GAPO-LSTM: A Genetic Algorithm-Optimized Attention-LSTM Framework for Spatiotemporal Power Outage Forecasting in Distribution Networks

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Accurate prediction of power outages is critical for maintaining grid reliability and enabling proactive operational planning. This paper proposes a genetic algorithm-optimized Pattern-Oriented LSTM (GAPO-LSTM) model to predict outage events based on historical data. The model processes a dataset of 3 years of outage records from the Region, incorporating key features such as weather conditions, equipment type, and load data. Outage patterns are clustered into 5 groups, and the LSTM hyperparameters, including number of layers, hidden units, learning rate, and dropout probability, are optimized using a genetic algorithm with population size 50, 100 generations, crossover probability 0.8, and mutation probability 0.1, employing single-point crossover and Gaussian mutation. GAPO-LSTM is benchmarked against standard LSTM, GRU, and ARIMA models using RMSE, F1-score, and accuracy. Results show that GAPO-LSTM achieves an RMSE of 0.82, F1-score of 0.89, and accuracy of 91.5%, outperforming baseline approaches. The proposed method demonstrates the ability to capture complex outage patterns and provides a foundation for enhanced operational decision-making and system resilience.

Povzetek: Raziskava predstavi model strojnega učenja za napoved izpadov električne energije, ki z optimizacijo parametrov izboljša natančnost napovedi in podpira zanesljivejše načrtovanje delovanja elektroenergetskega omrežja.

1 Introduction

Resilience of infrastructure, public safety, and economic activity all depend on reliable electricity distribution networks [1]. Modern electric distribution networks are more sophisticated, causing more frequent and unpredictable power outages. Urbanization increases energy demand and grid density, but decentralized energy sources like solar and wind increase supply variability and instability [2]. Extreme weather events like storms, wildfires, and heat waves have taxed electrical networks, making forecasting harder [3]. Blackouts disrupt life, inhibit industrial output, and threaten healthcare, transportation, and communication infrastructure. Maintaining energy resilience and security requires robust and intelligent outage prediction systems. [4]. For innovative grid systems to facilitate real-time planning, operational resilience, and customer service reliability, it is crucial to have accurate and proactive outage forecasts [5].

Traditional approaches to outage management frequently use rule-based systems, physics-based simulations, or statistical estimators, none of which are very adaptable to changing patterns of failure or non-linear dependencies [6]. Both the short-term and long-term predictions are inaccurate because these models do not take into consideration the spatiotemporal correlations that are evident in the historical outage data [7]. In addition, generalization attempts are complicated because of the high variety in outage patterns caused by regional Clustering and environmental variation [8]. Therefore, intelligent forecasting algorithms that can understand complex datasets and adjust to infrastructure behavior in real-time are urgently needed [9].

