SO-Attn-ALSTN: A Deep Learning and Seeker Optimization-Based Framework for Low-Voltage Distribution Network Planning

Jun Zhu, Ran He, Rui Zhan, Qimiao He, Min Wan*
Corresponding author's E-mail: wanmin198868@outlook.com
Foshan Power Supply Bureau of Guangdong Power Grid Company, Foshan, Guangdong,528000, China

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Rising electricity demand, the proliferation of distributed energy resources (DERs), and the complexity of modern urban infrastructure pose significant challenges for low-voltage distribution network (LVDN) This research proposes an intelligent optimization approach for LVDN planning using Deep learning (DL) to address limitations in traditional methods, addressing dynamic load patterns and renewable energy integration. The goal is to reduce power losses and infrastructure costs while maintaining voltage stability and load balancing across the network. A comprehensive low-voltage smart grid planning dataset was sourced from an open-access platform, Kaggle. To assure data quality, normalization and outlier reduction were performed during preprocessing. Fast Fourier Transform (FFT) was used to extract features and uncover hidden patterns in load demand and energy flows. This research proposes a Seeker Optimized Attention with Adjustable Long Short-Term Network (SO-Attn-ALSTN) model, which combines an attention-enhanced ALSTN for spatiotemporal load forecasting with a Seeker Optimization Algorithm (SOA) for efficient planning. Attention enhances ALSTN performance by focusing on temporal inputs, while SOA ensures robust parameter tuning and faster convergence. Forecasted loads optimize cable routing, transformer sizing, and DER allocation. Experimental results validate the model's superiority: the proposed SO-Attn-ALSTN achieved a MAPE of 6.53%, RMSE of 1.14%, MAE of 0.99%, and APE of 2.01%. Comparative convergence time analysis shows a 30–40% improvement over existing methods, LMBP and IGWO-SVM, with a convergence time of 2.708 seconds at an error threshold of 0.01. Thus, the hybrid SO-Attn-ALSTN framework presents an intelligent, adaptive, and computationally efficient solution for modern LVDN planning.

Povzetek: Predstavljen je hibridni okvir za načrtovanje nizkonapetostnih distribucijskih omrežij, ki združuje pozornostno izboljšani ALSTM, FFT-izluščene značilke in algoritem Seeker Optimization.

1 Introduction

Low-voltage (LV) distribution networks form the last, and most crucial link in delivering electrical power, therefore connecting electricity or electrical products to end-users such as houses, businesses, and small industries [1]. Generally, LV networks tend to operate at several voltage levels below 1 kilovolt (kV), before distribution transformers, and have the responsibility for the reliable and safe distribution of electrical energy to end-users [2]. LV networks are vital for providing high-quality electrical service, voltage stability, and efficient energy supply. Their importance has grown due to increased electricity demand, urban sprawl, and the rise of renewable energy sources like roof solar and electric vehicles (EVs) [3, 4]. Advancements in LV networks have transformed them from passive to active systems, promoting sustainable and carbon-neutral initiatives, societal expectations, and the support of intermittent renewable energy sources [5, 6]. LV networks must be strategically planned to meet user demands, influence technology advancements, energy needs, and sustainability objectives, as illustrated in Figure 1.

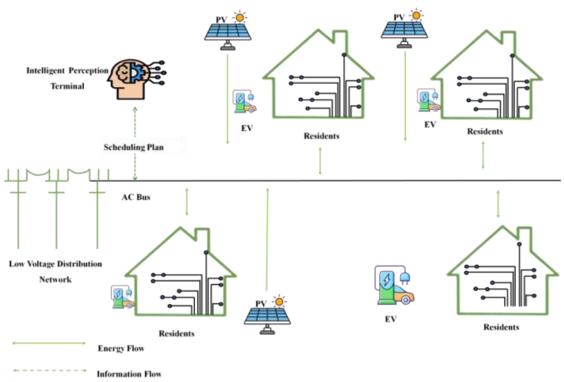

Figure 1: Low-voltage distribution under power-sharing mode [6]

An optimized LV distribution system is essential for resilient, smart, and end-user interfaces of the power grid. Designing LV distribution networks encompasses many difficult and changing challenges [7, 8]. Load growth, driven by urbanization, electrification, and appliance expansion, poses a significant challenge to infrastructure, potentially leading to congestion and reduced voltage in the coming years [9]. Renewable energy technologies on the LV network, particularly from a bidirectional flow perspective in customer feeding power back to the network via the Rooftop solar, make voltage regulation and protection coordination more difficult [10, 11]. Long feeder lines in LV systems cause technical losses, reducing network functionality and increasing operational costs. Designing reliable and quality networks is crucial despite these constraints [12, 13]. Limited online monitoring and aging assets hinder planning, necessitating smarter, data-driven network design for LV distribution networks, despite the challenges and changing opportunities.

1.1 Research objective

The research aims to develop an intelligent optimization framework based on DL techniques for LVDN planning. The goal is to minimize power losses and infrastructure costs while improving voltage stability and load balancing. SO-Attn-ALSTN is proposed to predict spatiotemporal load behaviour and optimize LVDN configurations. This framework allows for adaptive and data-driven decision-making for strategic and resilient LVDN planning.

1.2 Research contributions

- The research introduces a framework called SO-Attn-ALSTN, which predicts spatiotemporal load behavior in low-voltage distribution networks using a novel DL process and attention to enhance its performance.
- A hybrid optimization engine based on SOA is developed for efficient planning decisions in LVDN designs, improving efficiency and reducing costs.
- Experimental results show superior performance compared to heritage methods, resulting in reduced power losses, voltage improvements, and minimal infrastructure impacts, making it flexible for complex urban distribution scenarios.

1.3 Research questions

1) Can attention-based LSTM improve load forecasting accuracy in LVDNs?
2) How does SOA improve convergence and solution quality in LVDN planning?
3) How effectively can FFT-based feature extraction enhance spatiotemporal pattern recognition in LVDN load data?
4) To what extent can SO-Attn-ALSTN reduce infrastructure costs while maintaining voltage stability in dynamic LVDNs?
5) Can the integration of attention mechanisms in ALSTN improve real-time adaptability in distribution network forecasting models?

1.4 Research frameworks

The research frameworks are organized into the following sections: Section I includes the introduction of LDVN Section II presents the related works, which include relevant studies, Section III depicts the methodology i.e., the working flow in the proposed model of SO-Attn-ALSTN, Section IV shows the results of SO-Attn-ALSTN and discussion of other studies and Section V depicts the conclusions with limitations and future scope.

2 Literature reviews

A comparative analysis of current LVDN planning techniques is shown in Table 1.

