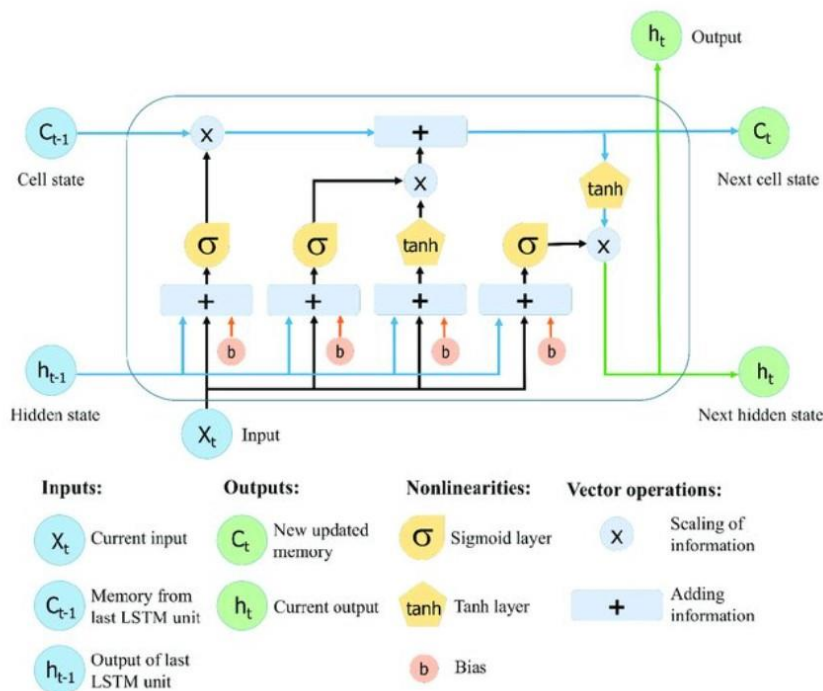


Figure 1. LSTM Architecture for Complex problems

Due to the elimination of the vanishing gradient problem, the design now incorporates the LSTM without modifying the training model. Here in Figure 1 we can observe the structure of an LSTM network, with X_t representing the input data, C_t representing the current cell state, and h_{t-1} representing the previous cell state. This model is very helpful in solving complex and continuous problems like economic load dispatch, emission problems etc. The elimination of the requirement to maintain a fixed set of states is one of the many advantages that LSTMs offer over hidden Markov models (HMMs). Learning rates, input biases, and output biases are only a few of the many customisable factors available to LSTMs, in contrast to HMMs that have a fixed number of states. The network can adapt and perform better since these parameters give control and flexibility while learning. Figure 2 shows the flow diagram for the emission dispatch with LSTM. Thus, in contrast to the limitations of HMMs, LSTMs provide a robust and versatile framework for describing sequential data.