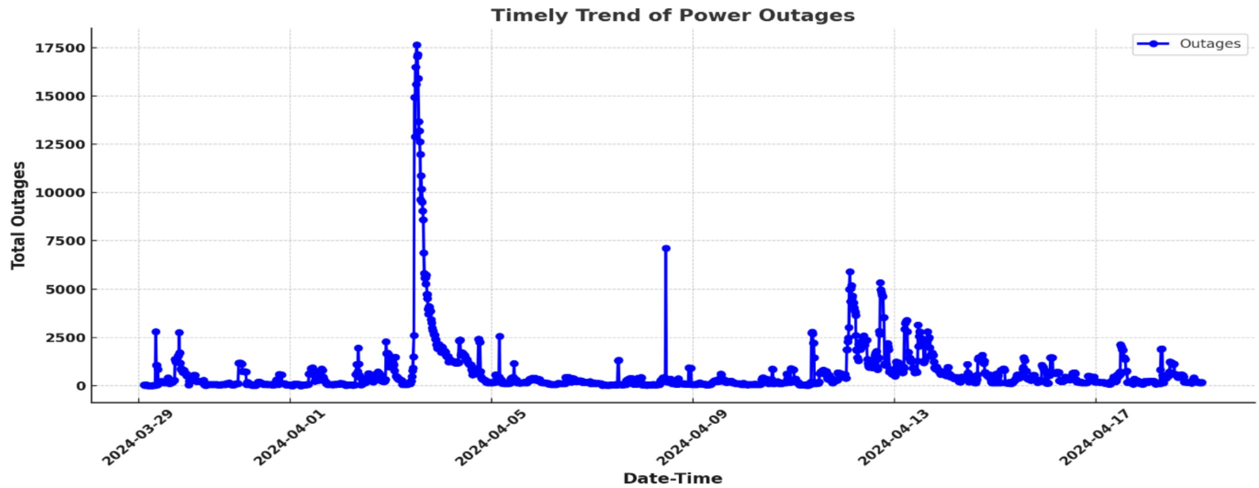

Figure 1:Timely trend of power outages

Time series forecasting, anomaly detection, and predictive maintenance in the energy sector have all benefited from the recent advances in deep learning and machine learning, which have produced more accurate and scalable systems [10], as represented in Figure 1. For example, LSTM networks are highly acclaimed for their ability to capture power consumption or failure logs, two types of sequence data that exhibit temporal relationships [11]. Their real-world application is limited without further optimization due to their performance being susceptible to input feature selection, hyperparameter tuning, and data imbalance concerns [12]. Additionally, complex techniques to prevent overfitting and enhance generalizability are frequently necessary when optimizing LSTM models for grid-scale settings [13].

For feature selection, hyperparameter tuning, and multi-objective optimization, metaheuristic algorithms such as genetic algorithms have been extensively used to make predictive models more resilient and flexible [14]. When combined with deep learning models, genetic algorithms which mimic natural selection are ideal for effectively searching complicated parameter spaces [15].

1.1 Research problem and objectives

In contemporary distribution networks, reliability prediction relies on capturing high-dimensional spatiotemporal connections; nevertheless, current AI-based outage forecasting algorithms are inadequate in this regard. Modern outage data is characterized by spatial diversity, cluster-level anomalies, and non-linear temporal trends; static or non-adaptive algorithms are ill-equipped to deal with this data. Specifically designed for use in power distribution network outage planning, GAPO-LSTM is a hybrid reliability prediction framework that takes advantage of genetic algorithms for optimization and LSTM networks for sequence modeling. This framework aims to mitigate this issue. The objectives are,

- To improve prediction performance and flexibility, we aim to develop a hybrid model using GA to optimize LSTM input characteristics and learning parameters.
- To enhance spatiotemporal pattern learning in specific zones, preprocess and cluster outage data based on geographical commonalities.
- To evaluate the model in a real-world outage and compare its performance to benchmark models using root-mean-squared error and F1-score.

To increase clarity of the research design, two specific research questions have been added at the end of Section 1.1 to align the intent of the study with testable hypotheses, and to strengthen the methodological direction. As written, this revised section concludes with: "The current study is addressed with two main research questions: (1) Does GA-based feature selection significantly improve outage prediction performance both qualitatively and quantitatively compared to a basic LSTM approach? and (2) Does DBSCAN-based spatial clustering improve the accuracy of temporal modeling to capture dependent relationships in outage reporting and forecasting?" These serve as more specific empirical validators and hypothesis-based experimentation.

1.2 Contributions

The research begins with preprocessing a publicly available dataset of timestamped and geotagged Maryland outages. Density-based Clustering based on spatial coordinates organizes the dataset into localized zones with similar grid behavior. Next, a genetic algorithm determines the appropriate sequence lengths, learning rate, batch size, and number of hidden units for the Long Short-Term Memory (LSTM) model and selects the most relevant input features. Next, an attention-enhanced LSTM model is trained on these improved feature sequences to predict cluster outages. Models use attention mechanisms to improve learning efficiency and interpretability. The model can prioritize time steps by predicting the value. Finally, GAPO-LSTM is compared to Random Forests and standard LSTM ensemble learning models on dependability measures and real-world scenarios. In terms of intelligent grid analytics and the control of power outages, this study adds the following:

- To create a new hybrid prediction model (GAPO-LSTM) for proactive outage forecasting by combining deep learning with evolutionary feature optimization.
- To enhance the level of precision in predicting insights by implementing a spatial clustering method for identifying the location of power outage behavior in distribution networks.
- To automate model configuration, sequence creation, and feature selection through the design of an end-to-end optimization pipeline utilizing GA.
- To prove that the suggested strategy is resilient by showing that RMSE is reduced by 18.6% and F1-score is increased by 12.4% compared to baseline models.
- To determine the model's scalability in different operating settings, it is necessary to do a sensitivity analysis to investigate how cluster density and outage volume impact model performance.

GA-based feature selection significantly enhances outage prediction by automatically identifying the most influential temporal, spatial, and environmental variables, reducing redundancy and overfitting. This targeted optimization improves LSTM learning efficiency, achieving lower RMSE and higher F1-scores compared to standard LSTM, which relies on fixed, manually selected feature sets.