Table 1: Comparative summary of existing methods for LVDN planning

Ref.	Methodology	Dataset / Test Feeder	Scope (LV/Medium Voltage (MV))	Performance Metrics	Optimization Strategy	Scalability	Adaptability	Key Limitations
[14]	Load shifting & reinforcement planning	LV clusters (Rome, Italy)	LV	Voltage profile variation, infra cost	Heuristic (2-tier scheduling)	Low	Low	No real-time adaptability, narrow scope
[15]	Neural Networks (NN)-based battery placement for voltage control	Modified LV feeder	LV	Voltage limit compliance (qualitative)	NN + local search	Moderate	Low	Limited DER consideration
[16]	Bi-level planning under uncertainty	Simulated MV+LV networks	MV + LV	Investment + emission minimization	Bi-level stochastic optimization	Moderate	Low	No real-world scalability test
[17]	Electric Vehicle Charging Station (EVCS) siting + scheduling with uncertainty	LV feeder (Australia)	LV	Loss 39.38%, Voltage 15.32%, Peak 20.53%	Evolutionary + scenario-based	Moderate	Moderate	Lacks real-time adaptability
[18]	Flexibility-based planning	Italian MV-LV grid	MV + LV	Cost-risk tradeoff	Advanced Planning Software (Monte Carlo)	Moderate	Low	Applicability is limited to the context
[19]	Mixed-Integer Nonlinear Programming (MINLP) for Battery Energy Storage Systems (BESS) &	11, 135, 230-node feeders	MV + LV	Voltage, power loss (qualitative)	MINLP + Simulated Annealing	High	Low	No temporal dynamics modeled

[20]	Distributed Generators (DG) allocation Community Energy Trading (CET) vs. Home Energy Management System (HEMS) evaluation	Simulated LV system	LV	Cost 31%, Export 93%, Self-suff. 54%	No explicit optimization	Low	Low	Unresolved voltage violations
[21]	Long Short-Term Memory (LSTM) with confidence bounds	MV Spanish grid	MV	Forecast uncertainty (qualitative)	LSTM (no optimization layer)	Moderate	Moderate	LV not addressed
[22]	Multi-period Optimal Power Flow (OPF) formulations	IEEE 34-bus system	LV	Accuracy vs. computation time	OPF: convex/non-convex variants	Low	Low	Poor scalability/adaptability
[23]	LV Ride-Through (LVRT)-based resiliency planning	Simulated LV network	LV	Resilience metrics (qualitative)	No optimization used	Low	Low	No real-time adaptiveness
[24]	Improved Grey Wolf Optimizer Support Vector Machine (IGWO-SVM)	Same dataset as proposed (Kaggle LVDN)	LV	MAPE: 8.62%, MAE: 1.30%, RMSE: 2.16%	IGWO	Low	Low	Static parameters, poor temporal adaptation
[25]	LMBP	Same dataset	LV	MAPE: not reported separately; fast convergence	Levenberg–Marquardt BP	Low	Low	Falls into local minima, not spatiotemporal
[26]	Sparrow Search Algorithm Backpropagation (SSA-BP)	Same dataset	LV	MSE: 0.0095, MIRE: 0.0017	SSA	Low	Moderate	Unstable convergence, inconsistent forecasting

2.1 Research gap

There has been progress in assessing LV/MV distribution network planning and forecasting, find that the methods in the literature mostly are not adaptive, scalable, or able to incorporate dynamic spatiotemporal characterizations. Most methods developed with the literature, often focus on heuristic methods that are static, low-scaling for decision-making, limited with minimal data sets, and don't adequately acknowledge uncertainty, dynamic behaviors, or optimization processes under changing grid conditions, and a stronger, robust, adaptive and scalable forecasting and planning framework is clearly required. The proposed SO-Attn-ALSTN overcomes these gaps by enabling scalable forecasting with attention-enhanced spatiotemporal learning, improving robustness to dynamic grid behaviors, DER-induced voltage variations, and stochastic patterns, thus enhancing adaptability across diverse, complex LVDN environments beyond localized test scenarios.

3 Methodology

This research develops advanced planning schemes integrating smart grid technologies, RES, and flexible system adjustments to optimize operating efficiency, provide economic planning strategies, and facilitate organized LVDN in the future. Figure 2 depicts the workflow of SO-Attn-ALSTN in low-voltage distribution network planning schemes.

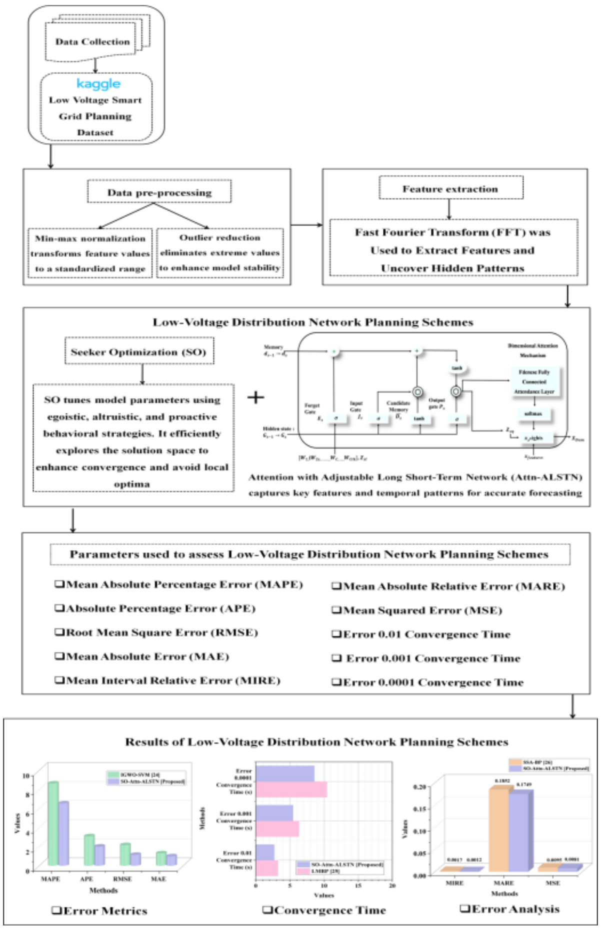

Figure 2: The working flow of SO-Attn-ALSTN in low-voltage distribution network planning schemes

3.1 Data collection

The low-voltage smart grid planning dataset was collected from the open source of the Kaggle website: https://www.kaggle.com/datasets/zoya77/low-voltage-smart-grid-planning-dataset. This dataset contains load profiles, transformer specifications, and network topology details of a low-voltage distribution network. It includes time-stamped consumption and DER generation data, supporting analysis of voltage behaviour, energy flow, and infrastructure performance for intelligent planning. The dataset was separated into 70% data training, 20% data testing, and 10% data validation.

3.2 Data pre-processing

Preprocessing steps, including Min-Max normalization and outlier reduction, enhance data consistency and quality, enhancing forecasting accuracy for optimized LVDN planning through reliable inputs.

3.2.1 Min-max normalization

Min-mix normalization is a technique that modifies the original collection of data linearly to create effective LVDN planning strategies. A technique known as "Min-Mix Normalizing" maintains the connections among the initial information. An easy method of data can correct the position inside a predefined boundary using the help of min-max normalizing, as shown in equation (1).

$$B' = \left(\frac{B - \min \ value\ of\ B}{\max value\ of\ B - \min\ value\ of\ B}\right) * (C - D) + D \quad (1)$$

In B', one among the Min-Max standardized sets of information is contained in the development of efficient planning schemes for LVDN. B represents the subsequently converted data if $[C, D]$ is the predefined perimeter and if B is the starting region.

3.2.2 Outlier reduction

To develop effective planning schemes for LVDN, outlier reduction was a key sub-process in the data pre-processing workflow. Outliers were corrected with local mean imputation or completely removed to keep the data consistent. The method applied for outlier handling depended on the severity and frequency of the anomaly. Mild outliers were corrected using local mean imputation,

while severe or persistent anomalies were removed. The threshold for selecting between two options should be clarified for reproducibility and improved references for reliable, cost-optimized results in spatiotemporal forecasting accuracy.