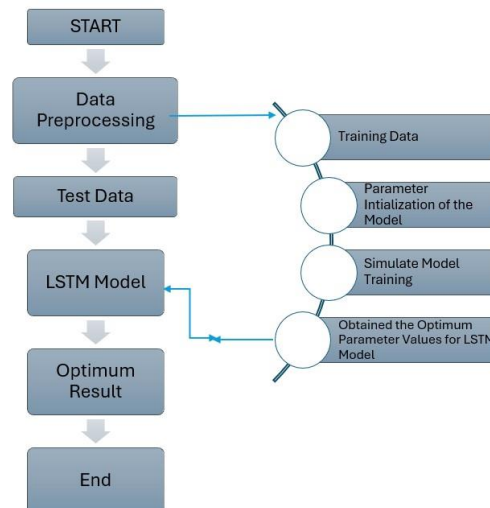


Figure 2. Flow chart for the LSTM based Emission Dispatch

The LSTM model has been applied to various fields and has shown promising results in solving optimization problems. Here are some applications of the Recurrent neural network. The LSTM based model has been successfully employed in solving complex engineering design problems. These include structural optimization, vehicle routing problems, scheduling problems, and facility layout optimization. By leveraging the algorithm's ability to balance exploration and exploitation, it can effectively find near-optimal solutions in these domains. Feature selection is critical in the fields of machine learning and data mining to recognize important & useful characteristics from a given dataset. The LSTM has been applied to feature selection tasks, where it helps identify the most discriminative features while minimizing redundancy. This application has been useful in various domains such as image recognition, bioinformatics, and text classification. The LSTM has been utilized in image processing and computer vision applications. It has been employed for image denoising, image segmentation, object detection, and image registration. The LSTM's ability to optimize complex objective functions makes it a suitable choice for solving challenging image-related problems. Clustering aims to group similar data points together. The LSTM has been used for clustering tasks, where it optimizes the clustering objective function to find optimal cluster centers and assignments. This application has been applied in various fields such as customer segmentation, pattern recognition, and anomaly detection. The LSTM has been employed for training and optimizing neural networks. It can be used to fine-tune the network's parameters, such as weights and biases, to improve its performance. By exploring the search space effectively, the LSTM helps in achieving better convergence and avoiding local optima. The LSTM has been utilized in energy-related optimization problems, such as power distribution and energy management systems. It helps in determining optimal energy allocation, load balancing, and resource utilization, leading to efficient energy usage and cost reduction. It's important to note that while the LSTM has shown promising results in these applications, the choice of optimization algorithm depends on the specific problem and its characteristics. Comparisons with other algorithms and careful parameter tuning may be necessary to determine the most suitable approach for a given problem.

3 CASE STUDY

The presented research focuses on evaluating the effectiveness of Long short-term memory (LSTM) based recurrent neural network for a real-world MAED problem. The MAED problem, which involves additional tie-lines and area power balance restrictions, is known to be more complex and challenging compared to the conventional Economic Dispatch problem. The evaluation of hybrid model is conducted on test systems of various sizes and nonlinearities. Specifically, three test systems consisting of 3-unit, 13-unit, and 40-unit configurations are considered. The optimization objective is to determine the optimal settings for actuator loading points and target values. The load demand for the three test unit systems are as follows: 850 MW, 1800 MW, and 10500 MW, respectively. The objective function for the optimization problem is the minimization of fuel costs and emission rate. This objective function, denoted as equation (3), is applied to each of the different unit systems. To compare the performance of LSTM with other optimization techniques, five different methods are considered: 1. Firefly Optimization (FFO), 2. Salp Swarm Optimization (SSO), 3. Squirrel Search Optimization (SO), 4. Particle Swarm Optimization (PSO), 5. Grasshopper Optimization (GO).

By conducting a comparative analysis of these techniques on the same MAED problem, the research aims to assess the effectiveness of LSTM in achieving optimal solutions. This evaluation will provide insights into the suitability and performance of LSTM in addressing real-world MAED challenges. In multi-area problems, key factors such as the number of system data units, corresponding load demands, and the highest and lowest area

values play a significant role. These factors are taken into account in the proposed LSTM to address the challenges in MAED problems. The LSTM incorporates oil cost coefficients (a, b, and c) specific to each system size (3-unit, 13-unit, and 40-unit), considering valve-point loading effects and nitrous oxide emission rate coefficients (alpha, beta, and gamma). Additionally, ramp rate limits and B-coefficients are considered to manage the rate at which the power output can change. Weightage factors are also taken into consideration to balance economic and emission objectives. The implementation of the proposed algorithm requires careful planning of the number of units. Each unit represents a harem within the algorithm. Furthermore, another set of best solutions is considered to promote the intensification phase. Real power values, within the constraints of maximum and minimum limits, are incorporated into the optimization process. The system operates according to the optimization initialization, ensuring that the power generation aligns with the specified parameters and constraints. The proposed algorithm has been designed to accommodate non-convex constraints that often arise in MAED problems, allowing for efficient solutions. The specific data required for implementing the algorithm is provided in the table below.

Table 1 Constraints and its values

Constraints	Value
Total power demand (MW)	10500
The Line Limit (MW)	200/100
Area load demand (%)	3/13/40
Population size	100
itr_{min} / itr_{max}	1/1000

By integrating solar and wind sources into the system, the proposed algorithm effectively addresses the generation cost and emission rate reduction and valve loading effect constraints across all unit systems. This integration enables the system to meet the load demands efficiently. The algorithm is designed to detect the presence of renewable sources. In cases where the load demand exceeds a predefined limit, the algorithm activates the renewable systems to contribute power. This ensures that the renewable sources are utilized appropriately to support the overall energy generation and balance the load requirements.