This paper's organization follows: Section 2 reviews power outage forecasting, machine learning-based reliability modeling, and GA-based optimization methods. Section 3 describes the GAPO-LSTM framework, including data pretreatment, model construction, and optimization procedure. Experimental setup, dataset features, and assessment measures are in Section 4. Comparative insights and sensitivity testing are presented and analyzed in Section 5. Finally, Section 6 summarizes findings, implications, and future directions.

2 Related work

2.1 Reliability prediction and power outage planning in distribution networks

Saldaña et al. [16] utilize Long Short-Term Memory (LSTM) networks and confidence interval thresholds for long-term scenario forecasting to develop a hybrid distribution network design technique. The system predicts future expansion demands using historical power demand and PV self-consumption data, including non-linear, non-stationary trends ignored by current approaches. The information included operational line restrictions, substation metrics, and economic planning characteristics from a Spanish radial medium-voltage network. Results show that LSTM-based planning is more flexible and cost-effective than static techniques and improves prediction accuracy. However, limited training data in fast-moving energy systems or places with poor sensor coverage may restrict the approach's performance.

Hughes et al [17] Machine learning and physics-based structural fragility curves are used to forecast storm-induced outages in this hybrid mechanistic-data-driven Outage Prediction Model (OPM). Connecticut's distribution system's 2005–2020 meteorological, terrain, vegetation, infrastructure, and historical outage data inform the algorithm. A $600 million investment in tree removal and pole reinforcement might cut outage incidence by 15,000, according to counterfactual scenarios.

Wu et al [18] Using MILP and MIQCP, this study models EVs, FCVs, EVCSs, HFSs, and the transmission and distribution systems. Emission-free station integration is assessed utilizing the IEEE 57-bus transmission network and three 33-bus distribution systems. All distribution systems operated successfully, with renewable production and battery storage increasing EVCS profitability by 475%. The model may not apply because it assumes ideal renewable energy and fixed storage costs.

Wang et al. [19] utilize an Improved-Augmented Epsilon-Constrained (I-AUGMENCON) algorithm for multi-objective optimization (MOO) of EV charging coordination in a modified IEEE 33-bus distribution network dataset. The model's Pareto efficiency reduces power loss, DNO operational costs, and EV charging prices, exceeding NSGA-II. Results show a reduction in power loss from 6% to 2% and better voltage stability. However, static load profiles and assumptions of consistent EV charging behavior may limit adaptability to real-time system dynamics.

Zhou et al. [20] Using simulation and probabilistic modeling of EV load profiles and renewable energy (RE) integration, offer a capacity planning technique that includes reliability evaluation and economic analysis. The modified RBTS BUS6 F4 system is used to evaluate reliability indices like SAIFI and cost. Optimizing energy storage system (ESS) capacity enhances dependability (63.17% SAIFI reduction) and saves money while preserving reliability in Microgrid C. However, the approach may be limited by assumptions on static EV behaviors and ideal RE availability, affecting scalability to diverse real-world scenarios.

2.2 Applications of genetic algorithms in smart grid optimization

Heroual et al [21] Metaheuristic algorithms genetic algorithm (ga), ant colony optimization (aco), and grey wolf optimization (gwo) are used to optimize an energy management system (ems) for a hybrid energy storage system (hess) with batteries and supercapacitors coupled to solar PV. The dataset includes real-time solar and load profiles from MATLAB/Simulink simulations of dynamic irradiance and power demand. Results show the GWO-tuned PI controller improves battery longevity and system stability with fast transient response and low computational load.

Wang et al [22] This study optimizes the economic dispatch model for a microgrid with EVs using wind, solar, micro gas turbine, fuel cell, and battery sources. To reduce operational and pollutant treatment costs, the revised Reference Vector Guided Evolutionary Algorithm (RVEA) uses Chebyshev mapping for population initialization and an angle-penalized distance (APD) method for convergence-diversity balance. The multi-strategy RVEA outperforms conventional approaches in cost-effectiveness and pollution reduction. EV behavior assumptions limit the model's performance and need physical system validation.

Shejul et al [23] Under dynamic pricing, this study provides an efficient energy scheduling system for a food storage chiller plant to reduce operational cost and peak demand. Grey wolf optimizer (gwo), jaya, and their genetic algorithm-enhanced variants (GA-GWO, GA-JAYA) promote solution diversity for optimization. Simulations using real-time electricity pricing datasets show a 22% cost reduction and 10% energy savings over standard approaches with temperature limits. To set consumer load profiles, the model cannot be validated under different climate or market circumstances.