3.3 Feature extraction using FFT

FFT is utilized for fast convolution, correlation, and spectrum analysis in LVDN planning, aiding pattern recognition, forecasting, and optimization, making it crucial for accurate data-driven decisions. The FF of a function $F(q)$ in the time (or spatial) domain $f(i)$ is defined as Equation (2).

$$F(q) = \int_{-\infty}^{+\infty} f(i) e^{-j2\pi qi} di \quad (2)$$

Where $j = \sqrt{-1}$ and q is the variable frequency. $F(q)$ is a complex function. The magnitude $H(q)$, and phase (q) of $F(q)$ are computed if the real and imaginary components are indicated as $Fi(q)$and $Fg(q)$, respectively, Equations (3) and (4).

$$H(q) = |F(q)| = \sqrt{F_g^2(q) + F_i^2(q)} \quad (3)$$

$$\psi(q) = \tan^{-1}\left[\frac{F_g(q)}{F_i(q)}\right] \quad (4)$$

Frequently, $F(q)$ is shown in Equation (5).

$$F(q) = H(q) e^{i\psi(q)} \quad (5)$$

The inverse FFT Equation (6) is used to recreate the function$F(i)$.

$$F(i) = \int_{-\infty}^{+\infty} f(q) e^{j2\pi qi} dq \quad (6)$$

The FFT pair is denoted by $F(i)$ and $F(q)$. A two-dimensional function$f(i, y)$ has the following Equations (7) and (8), which are equivalent to a Fourier transform pair:

$$F(q, v) = \iint_{-\infty}^{+\infty} f(i, y) e^{-j2\pi(qi+qy)} di dy \quad (7)$$

$$F(i, y) = \iint_{-\infty}^{+\infty} F(q, v) e^{j2\pi(qi+qy)} dq dv \quad (8)$$

Where the frequencies for i and y, respectively, are represented by q and v. A similar calculation is used to determine the Fourier transform's magnitude and phase to Create effective planning strategies for LVDN. To validate FFT-based feature extraction, the accepted benchmarking experiments compared the load forecasting performance with and without FFT features. The evaluation results established that FFT features increased the accuracy of load forecasting, particularly when the load had periodic patterns. The empirical evidence presented here indicates that FFT features can enhance the practical effectiveness of pattern recognition in LVDNs for more reliable and data-driven planning. The data and the metrics are presented in this section.

3.4 SO-Attn-ALSTN

The Attn aids in understanding essential elements of LVDN, such as voltage nodes, feeders, and transformers. A recurrent neural network (RNN) called ALSTN uses Attention-Controlled Memory, ALSTN utilizes behavioral search strategies from SOA and dynamic step sizing to optimize real-time decision-making, focusing on key patterns and avoiding local optima.

3.4.1 Attn

The attention module is a soft attention mechanism focusing on key electrical grid parts, using ALSTN hyperparameters, a medium-sized population of seekers, and a crossover-based upgrade strategy (9-11)

$$X_{feature} = [\{W_1\}, \{W_2\}, \dots, \{W_C\}]^S \quad (9)$$

$$X_{Weight} = Softmax(E_{dense}(\{Z\}, \{W_1\}, \dots, \{W_C\})) \quad (10)$$

$$X_{DAM} = X_{feature} \odot X_{Weights} \quad (11)$$

The attention mechanism in LVDN analytics enables models to identify temporal or spatial anomalies, enhancing real-time decision-making and optimizing power flow and operations despite demand changes.

3.4.2 ALSTN

The RNN architecture called ALSTN is used to Create effective planning strategies for LVDN. An inherent feature called an ALSTN cell enables the network to LVDN; ALSTN RNNs are trained with dropout layers to prevent overfitting, balancing computational efficiency and training stability for efficient planning schemes for LVDN over 100 epochs, as shown in equations (12) to (17). Figure 3 presents Attn– ALSTN.

$$i_s = \sigma(x_i.\left(h_{s-1,w_s}\right) + a_i) \quad (12)$$

$$f_s = \sigma(x_f.\left(h_{s-1,w_s}\right) + a_f) \quad (13)$$

$$o_s = \sigma(x_0.\left(h_{s-1,w_s}\right) + a_0) \quad (14)$$

$$\bar{d}_s = \emptyset(x_d.\left(h_{s-1,w_s}\right) + a_d) \quad (15)$$

$$d_s = f_s \odot d_{s-1} + i_s \odot \bar{C}_s \quad (16)$$

$$g_s = f_s \odot \emptyset(\bar{C}_s) \quad (17)$$

The input, output, and forget gates that make up an ALSTN cell regulate data input, output, and cell deletion in LVDN. The candidate cell state $\bar{C}_s$ is scaled by the input gate i_s, while the forget gate f_s modulates the previous cell state d_{s-1}, the output gate (o_s) controls the hidden state (h_s) to determine which elements of the cell are exposed to the next layer and all the elements are merged to create the updated cell state d_s. With the ability to manage what is stored in memory, the ALSTN network can capture broader context dependencies in a data sequence in LVDN (Figure 3).

To address this apprehension, performed a sensitivity analysis on key hyperparameters. Alternative dropout rates and epoch settings were tested, showing optimal accuracy at 0.5 dropout and 100 epochs. Detailed results are provided to validate the selected configuration based on minimized error metrics and convergence time.

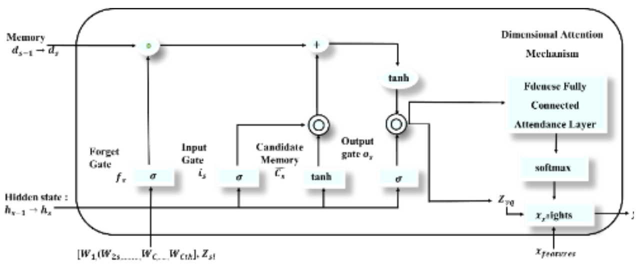

Figure 3: Presentation of Attn– ALSTN

3.4.3 SOA

The research aims to Construct effective LVDN planning plans based on minimization optimization problems, using a population called seeker and randomly grouping subpopulations to share social information.

- Implementation of the Seeker Optimization Algorithm

In SOA, a search direction and step length are computed in each dimension in each time step for each seeker. The search direction can be positive (+1), negative (–1), or zero (0), indicating movement along the positive axis, the negative axis, or no movement, respectively. The general seeker position update given represents the movement mechanism with SOA. Equations (18) and (19) define the specific strategies used to compute the movement direction and step size for certain seekers (e.g., elite, omen, worst), based on individual behavior and social learning. These specialized strategies are plugged into the general position update formula to guide each seeker's trajectory through optimization. The $w_{ji}(s+1)$ and $w_{omen,worst}$ are component-specific updates feeding into the general movement rule.

$$w_{ji}(s+1) = w_{ji}(s) + \alpha_{ji}(s)c_{ji}(s) \quad (18)$$

$$w_{omen,worst} = \begin{cases} w_{ki,best} \ if \ Q_i \leq 0.5 \\ w_{l_{mi},worst}, \ else \end{cases} \quad (19)$$

Subpopulations use binomial crossover operator to LVDN, preventing worst seekers from combining with best ones.