4 DISCUSSIONS

Three test systems, each representing a multi-domain idea, are used in computational simulations to assess the efficiency of the proposed DRNN(LSTM) method. The first test system consists of 40 individual parts spread across four distinct regions. The second test setup is a three-area system with thirteen generators. Last but not least, we have a three-generator, two-zone test system. The functionality of the proposed LSTM method is evaluated using these systems as case studies. The evaluation is performed by using a MATLAB (2023a) machine with an i5 processor and 8 GB of RAM to implement the LSTM method. To guarantee the validity and consistency of the results, we run each test system 100 times independently. The performance of the LSTM technique is compared against existing optimization algorithms such as FFO, SSO, SO, PSO, and GO. These contemporary approaches are applied to the same constraints and test systems for a comprehensive comparison. Through the evaluation, the appropriateness and effectiveness of the proposed LSTM approach are thoroughly assessed. The objective is to determine how well the LSTM technique performs in solving the MAELD problem compared to the other optimization algorithms. By conducting these comparative analyses and examining the results across the three case studies, valuable insights can be gained regarding the performance and suitability of the LSTM technique for multi-area optimization problems.

Table 2 showcases the cost-effective values achieved using the LSTM for different load demands and unit configurations. For a load demand of 850 MW and a system consisting of 3 units, the LSTM achieved a cost of 3075.8 Rs. Additionally, the valve loading effect for this configuration amounted to 3189.9 Rs. In the case of a load demand of 1800 MW and a system comprising 13 units, the LSTM yielded a cost of 10404.2 Rs. The corresponding valve loading effect for this configuration was 11390.5 Rs. Finally, for a load demand of 10500 MW and a system comprising 40 units, the LSTM resulted in a cost of 89005.1 Rs. The valve loading effect for this configuration amounted to 94077.1 Rs. These values represent the cost-effective outcomes achieved by the LSTM for each load demand and unit configuration. The algorithm effectively balances the cost optimization objectives and takes into account the valve loading effects, providing practical and efficient solutions for the given MAED problem.

Table 2 Cost effective value with LSTM

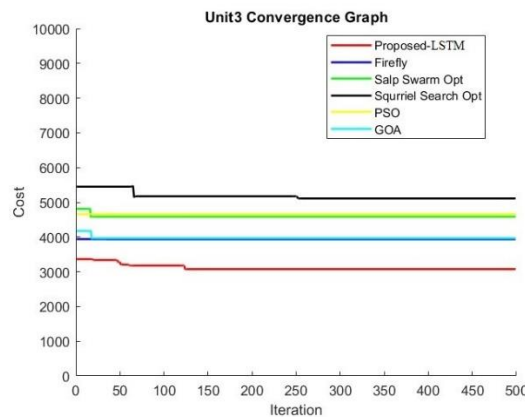
Load Demand in MW	No of Units	Cost (Rs)	Valve loading effect (Rs)
850	3	3075.8	3189.9
1800	13	10404.2	11390.5
10500	40	89005.1	94077.1

The table 3 compares the cost, emission rate, and loading effect values achieved by different algorithms for three different unit systems: a 3-unit system, a 13-unit system, and a 40-unit system. For the 3-unit system, the LSTM algorithm achieves a cost of 3075.8, an emission rate of 0.098841, and a loading effect of 3189.9. Among the compared algorithms, the LSTM algorithm has the lowest cost and emission rate, indicating its effectiveness in optimizing the system's economic and environmental objectives. For the 13-unit system, the LSTM algorithm achieves a cost of 10404.2, an emission rate of 68.05803, and a loading effect of 11390.5. It performs competitively compared to the other algorithms, with a reasonable cost and emission rate. In the case of the 40-unit system, the LSTM algorithm achieves a cost of 89005.1, an emission rate of 44854.68, and a loading effect of 94077.1. Again, the LSTM algorithm demonstrates its effectiveness by providing a competitive cost and emission rate compared to the other algorithms. Among the compared algorithms, it can be observed that the LSTM algorithm consistently provides favourable results in terms of cost, emission rate, and loading effect across the different unit systems. It outperforms or performs comparably to the other algorithms, showcasing its suitability and effectiveness for MAED problems.