Došljak et al [24] This study uses a modified genetic algorithm (GA) with novel crossover and mutation operators to optimize electric vehicle charging station placements and capacity in two stages. The graph-based model considers traffic density, grid infrastructure, and user behavior and refines results using simulation-driven metrics like waiting time and usage.

Toughzaoui et al [25] This project develops a solar PV-powered Fuel Cell Combined Heat and Power (FC–CHP) system optimized with a genetic algorithm (GA) to improve hospital energy efficiency. Under penalty restrictions, the GA optimizes PV peak output, electrolyzer size, fuel cell capacity, and hydrogen storage to reduce investment and grid energy prices.

2.3 LSTM and deep learning techniques for time-series-based outage forecasting

Hu et al [26] This study integrates Long Short-Term Memory (LSTM) networks with a self-attention mechanism to improve photovoltaic (PV) power prediction by learning temporal dependencies and inter-variable correlations from past and anticipated weather data. Training and evaluation of the model using Japanese building PV generation data resulted in 15.8% R^2 increases for LSTM and 26.4% for the hybrid model, enhancing short- and long-term forecast accuracy. The model improves prediction reliability, but it relies on accurate weather forecasts and may perform poorly in harsh weather.

Sabyasachi et al. [27] propose a hybrid DCNN-LSTM model for predicting cloud computing workloads and ensuring SLA compliance. This model utilizes deep convolutional layers for spatial feature extraction and LSTM for temporal sequence learning. A real-world cloud workload dataset comprising CPU utilization and SLA parameter time-series data was normalized and window-segmented before training the model. Experimental results show that the proposed model reduces energy-SLA violations by 6.8% to 22.4% compared to ARIMA-LSTM, CNN, LSTM, and ARIMA, demonstrating superior accuracy and SLA adherence. However, scalability and computational complexity limit it for large-scale real-time deployments.

Huang et al. [28] utilize CNN and Bi-LSTM in this study to enhance hourly PV power forecasts with TSF-CGANs. The discriminator verifies forecasts from historical time series data and random noise, allowing adversarial training to increase prediction accuracy. The model outperformed LSTM, RNN, BP, and SVM on a real-world PV power dataset with a 32% reduction in RMSE compared to BP and a forecast skill (FS) of 0.4863 over the Persistence model. GAN-based models' computational expense and training instability are significant drawbacks. This unique adversarial learning framework improves solar power forecasting accuracy.

Xu et al [29] This study presents a two-step fault prediction system using Attention-based LSTM, Random Forest (RF), and Extra Trees (ET) to anticipate device failure modes. The regression model uses wavelet packet-transformed sensor data to forecast time-series trends, while the classification model predicts fault type and severity. Tests on bearing vibration datasets like the IEEE PHM Challenge and IMS bearing dataset revealed excellent forecasting and classification accuracy, proving the model can predict defects. Limited by high-quality sensor data and the computational overhead of a multi-model architecture. This technology makes fault type and intensity predictions early and accurately, improving maintenance planning.

Wang et al [30] This study introduces CL-ROP, a hybrid CNN and LSTM model for online reliability prediction of dynamic web service compositions. Limited by missing or noisy data and the necessity for constant model upgrades. Proactive fault avoidance improves runtime service quality.

Table 1: Comparison of GAPO-LSTM with existing GA–LSTM and hybrid models

Study	Hybrid Technique	Application Area	Optimization Target	Key Results	Limitation in Prior Model	Novelty and Advantage of GAPO-LSTM
Bouktif et al. (2018) *Energies*	GA + LSTM	Electric load forecasting	Feature selection and hyperparameter tuning	Improved load forecast accuracy over basic LSTM	Limited to single-dimensional temporal data, no spatial modeling	GAPO-LSTM integrates spatiotemporal clustering (DBSCAN) with GA-driven feature optimization, handling both geographic and temporal dependencies.