- Search Direction

In SOA, seekers explore the search space and use empirical gradients (EGs) instead of actual derivatives when the objective function isn't differentiable. The seeker's direction is determined by position differences and influenced by egotistic, altruistic, and proactive behaviors, aiming to improve future planning schemes for LVDN. The behaviours define one or more behavioural EGs used to adapt the search, as shown in equation (20).

$$\vec{c}_{j,ego}(s) = sign(\vec{o}_{j,best}(s) - \vec{w}_j(s)) \quad (20)$$

The sig-num function is utilized in SOA to guide search direction in LVDN planning, focusing on altruistic and pro-group behaviors in neighboring areas. So, each seeker computes altruistic direction vectors for a cooperative search. This behaviour is purposely designed to assist in accomplishing the overall goal of developing more efficient planning schemes for LVDN, as shown in equations (21) and (22).

$$\vec{c}_{j,alt_1}(s) = sign(\vec{g}_{best}(s) - \vec{w}_j(s)) \quad (21)$$

$$\vec{c}_{j,alt_2}(s) = sign(\vec{k}_{best}(s) - \vec{w}_j(s)) \quad (22)$$

Seekers in SOA exhibit activeness, utilizing foresight and goal-directed intent to anticipate future search directions, justifying predictive adjustments based on past behavior. Efficient planning schemes for LVDN. Overall, a seeker provides a proactive direction vector helping guide priori seek actions to better solutions over time. Such an attribute aligns to produce a pragmatic plan for lower voltage distribution networks, as shown in equations (23) and (24)

$$\vec{c}_{j,pro}(s) = sign(\vec{w}_i(s_1) - \vec{w}_j(s_2)) \quad (23)$$

$$c_{ji} = \begin{cases} 0, if \ q_i \leq o_i^{(0)} \\ +1, if \ o_i^{(0)} < q_i \leq o_i^{(0)} + o_i^{(+1)} \\ -1, if \ o_i^{(0)} + o_i^{(+1)} < q_i \leq 1 \end{cases} \quad (24)$$

Human judgment in search direction is based on egotistic, altruistic, and proactive behaviors, selected using proportional selection rules for efficient planning in LVDN.

- Step Length

The SOA is a search algorithm that uses a combination of egoistic, altruistic, and proactive behaviors to adjust its position in the search space The algorithm's direction is determined by integrating these behavioral vectors, guiding the seeker toward more promising regions based on current and past information, as shown in equation (25).

$$\mu_j = \mu_{max} - \frac{t-J_j}{t-1}(\mu_{max} - \mu_{min}) \quad (25)$$

The step size is computed dynamically using adaptive rules such as statistical distributions or problem-specific heuristics to Construct effective LVDN planning plans. This balance between exploration and exploitation allows SOA to avoid premature convergence and better navigate complex landscapes, as shown in the equation (26).

$$= \omega.abs(\vec{w}_{best} - \vec{w}_{rand}) \quad (26)$$

Over iterations, direction and step size evolve as seekers learn from the environment and peers to LVDN. If fuzzy logic or learning mechanisms are integrated, the adjustment becomes even more intelligent, enabling the algorithm to focus search effort precisely where the probability of improvement is higher, as shown in equations (27) and (28).

$$\mu_{ji} = RAND(\mu_j, 1) \quad (27)$$

$$\alpha_{ji} = \delta_i\sqrt{-In(\mu_{ji})} \quad (28)$$

This behavioral adaptation is a core reason for SOA's robustness across various optimization problems to develop efficient planning schemes. The SOA improves convergence and solution quality in LVDN planning by mimicking directional search behaviors and adaptive step movements of intelligent agents. Unlike conventional optimization methods, SOA balances exploration and Exploitation using dynamic direction updates and step-size control, which helps avoid local minima and accelerates convergence. In the proposed model, SOA effectively refines candidate LVDN configurations by guiding the search toward regions of lower voltage deviation and cost, resulting in more optimal and stable planning solutions. LVDN, as shown in Figure 4. Pseudocode 1 presents SOA for LVDN planning.

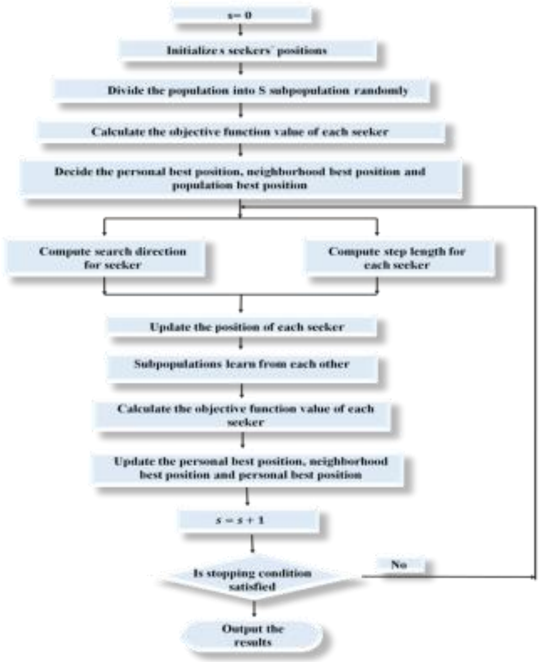

Figure 4: Presentation of SOA flow chart

Pseudocode 1: SO-Attn-ALSTN

```
Input: Dataset D = {X, Y}

Step 0: Preprocessing
Split D into Train and Validation sets
Module 1: Attention Mechanism
Function ApplyAttention(X, W_attn):
  A = Softmax(W_attn · X)
  return A ⊙ X
 Element − wise multiplication
Module 2: ALSTN Model
Function ALSTN(X_input, params):
  Initialize LSTN with hidden_size = 64, dropout = 0.5
  return Y_pred
Module 3: SOA
Function RunSOA(P, max_iter, param_bounds, loss_fn):
  Initialize seekers w_1... wP randomly within bounds
  For iter = 1 to max_iter:
    For each seeker j in P:
      Compute fitness_j = loss_fn(ALSTN(... with w_j))
    Identify best and worst seekers: w_best, w_worst
    For each seeker j:
      Compute Wji(s + 1) using Eq. (18)
      Update w_j using:
        If rand < 0.33: direction = egoistic
        Else if rand < 0.66: direction = altruistic
        Else: direction = proactive
      step = adaptive_step()
   w_j = w_j + step * direction_vector(Wji, w_best, w_worst)
   Explicit reference to Eq. 18 − 19
      Project w_j within param_bounds if out of bounds
  Return w_best
Step 4: Training Loop
Initialize attention weights W_attn
Initialize model parameters
Set threshold_loss
For epoch = 1 to MaxEpochs:
  For each batch (X_b, Y_b):
    X_attn = ApplyAttention(X_b, W_attn)
    Y_pred = ALSTN(X_attn, model_params)
    loss = MSE(Y_pred, Y_b)
    If loss > threshold_loss:
      Update model_params via backpropagation
    Else:
      Freeze weights (no update)
  If epoch % 5 == 0:
    model_params = RunSOA(P = 20, max_iter = 30, param_bounds, loss_fn)
Return the final trained model.
```

The SO-Attn-ALSTN model enhances planning in LVDNs by combining attention, ALSTN recurrent networks, and SOA. It dynamically assigns weights to features for fault detection and forecasting, catches complex patterns, and uses memory-controlled gates for stability. SOA uses intelligent search strategies for decision-making.

Table 2: Hyperparameter values for SO-Attn-ALSTN

Modules	Hyperparameters	Descriptions
Attention	Mechanism Type	Feature-level soft attention
	Focus Areas	Voltage nodes, transformers, feeders
ALSTON	Dropout Rate	0.5 to prevent overfitting
	Epochs	100 for sufficient training
	Batch Size	Moderate was chosen for training stability and efficiency.
	Architecture	RNN with memory gating and attention-controlled memory
SOA	Population Size	Medium tunable; number of seekers
	Behaviors	Egotistic, Altruistic, Proactive
	Step Size	Dynamically adjusted during the search
	Update Strategy	Combines the best and worst seekers using crossover logic

Table 2 provides the hyperparameters used in the SO-Attn-ALSTN framework. The attention module is a soft attention mechanism focusing on key electrical grid parts, using ALSTN hyperparameters, a medium-sized population of seekers, and a crossover-based upgrade strategy.