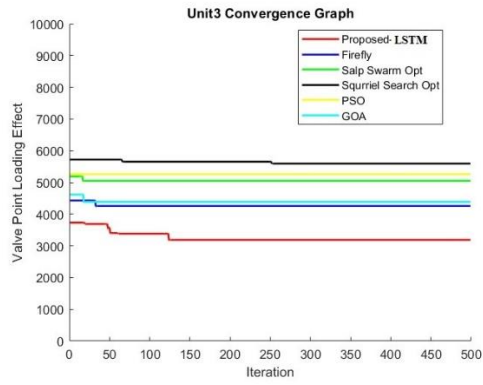
Table 3 Comparison of Optimization Algorithms for MAED : Cost, Emission Rate, and Loading Effect

Unit system	3 unit			13 unit			40 unit		
Algorithm	Cost	Emission rate	loading effect	Cost	Emission rate	loading effect	Cost	Emission rate	loading effect
LSTM	3075.8	0.098841	3189.9	10404.2	68.05803	11390.5	89005.1	44854.68	94077.1
FFO	3938.0	0.092171	4256.8	11058.8	305.3492	12218.9	91699.4	49641.88	96871.3
SSO	4586.7	0.089759	5053.9	11530.7	308.3503	12205.6	95394.6	53561.84	100649.9
SO	5111.7	0.088515	5596.4	10712.8	80.62963	11811.6	96249.0	54626.74	101290.4
PSO	4658.1	0.090472	5261.8	12710.1	1177.057	13856.6	106449.5	87699.01	111437.6
GO	3966.3	0.092091	4386.3	11135.9	450.74	12422.9	93186.1	47698.67	98264.6

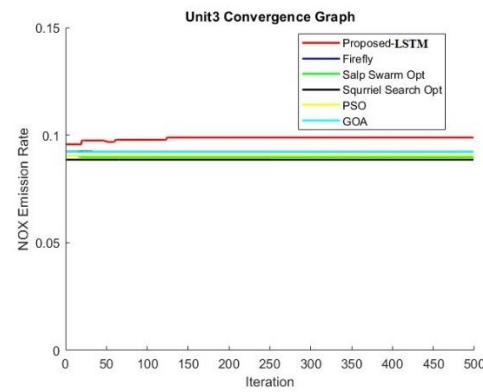
Figure 3 to 5 illustrates the convergence graph of the proposed system using 3,13 and 40 units system with the LSTM compared to other techniques. The results indicate that the LSTM technique consistently achieves lower costs, even in single area systems, while meeting all requirements. By dividing the system into distinct areas, the LSTM technique can effectively balance the load and generation within each area, resulting in lower costs. It highlights the steady improvement and convergence towards optimal solutions achieved by the LSTM approach. Overall, the findings indicate that the LSTM technique is highly effective in reducing costs, emission rate even in single area systems. The algorithm successfully meets all requirements, ensuring the optimization of economic dispatch while satisfying the constraints of the multi-area system. The use of the LSTM technique provides reliable and efficient solutions for the given MAED problem.



(a)

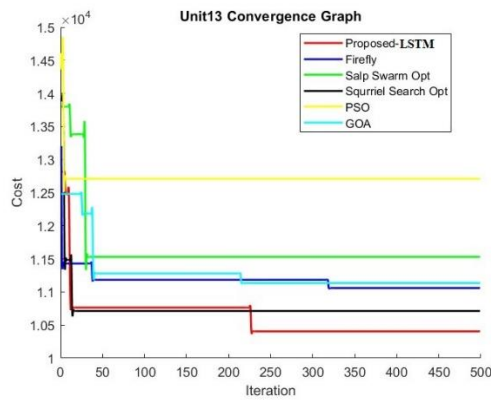


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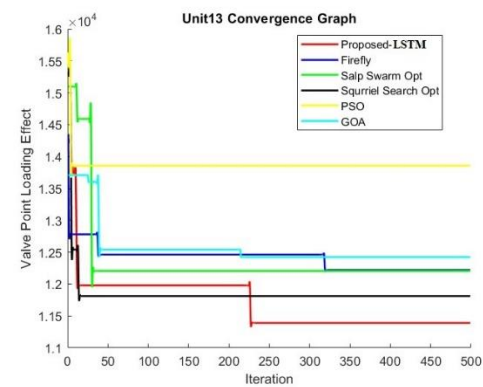