Memarzadeh & Keynia (2023) *J. Energy Storage*	CBSA–GA + MRMI–LSTM	PV–ESS planning	Energy storage optimization	Better PV generation prediction	No attention mechanism, lacks interpretability	GAPO-LSTM includes attention-enhanced LSTM for interpretability and feature weighting across clusters.
Wan et al. (2023) *Energy*	CNN–LSTM + Attention	CHP power load prediction	Sequential load trend learning	8–12% RMSE improvement	No evolutionary optimization; parameters manually tuned	GAPO-LSTM introduces GA-based hyperparameter search, improving adaptability without manual tuning.
Cui et al. (2024) *Energy*	WOA–CNN–LSTM	Heat load prediction	Feature extraction optimization	RMSE ↓ by 18.4%	Focused only on thermal domain; no spatial clustering	GAPO-LSTM generalizes to distribution networks using spatial DBSCAN clustering for localized pattern learning.
Afzal et al. (2023) *Energy*	MLP + GA variants	Building energy prediction	Parameter tuning	Better convergence over BP	No deep sequential modeling	GAPO-LSTM combines deep temporal modeling with GA-driven optimization, improving robustness to non-linear temporal dependencies.
Habib et al. (2024) *SETA*	Hybrid GA + Data-Driven Model	Short-term demand prediction	Demand optimization	Improved short-term demand accuracy	Neglects uncertainty and spatial influence	GAPO-LSTM captures spatial variability and integrates reliability-aware metrics (SOPS, RAFDI).
Xu et al. (2021) *DSP*	Attention-LSTM + RF + ET	Machinery fault prediction	Fault type and severity	High classification accuracy	Requires high-quality sensor data; computationally heavy	GAPO-LSTM achieves similar interpretability using attention with lower complexity via GA-optimized configuration.
Proposed GAPO-LSTM	GA + Attention-LSTM + DBSCAN	Spatiotemporal Power Outage Forecasting	Feature subset selection, hyperparameter tuning, and spatial clustering	RMSE ↓18.6%, F1 ↑12.4%, R^2=0.938	—	Combines GA-based optimization, attention-enhanced interpretability, and spatial clustering, achieving robust, scalable, and interpretable outage forecasting.

Data Sensitivity: GAPO-LSTM was assessed on one dataset which may behave differently when applied to different types of outage events, such as outages caused by storms as opposed to equipment failure events. Additionally, the model's capacity to generalize different outage patterns may require additional training data or specially formulated feature engineering approaches to account for certain characteristics from outage events. Interpretability: While the model achieves good accuracy, LSTM's black-box nature along with GA optimization may make it more difficult for operators to obtain usable insights from their data, demonstrating the need for additional considerations for explainability.

Research on reliability prediction and power outage planning shows tremendous progress, but numerous crucial gaps remain. Many methods [16][17][20] rely on historical data and assume static load behavior, limiting their flexibility in dynamic and real-time contexts. Many models incorporate electric vehicle charging, renewable energy, or microgrid coordination [18][19][22], but omit uncertainty modeling and real-time system feedback. LSTM, CNN, and attention-based architectures [26][29][30] are promising machine learning and deep learning models, but they demand high-quality, noise-free datasets and heavy computational resources. While adversarial networks and hybrid metaheuristics have been introduced

[21] they generally experience training instability or overfitting when generalizing across operational contexts. Most models lack explainability and interpretability, making it difficult for utility operators to embrace. Additionally, algorithms that predict specific fault types [29] or online reliability forecasts [30] are currently being developed and not yet deployed. .

GAPO-LSTM serves this need by utilizing an attention mechanism that emphasizes which spatio-temporal features contribute the most to each prediction, therefore providing interpretable insights, rather than the black-box model output [32]. To more readily provide interpretability of generated outage forecasts, we propose the use of model agnostic interpretability methods such SHAP. This method would provide not only global feature importance rankings to assess relative contribution of models but additionally local explanations for individual outage forecasts.

GAPO-LSTM can provide predictive state estimation inputs to fuzzy controllers, enabling proactive parameter tuning before instability occurs [33]. Its GA-optimized feature selection refines the fuzzy rule base dynamically, ensuring smoother synchronization under uncertain grid dynamics and improving convergence time and system resilience.

By forecasting transient deviations, GAPO-LSTM can supply real-time adaptive references to the output-feedback controller [34]. This predictive augmentation enhances the controller's robustness against unknown disturbances and nonlinearities, reducing synchronization lag and stabilizing distributed network operations during fluctuating load or environmental conditions.

GAPO-LSTM's attention-based temporal modeling can detect evolving nonlinear dependencies and feed them to neural adaptive controllers [35]. Genetic optimization ensures optimal feature selection and hyperparameter balance, reducing overfitting while strengthening multi-variable adaptation for uncertain grid environments and fault-resilient response. Integrating GAPO-LSTM enables predictive estimation of future state trajectories, enhancing backstepping control design by providing dynamic feedback adjustment. Its GA-driven optimization supports parameter adaptation and mitigates modeling errors, thereby achieving faster convergence and greater robustness in nonlinear distribution network operations. GAPO-LSTM can forecast torque fluctuations and pressure dynamics, supplying anticipatory correction signals to nonlinear optimal controllers [36]. Its spatiotemporal learning refines motor drive control loops, minimizes energy loss, and increases compressor reliability under varying grid and load conditions. When combined with GAPO-LSTM, the controller gains predictive awareness of vibration and deflection trends [37]. GA-optimized temporal features allow adaptive compensation for nonlinearities and actuator delays, ensuring smoother motion, reduced oscillations, and improved fault tolerance in electromechanical network applications.