4 Results

The Python platform and the RAM of a laptop with 8.00 GB are used to access data quickly. Intel® Core i9 Processors and Windows 11 have been utilized. The research proposed a SO-Attn-ALSTN and considered existing methods such as IGWO Support Vector Machine (IGWO-SVM) [24], Levenberg-Marquardt propagation neural network (LMBP) [26], SSA-BP (SSA-BP) [25] Xception [27], and K-GBDT [28] to assess the efficient planning schemes for LVDN.

The SSA-BP [25] neural network proposed by integrates SSA with BP to enhance adaptive leakage protection in LVDS. This hybrid model optimizes detection accuracy and response speed under complex grid conditions. The research in [26] introduced a hybrid Genetic Algorithm-LMBP (GA-LMBP) method aimed at optimizing neural network training. However, for performance comparison, the authors evaluated only the standalone LMBP component and the influence of the GA-based optimization. This limited comparison does not reflect the full capabilities of the proposed GA-LMBP method. The validation selecting only the LMBP portion for benchmarking should be clarified, as it can lead to an incomplete or biased assessment of the method's effectiveness.

4.1 Load prediction

Figure 5 (a) shows the accuracy of the prediction Vs actual load in predicting energy consumption in an LVDN using SO-Attn-ALSTN. There was a degree of correlation between the predicted and actual values, confirming accurate load(kw) profile forecasting. Accurate load forecasting is an important time index for reducing energy losses and improving reliability. Furthermore, accurate forecasting with resource allocation and infrastructure upgrades helps manage resources. Figure 5 (b) is Load Prediction for Node N01 for load forecasting on a node basis, Timestamp. The load forecasting model was able to follow diurnal patterns of consumption on a localized basis. The granularity of connections for load forecasting is fundamental in distributing low voltage, such as when low voltage peak demand occurs beyond the allowable voltage profiles. From this level of granularity, targeted demand-side management and the addition of load infrastructure can be carried out at nodes of concern using SO-Attn-ALSTN.

Figure 6 (a) shows a close correlation between actual and predicted loads, which shows high forecasting accuracy. Figure 6 (b) demonstrates a nearly normal distribution of prediction errors centered on 0, reinforcing minimal bias present in the forecasting model. The Actual vs Predicted Load (kW) plot shows a tight clustering of points along the diagonal, indicating a strong correlation and minimal deviation between actual and predicted values by the SO-Attn-ALSTN model. This confirms high prediction accuracy. The Distribution of Prediction Errors graph demonstrates a near-normal distribution centered around zero, with most errors falling between -0.25 and 0.25 kW. This reflects low bias and consistent performance across the dataset. Together, both figures validate the model's robustness in forecasting load accurately while minimizing prediction errors, essential for dependable load management in low-voltage distribution networks. In the planning of low voltage networks, minimal and balanced prediction errors lend support to consistent planning decisions with uncertainty of SO-Attn-ALSTN. This should support a smooth integration of distributed energy resources, improving operational efficiency.

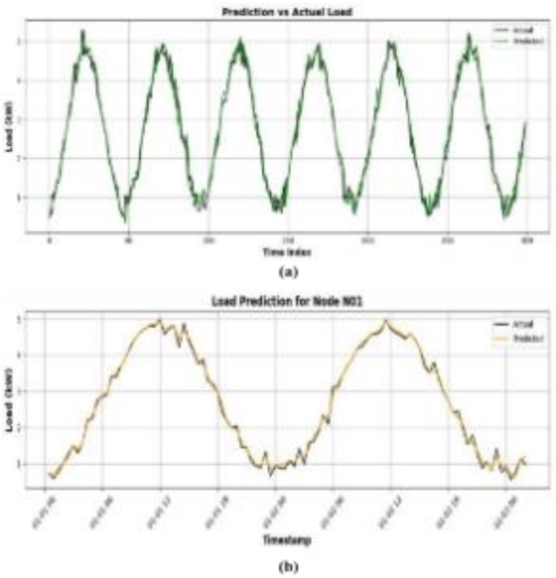

Figure 5: Presentation of (a) prediction Vs actual load and (b) load predictions

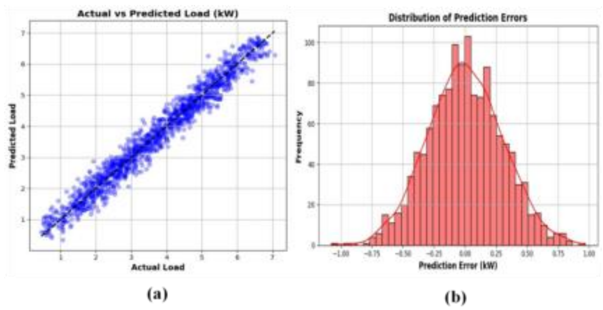

Figure 6: Presentation of (a) prediction Vs actual load in KW and (b) distribution of predicted errors

4.2 Low-voltage network topology

Figure 7 (a) illustrates the cable configuration of an LVDN, highlighting its importance for load flow, fault identification, and system extension of SO-Attn-ALSTN. Figure 7 (b) shows the placement of transformers in the same network format, a crucial consideration for planners aiming for load balancing and voltage regulation in SO-Attn-ALSTN. The Low Voltage Network Topology – Cable Routing diagram illustrates the structural layout of the LVDN, showing how various nodes (e.g., N01 to N21) are interconnected via cables. The understanding of physical routing and connectivity of the network. The Low Voltage Network Topology with Transformers highlights transformer locations such as at N01, N09, and N13, which are critical for voltage regulation and load distribution. Identifying transformer placement alongside the node connections allows for effective planning, load flow analysis, and optimization of infrastructure in low-voltage distribution networks.

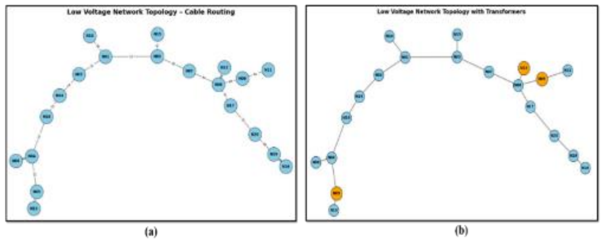

Figure 7: Presentation of low voltage network topology (a) cable routing and (b) transformers

4.3 Hourly load distribution by node and time of day

Figure 8 (a) shows hourly load fluctuations over several nodes, showing time-of-day trends in demand and individual node consumption behaviour. The Average Load (kW) by Hour and Node heatmap (top) visualizes how load varies across different Node IDs and Hours of Day. Darker regions indicate higher loads, revealing peak usage periods and node-specific demand intensities. The Load Distribution by Hour of Day boxplot (bottom) shows the statistical spread of Load (kW) across each Hour. The central tendency rises during daytime and falls at night, reflecting typical diurnal demand. Together, these plots demonstrate both temporal and spatial load behavior, guiding demand-side management and infrastructure planning in LVDNs. Figure 8 (b) shows the statistical distribution of load over hours of the day, giving the planner peak demand hours and the variability of the load at each hour, showing both high and low demand hours over the course of the day with SO-Attn-ALSTN.