(c)

Figure 3 Convergence graph with 3-unit system (a) cost (b) Valve point loading effect (c) Emission rate



(a)



(b)

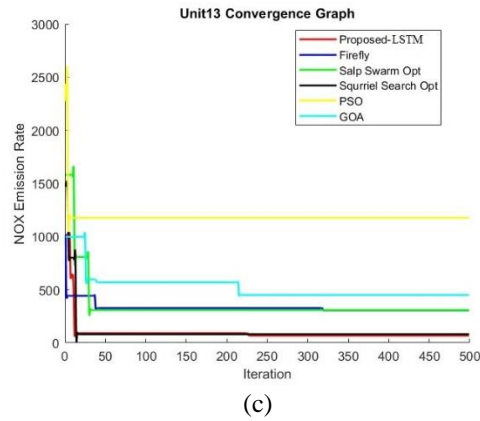


Figure 4 Convergence graph with 13-unit system (a) cost (b) Valve point loading effect (c) Emission rate

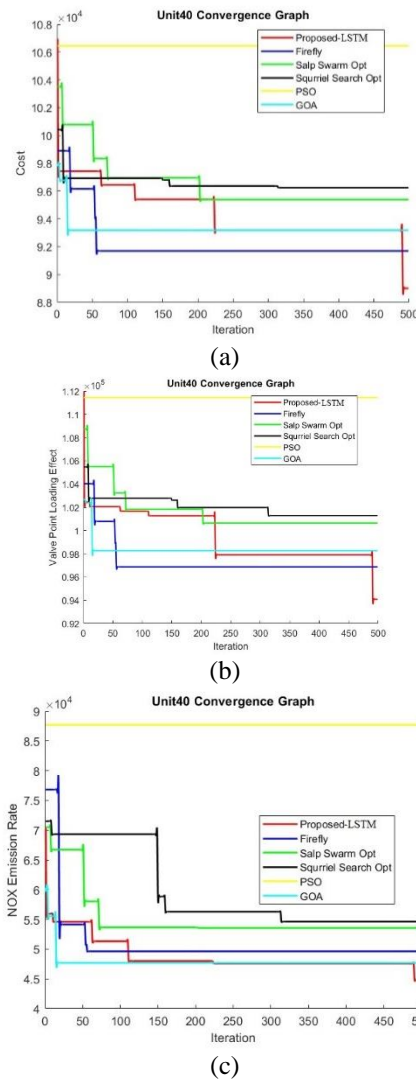


Figure 5 Convergence graph with 40 unit system (a) cost (b) Valve point loading effect (c) Emission rate

5 CONCLUSION AND FUTURE SCOPE

The recurrent LSTM model was employed as an optimization tool in this work to solve MAELD problems. The goal of linked power systems was to minimize fuel costs and emissions while satisfying load needs and adhering to technological limits. The results revealed that the suggested LSTM technique outperformed existing optimization strategies such as firefly, Salp Swarm, Squirrel search, Particle Swarm, and Gross Hopper in terms of achieving improved trade-off solutions. The LSTM approach successfully addressed MAELD problems in four areas with 3, 13, and 40-unit systems, and it outperformed other techniques without violating constraints.

By incorporating the concepts of evolutionary algorithms and heuristic search approaches, the LSTM method provided efficient and reliable solutions for MAELD problems. The proposed methodology allowed for the optimization of both Economic Load Dispatch (ELD) and non-convex ELD problems with excellent convergence properties. The simulation results, obtained using the MATLAB platform, demonstrated the ability of the LSTM approach to deliver high-quality cost solutions while adhering to all constraints. The findings confirmed the effectiveness of the LSTM optimization method in allocating power generation units optimally. Overall, this research contributes to the understanding and application of various optimization algorithms for solving MAELD problems, particularly in the presence of renewable energy sources. The LSTM method offers a viable and efficient approach to address the complex challenges of while achieving cost-effectiveness, Emission rate and satisfying technical constraints. Further investigation can be conducted to refine and enhance the performance of the LSTM algorithm by incorporating additional heuristics or hybridizing it with other optimization techniques. This can potentially improve the convergence speed and solution quality of the algorithm.

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