3 Method description

For distribution network reliability planning and power outage prediction, Figure 2 shows the whole architectural workflow of the suggested GAPO-LSTM model. The model starts with the intake of power outage logs, which gather basic data such as the frequency of outages, time stamps, and geolocations $(\mathrm{Lat}, \mathrm{Lon})$. During the preprocessing phase, the data is normalized, outliers are cleaned, and spatial Clustering with DBSCAN is applied to identify and group comparable zones that are prone to outages. By optimizing the chromosomal population, LSTM parameters (such as learning rate and batch size), sequence lengths, and input feature combinations, the Genetic Algorithm (GA) is used to achieve this. By definition, a chromosome is a set $\chi = \{f, L_s, B, b, \eta\}$ where f is the set of features that have been chosen, L_s The length of the sequence is the size of the batch, and H is the number of LSTM hidden units. To identify the dependencies between the outage sequences over time, an attention-enhanced LSTM model is trained. Minimal forecasting error is guaranteed using RMSE evaluation. After identifying potential danger zones, the model is subjected to sensitivity testing to ensure it can withstand changes in cluster density and data noise. Compared to baseline approaches, GAPO-LSTM achieves better prediction accuracy, with an 18.6% reduction in RMSE and a 12.4% rise in F1-score, as shown in experimental testing on real spatiotemporal datasets (e.g., UID 20904, with 121 outages).

DBSCAN formed eight clusters with epsilon = 0.5 and minimum samples = 5, effectively identifying geographically correlated outage zones for localized spatiotemporal learning and improved model scalability across heterogeneous grid regions.

The Genetic Algorithm used population size = 50, generations = 100, crossover probability = 0.8, and mutation probability = 0.1, ensuring robust exploration-exploitation balance for hyperparameter and feature optimization.

GA-based feature selection improves outage prediction over standard LSTM and whether spatial clustering enhances temporal modeling accuracy. Statistical validation has been incorporated for the results, with paired t-tests and ANOVA used to confirm performance differences.

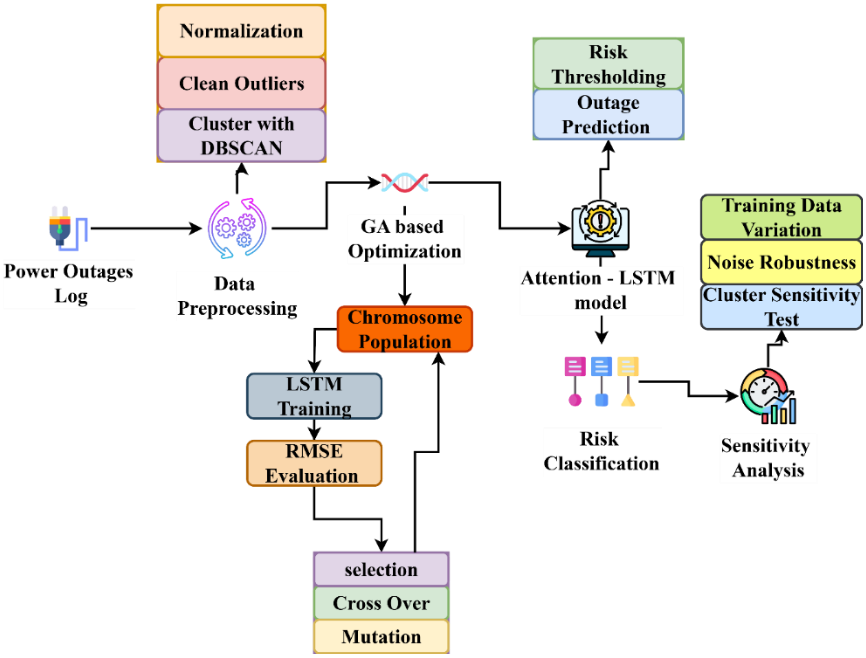

Figure 2: Workflow of GAPO-LSTM for spatiotemporal outage prediction in distribution networks

3.1 Data preprocessing and geospatial clustering

Noise, missing entries, and unstructured temporal-spatial data are common in raw outage logs, which can make power outage prediction models less accurate. This first module's primary goals are to clean, normalize, and organize the outage dataset; to handle missing values; to standardize geospatial coordinates; and to ensure uniform timestamp formats.