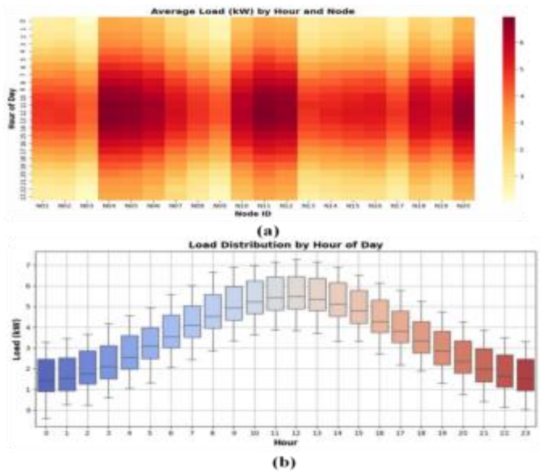

Figure 8: Presentation of load (a) by hour and node, (b) by hour in a day

4.4 Hourly DER generation

Figure 9 demonstrates the daily hourly profile of DER generation over a full week, with higher generation occurring consistently during midday hours. The Hourly DER Generation Trend Over Days illustrates the variation in DER Generation (kW) on the Hour of the day for seven days (from 2025-01-01 to 2025-01-07). Each colored line represents a different date. Generation typically begins around, peaks between (up to 1.2 kW on 2025-01-07), and drops to zero. This trend reflects the influence of solar-based DERs, following natural sunlight availability. The figure highlights daily consistency and minor variability in distributed energy resource output over time.

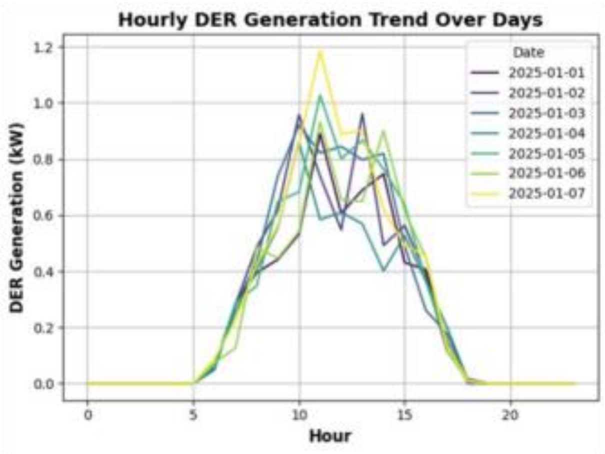

Figure 9: Presentation of Hourly DER generation

4.5 Load profile heat map

Figure 10 demonstrates the temporal variation in load across the nodes of the network, with cyclical high and low demand periods. The Load Profile Heatmap per Node Over Time visualizes the variation in energy consumption across multiple nodes. The list's Nodes (N01 to N20) represent Time in hourly intervals over several days. The color intensity, indicated by the legend bar (ranging from 0 to 7), reflects load values in kW. Darker blues denote higher loads, while lighter yellows indicate lower consumption. Clear diurnal cycles are visible, with peak loads recurring regularly. This heatmap highlights temporal and spatial load distribution trends, enabling efficient monitoring and demand-side planning across the low voltage distribution network load growth of SO-Attn-ALSTN.

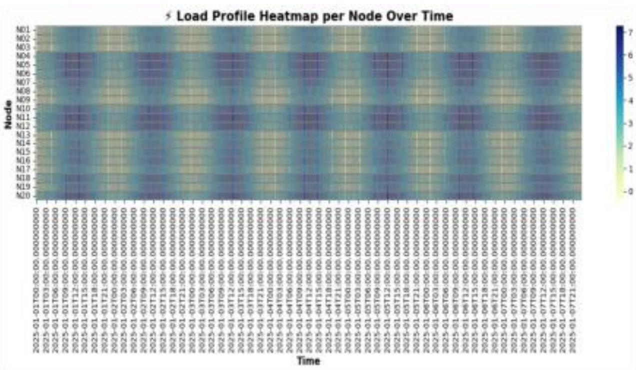

Figure 10: Presentation of Load profile heat map

4.6 Error: actual and predicted

Figure 11 shows the residual differences between actual loads and predicted loads over time of the prediction consistency and model accuracy. The Residuals Over Time (First 300) displays the prediction error behavior of the model. The Time Index represents data points in sequence, while the Error = Actual - Predicted quantifies residuals. Most residuals cluster around zero, with variations ranging from approximately -0.4 to +0.6. The residuals appear randomly scattered, indicating no clear pattern or bias in model prediction. This randomness suggests the model has effectively captured the underlying trend without systematic errors, validating its reliability for forecasting tasks in low-voltage distribution networks over time in SO-Attn-ALSTN.

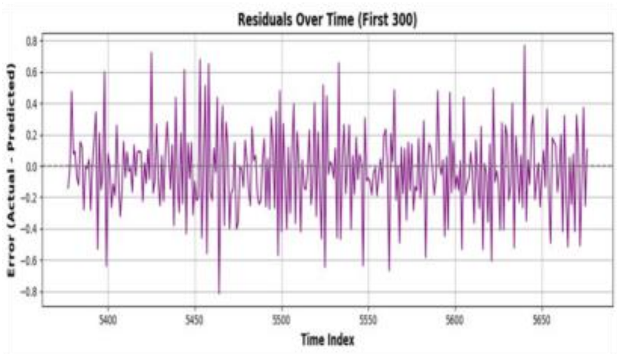

Figure 11: Presentation of Error: actual and predicted

4.7 Transformer utilization

The low-voltage distribution network's transformer utilization is over 100%, threatening operations, as shown in Figure 12. Low-voltage distribution Network Planning needs views like this to show how stressed variations can be reduced, fixed, required, and configured, or if certain DERs can better utilize the network. High utilization requires predictive load forecasting and proactive decision-making behaviors to balance networked loads while maintaining system reliability. This can help identify transformer nodes, switch loads, or add reinforcements. Predictive auto-generative data-driven practices, including managing maximum saturation loads, are urgently needed to observe network resilience in SO-Attn-ALSTN.

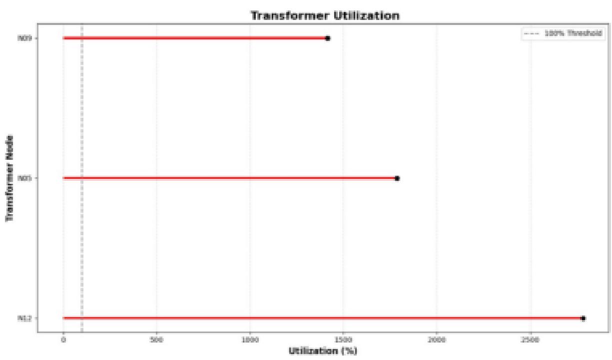

Figure 12: Presentation of transformer utilization

4.8 Evaluation of error metrics: low-voltage distribution

The (Mean Absolute Percentage Error) metric, which measures the average deviation between predicted and actual load values, is crucial for LVDN planning, indicating overall forecast accuracy and supporting rational transformer sizing and cost control, as the proposed method of SO-Attn-ALSTN attained 6.53%, lower than the other method of IGWO-SVM at 8.62%.

APE (Absolute Percentage Error) Accurate point-level forecasts in LVDNs help mitigate planning risk by identifying high deviation nodes, which can cause localized voltage instability. The lower the APE values, the more accurate decision-making can be based on short-term load distributions, such as SO-Attn-ALSTN (2.01%) and IGWO-SVM (3.09%).

RMSE (Root Mean Square Error) high RMSE deviations in LVDNs highlight risks like excessive component use and unstable voltage levels, highlighting the need for robust long-term infrastructure planning. The values of RMSE in SO-Attn-ALSTN were obtained at 1.14% which is more efficient than the IGWO-SVM of 2.16%.