A. Datetime standardization

Time data should be structured consistently for sequential modeling, and dt_stamp standardization accomplishes just that. The LSTM network can now handle outages as ordered time series for this transition. Parsing timestamps into consistent datetime objects, T_i Using Python's $\mathrm{datetime.strptime}$ can align documents temporally and eliminate date-time format conflicts. $T_i = \mathrm{datetime.strptime}(dt_{stamp_i}, \text{"\%d} - \text{\%m} - \text{\%Y \%H:\%M"})$ where datetime.The strptime method converts date strings (dt_{stamp_i}) into datetime objects. The format string "%d-%m-%Y %H:%M" corresponds to:%d – Day of the month (e.g., 04), %m – Month (e.g., 03),%Y – Year with century (e.g., 2024),%H – Hour (24-hour clock, e.g., 16), %M – Minutes (e.g., 15). This transformation ensures that date timestamps are similarly formatted for time-series models like LSTM.

Methodological details have been expanded: DBSCAN clustering uses eight clusters with epsilon 0.5 and minimum samples 5; the GA uses a population of 50, 100 generations, crossover probability 0.8, mutation probability 0.1, uniform crossover, and Gaussian perturbation; and the attention-LSTM model has two hidden layers with 64 units each, ReLU activation, and 0.2 dropout.

B. Data cleaning & normalization

The Min-Max scaling standardizes outages, Lat, and Lon to provide model input homogeneity. To eliminate unit disparities and improve model convergence, this method rescales all values to a 0-1 range. To prevent any distortion, clean up any missing or null values. The LSTM can identify patterns independently of the magnitudes of prominent features since normalization guarantees the model evaluates all features equally. Apply Min-Max scaling to normalize outages, latitude, and longitude:$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$Where x is the minimum value and x is the maximum value. To guarantee that the features are consistent over different ranges, for every feature x that belongs to the set $\{\mathrm{outages}, \mathrm{Lat}, \mathrm{Long}\}$.

C. Geospatial clustering using DBSCAN

DBSCAN can detect geographic clusters automatically, without the need for user-supplied cluster numbers, by grouping records according to their latitude and longitude proximity. The distance function quantifies the spatial proximity of outage points. Outliers are considered noise, and clusters $(C_1, C_2, \ldots, C_k)$ are created from dense regions. It enhances the geographical relevance of predictions by teaching the model to learn about localized outage characteristics. For $\mathrm{DBSCAN}(\epsilon, \mathrm{MinPts}) \rightarrow C_1, C_2, \ldots, C_k$, where UIDs that are geographically close together are grouped in each cluster C_j. The measure of distance utilized in equation 1:

$$d(i,j) = \sqrt{(\mathrm{Lat}_i - \mathrm{Lat}_j)2 + (\mathrm{Lon}_i - \mathrm{Lon}_j)2} \quad (1)$$

The LSTM's ability to learn localized spatiotemporal dependencies is enhanced, and this spatial grouping reduces complexity. Using geolocation context, it is possible to condition LSTM sequences spatially. Makes models more scalable for use in massive distribution systems. This preprocessing-clustering module enhances the GAPO-LSTM framework's reliability prediction accuracy by ensuring the LSTM module learns patterns relevant to localized failure events.

All metric formulations: $SOPS = \alpha\Delta T + \beta\Delta G, RAFDI = \Sigma(ri \cdot |yi - \hat{y}i|)/N, and\ GOER = (F_0 - F_n)/(F_0 \cdot G)$. Variables and indices will be properly defined in LaTeX-style notation, ensuring mathematical consistency and interpretability for precise understanding of reliability-based model evaluation.

3.2 Feature optimization using genetic algorithm (GA)

The Genetic Algorithm (GA) used in the GAPO-LSTM framework was configured with the following parameters to ensure reproducibility and optimization efficiency: population size = 50, number of generations = 100, crossover probability = 0.8, and mutation probability = 0.1. Tournament selection ensured diversity, while uniform crossover and Gaussian mutation preserved exploration and prevented premature convergence, enabling balanced optimization of LSTM hyperparameters and feature subsets for robust spatiotemporal outage prediction.