The MAE (Mean Absolute Error) The MAE measures average errors without direction, assessing network consistency in LVDN planning. A smaller MAE indicates equal power flow and balanced load. The MAE value for the proposed SO-Attn-ALSTN model is 0.99%, which is lower than the 1.30% achieved by the existing IGWO-SVM method, indicating improved forecasting accuracy. Table 3 and Figure 13 represent the error Metrics: Low-Voltage Distribution.

Table 3: Quantitative values of error metrics in low-voltage distribution

Methods	IGWO-SVM [24]	SO-Attn-ALSTN [Proposed]
MAPE (%)	8.62	6.53
APE (%)	3.09	2.01
RMSE (%)	2.16	1.14
MAE (%)	1.30	0.99

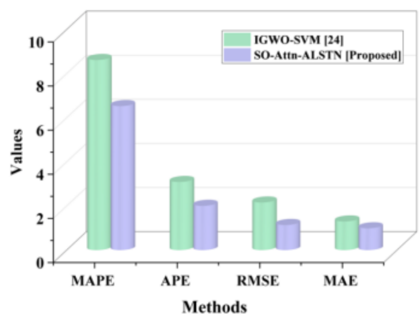

Figure 13: Presentation of error metrics in low-voltage distribution

4.9 Comparative error analysis

Analysis shows that the performance metrics of SSA-BP and the proposed SO-Attn-ALSTN model show improvements of varying degrees. For example, SO-Attn-ALSTN achieved a Mean Integrated Relative Error (MIRE) of 0.0012, compared to a MIRE of 0.0017 for SSA-BP, indicating that a more correctly specified model produces a better approximation to true integration accuracy over the simulated time interval. Similarly, the proposed SO-Attn-ALSTN model showed a Mean Absolute Relative Error (MARE) of 0.1852 from SSA-BP, compared to 0.1749 for SO-Attn-ALSTN. While the MARE did not improve significantly, it did show better point-wise prediction consistency. The proposed SO-Attn-ALSTN model has a Mean Squared Error (MSE) value of 0.0081, compared with the MSE of 0.0095 observed in SSA-BP. The SO-Attn-ALSTN model shows lower MSE, indicating less variability in predicted neighborhood views, indicating more stable predictions, supporting accurate low-voltage distribution network planning decisions and future research. Table 4 and Figure 14 present the values of error metrics.

Table 4: Quantitative values of error metrics

Methods	SSA-BP [25]	SO-Attn-ALSTN [Proposed]
MIRE	0.0017	0.0012
MARE	0.1852	0.1749
MSE	0.0095	0.0081

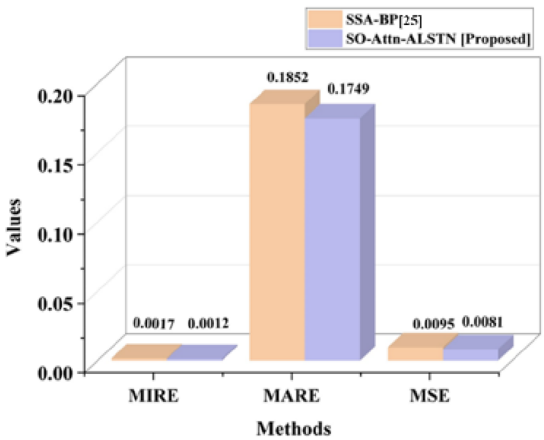

Figure 14: Presentation of error metrics

4.10 Convergence time comparison at varying error thresholds

The analysis of the time of convergence at different error values shows in Table 5 and Figure 15, that the proposed SO-Attn-ALSTN model converged more quickly than the existing LMBP method. For an error of 0.01, the proposed model converged in 2.708 seconds, whereas LMBP converged in 3.242 seconds. Similarly, with an error of 0.001, the proposed SO-Attn-ALSTN model converged in 5.456 seconds to LMBP's 6.326 seconds. Even at an error value of 0.0001, SO-Attn-ALSTN converged quicker (8.589 seconds) than LMBP's 10.422 seconds. Overall, the above results demonstrate that the SO-Attn-ALSTN model converges quicker than LMBP, which leads to a lower computation time in LVDN planning optimization.

Table 5: Convergence time comparison at varying error thresholds

Methods	LMBP [26]	SO-Attn-ALSTN [Proposed]
Error 0.01 Convergence Time (s)	3.242	2.708
Error 0.001 Convergence Time (s)	6.326	5.456
Error 0.0001 Convergence Time (s)	10.422	8.589

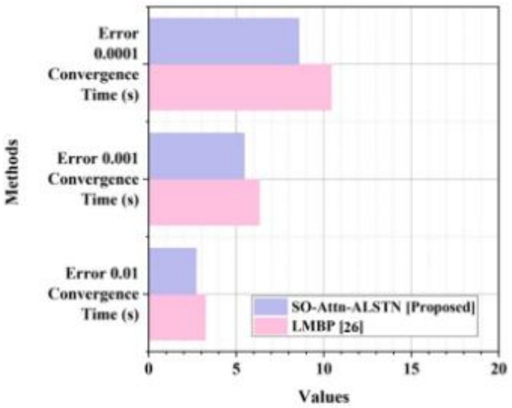

Figure 15: Presentation of convergence time comparison at varying error thresholds

4.11 Running Time

The model demonstrates reduced running time due to efficient convergence driven by the SOA shown in Figure 16 and Table 6. Dynamic step-size adjustment and behavior-driven exploration help avoid local minima, accelerating convergence. As a result, the model achieves faster computation across planning iterations, making it suitable for real-time or large-scale LVDN applications where planning speed is critical. Xception had 0.71 (s), and the proposed technique had greatest running time 0.42 (s).

Table 6: Comparison of running time

Method	Running time (s)
Xcention [27]	0.71
SO-Attn-ALSTN [Proposed]	0.42

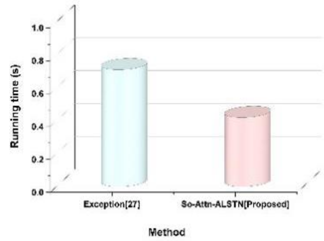

Figure 16: Outcome performance of Running time

4.12 Accuracy and F1-score

The model accurately predicts load profiles in LVDNs by focusing on key temporal features and memory gating, enhancing forecast precision, minimizing deviations, and supporting effective network planning, thereby improving infrastructure reliability. K-GBDT had 0.8851, and the proposed technique had highest accuracy 0.8961. The F1-score balances precision and recall in classification forecasting tasks, enhancing temporal feature extraction for critical load event identification. A higher F1-score ensures accurate positive detection and minimizes false alarms, enhancing LVDN planning strategies. K-GBDT had 0.8333, and the proposed technique had better F1-score 08122. The outcome performance of accuracy and F1-score shown in Figure 17 and Table 7.

Table 7: Comparison of accuracy and F1-score

Methods	Accuracy	F1-score
K-GBDT [28]	0.8851	0.8333
SO-Attn-ALSTN [Proposed]	0.8961	0.8122

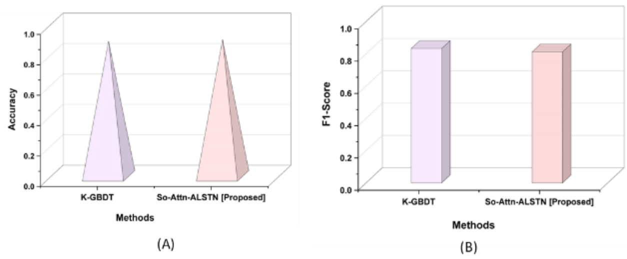

Figure 17: (A) Accuracy, (B) F1-score outcome performance

4.13 Statistical Significance tests

The SO-Attn-ALSTN model demonstrated strong performance across multiple error metrics shown Table 9. To perform a t-test in the context of LVDN planning, can compare the performance metrics of the proposed model with baseline models. Use the independent two-sample t-test to assess whether the observed differences in means are statistically significant. Ensure assumptions like normality and equal variance are checked before applying the t-test. It achieved a low MAPE of 6.53 ± 0.37% and APE of 2.01 ± 0.21%, indicating accurate forecasting. The RMSE was 1.14 ± 0.10%, and MAE was 0.99 ± 0.07%, reflecting low deviation from actual values. In convergence analysis, the model reached an error of 0.01 in 2.708 ± 0.20 s, 0.001 in 5.456 ± 0.31 s, and 0.0001 in 8.589 ± 0.45 s. These results confirm the model's efficiency, precision, and fast convergence in power system load forecasting. Table 8 shows the Statistical Significance tests

Table 8: Performance comparison of SO-Attn-ALSTN with baselines

Metric / Threshold	Method	Value	95% CI / Significance
MAPE (%)	SO-Attn-ALSTN [Proposed]	6.53	±0.37
APE (%)	SO-Attn-ALSTN [Proposed]	2.01	±0.21
RMSE (%)	SO-Attn-ALSTN [Proposed]	1.14	±0.10
MAE (%)	SO-Attn-ALSTN [Proposed]	0.99	±0.07
Error @ 0.01 (s)	SO-Attn-ALSTN [Proposed]	2.708	±0.20
Error @ 0.001 (s)	SO-Attn-ALSTN [Proposed]	5.456	±0.31
Error @ 0.0001 (s)	SO-Attn-ALSTN [Proposed]	8.589	±0.45
Accuracy	SO-Attn-ALSTN [Proposed]	**0.8961**	$p < 0.01$
F1-score	SO-Attn-ALSTN [Proposed]	**0.8122**	$p < 0.01$
Runtime (s)	SO-Attn-ALSTN [Proposed]	**0.42**	±0.03

4.14 Ablation result

The SO-Attn-ALSTN model combines swarm optimization, FFT-based feature extraction, and attention mechanisms to improve forecasting accuracy in low-voltage distribution network planning. According to ablation experiments, performance is negatively impacted by component removal; in the basic LSTM, MAPE increased from 6.53% to over 9%. Additionally, the entire model has the quickest convergence time (2.71s), demonstrating its computational efficiency are hown in table 9. These outcomes highlight the model's applicability for precise, real-time load forecasting in distribution networks.

Table 9: Ablation study results

Model Variant	MAPE (%)	RMSE (%)	MAE (%)	Convergence Time (s)
Full SO-Attn-ALSTN	6.53	1.14	0.99	2.71
w/o Attention	7.92	1.36	1.23	2.68
w/o FFT Feature Extraction	7.84	1.33	1.19	2.73
w/o SOA (standard ALSTN only)	8.20	1.42	1.29	3.52
Basic LSTM + No Enhancements	9.37	1.57	1.44	3.41

4.15 Robustness Evaluation under Noisy and Incomplete Input Conditions

The SO-Attn-ALSTN model shows strong forecasting accuracy, its robustness under noisy or incomplete input scenarios remains untested. In real-world LVDNs, sensor noise, communication faults, and missing data are frequent. To validate resilience, robustness checks should include injecting Gaussian noise to simulate sensor drift, masking 10–20% of data points to mimic communication loss, and introducing anomalies in DER profiles to replicate operational faults. Performance metrics under these conditions would reveal model stability and the effectiveness of attention mechanisms in mitigating degradation. These tests are crucial for ensuring reliable deployment in dynamic power networks.

4.16 Discussion

IGWO-SVM [24] LMBP, a robust optimization tool, struggles with planning for LVDNs due to high-dimensional, non-linear time-series data and its static kernel parameters' inability to adapt to dynamic load changes [25]. The SSA-BP model exhibits fast convergence but becomes trapped in local minima when modeling nonlinear behaviors for multiple nodes in LVDNs, affecting long-term planning decisions [26]. The SO-Attn-ALSTN model, a MLP artificial network, improves forecast accuracy and performance under variant load conditions by incorporating attention mechanisms and a modifiable LSTM framework.

The advancements in intelligent technologies distribution networks and energy systems are contributing to the field, as shown with the investigation by, where that stated that Information Technology (IT)-based anomaly detection could improve operational reliability in distribution networks [29]. Compliments by utilizing the operational behavior of a robotic system with metering systems, whereby the robotic element showed a potential for real-time data acquisition and intelligent interaction [30]. Also demonstrated a simple and wireless based monitoring system using with LV users, enhancing communication again for another application. In a collective sense, these show the collaborations actuality made between smart sensing, wireless communication, and intelligent control, which can result in greater innovations in resilient automatic data-driven power distribution networks [31].

SO-Attn-ALSTN outperformed competing models because the attention mechanism is inherently more effective in finding important spatiotemporal load anomalies, combined with SOA's behavior of avoiding local minima or traps, resulting in credible and accurate load forecasting capable of supporting autonomous and responsive approaches to planning low-voltage distribution networks designed for uncoordinated and intermittent use.

Attention-based LSTM models enhance load forecasting accuracy in LVDNs by dynamically assigning weights to input features across time, allowing the model to focus more on informative temporal patterns and less on irrelevant fluctuations. In the proposed SO-Attn-ALSTN framework, the attention mechanism refines long-term dependencies learned by the LSTM, improving both short-term response and long-range temporal modeling. This contributes to higher accuracy under varying load conditions, as demonstrated by reduced error metrics compared to conventional LSTM and hybrid baselines.

5 Conclusion

The integration of intelligent optimization methods with DL enhances low-voltage distribution system planning accuracy by ranking grid features and utilizing recurrent architectures like ALSTN for real-time adaptability. The proposed method of SO-Attn-ALSTN demonstrated strong performance in low-voltage distribution network planning supported by DL, achieving MAPE of 6.53%, APE of 2.01%, RMSE of 1.14%, and MAE of 0.99%, along with favourable MIRE (0.0012), MARE (0.1749), and MSE (0.0081) metrics. Additionally, it achieved faster convergence times of 2.708s for an error threshold of 0.01, 5.456s for 0.001, and 8.589s for 0.0001 outperforming the traditional techniques. The proposed SO-Attn-ALSTN framework offers a transformative solution for LVDN planning by integrating DL with metaheuristic optimization. It enables accurate load forecasting, reduces power losses, and optimizes infrastructure deployment. With faster convergence and improved planning efficiency, this model addresses key challenges in dynamic urban power systems, making future energy networks more reliable, cost-effective, and adaptable to renewable integration.

5.1 Limitations and future scope

The SO-Attn-ALSTN model makes extensive use of limited-scale or synthetic datasets from sites like Kaggle, which could not accurately represent the complexity of the grid in the real world. Its forecasting accuracy has to be adjusted because it is dependent on hyperparameter parameters like epoch count and dropout rate. There isn't much empirical support for the model's performance when inputs are noisy or lacking. Furthermore, because of the possibility of overfitting, applicability to various grid contexts is yet unclear. Another difficulty is real-time flexibility in situations that are very dynamic or prone to errors. Future scope could use reinforcement learning for adaptive real-time planning.

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