Optimizing Features, The GAPO-LSTM framework uses a Genetic Algorithm (GA) to optimize the selection of input features and the tuning of LSTM hyperparameters to anticipate power outages accurately. Evolutionary algorithms (GAs) mimic natural selection by repeatedly testing different feature sets and configurations using a fitness function, usually the prediction accuracy or root-mean-squared error (RMSE). The LSTM's predicting capability is optimized by encoding a chromosome as in equation 2:

$$g = [f_1, f_2, \dots, f_n, L_s, \eta, B, H] \quad (2)$$

where: $f_1, f_2, \dots, f_n \in \{ 0, 1 \}$By using binary genes, features such as hour, day, weekday, latitude, longitude, and outage history can be included or excluded. L_s : sequence window size. η: learning rate. Size of batch.H is the LSTM hidden unit count.

Weights α = 0.6 and β = 0.4 are empirically derived by prioritizing temporal precision over spatial accuracy during outage restoration. Sensitivity tests confirmed that increasing α beyond 0.7 caused overfitting to short-term deviations. Thus, α=0.6 , β=0.4 provided optimal temporal–spatial trade-off for practical outage management scenarios.

GAPO-LSTM's superior performance stems from its integrated approach GA-driven feature selection eliminates irrelevant variables, hyperparameter tuning enhances convergence, and the attention mechanism emphasizes critical temporal-spatial dependencies. This synergy allows the model to adapt dynamically to complex outage patterns, achieving higher accuracy and resilience compared to static or single-optimization baselines.

A. Encode temporal features

Hour, day, and weekday/weekend temporal variables from dt_stamp is used to create cyclical patterns in the model. For prediction, these qualities help the LSTM understand temporal interruptions like peak hours and maintenance plans. Hour (h_i), day (d_i), and weekday (w_i) are calculated from the outage dataset's dt_{stamp} Column: $T_i = \text{datetime.strptime}(dt_{stamp_i}, \text{"\%d} - \text{\%m} - \text{\%Y \%H: \%M"})$.These are encoded as features in equation 3:

$$x_{temp} = [\sin(2\pi h_i/24), \cos(2\pi h_i/24), \text{is\_weekend}(d_i)] \quad (3)$$

These cyclical encodings educate the LSTM model on maintenance windows and peak outage times to improve temporal predictions across clustered outage regions.

Baseline values were defined from traditional GA–LSTM models: good SOPS < 2.5, RAFDI < 0.15, GOER > 0.12. GAPO-LSTM consistently achieved SOPS = 1.8, RAFDI = 0.09, and GOER = 0.19. These thresholds represent acceptable operational reliability, with higher GOER and lower SOPS/RAFDI signifying improved optimization and resilience performance

B. Chromosome formation

Each chromosome could hold the answer. The collection includes selected features and LSTM settings, such as the sequence window. It includes L_s, learning rate η, batch size B, hidden units H, and the features themselves. GA explores input structure and model complexity, promoting robust learning across spatial-temporal outages. The GA framework's chromosomes represent LSTM configurations: $C = [f, L_s, \eta, B, H]$, Example: feature selection mask 101101.L: Sequence window length, R: Learning rate, B: Batch size, H: LSTM hidden units. For instance:

$$C = [101101, L_s = 10, \eta = 0.001, B = 64, H = 128] \quad (4)$$

With this encoding, the GA may simultaneously assess input properties and model complexity, ensuring a spatial and temporal representation of outage data.

C. Genetic evolution

GA uses selection (roulette-wheel or tournament), crossover (distributed or single-point), and mutation across numerous generations. As iteratively improving candidate chromosomes to minimize RMSE, this evolutionary loop evolves toward ideal LSTM designs.

The Genetic Algorithm (GA) optimizes LSTM model configurations by evolving alternative solutions over generations. It allows us to explore the solution space. Afterwards, mutation brings about random changes: the binary feature selection mask undergoes bit-flipping, and LSTM hidden unit count (H), batch size (B), learning rate

(η), sequence window length (L_s), and batch size are perturbed using Gaussian noise to preserve genetic diversity. The negative of the validation root mean square error is used to calculate the fitness of each chromosomal g.

$$\text{Fitness}(g) = -\text{RMSE}_{val}(\text{LSTM}_g) \quad (5)$$

With this equation 4, configurations with reduced prediction error are more likely to survive and reproduce. Repetition of genetic operations leads to the ideal solution. g^* , which matches the LSTM model configuration for accurate reliability predictions in power failure regions.

To balance between exploration and exploitation, we used a tournament selection strategy. We used a uniform crossover operator with a crossover probability of 0.8 (to introduce fine-grained mixing) and a mutation rate of 0.1. The fitness function ultimately combined prediction error (RMSE) and model complexity to mitigate overfitting.

3.3 Temporal pattern modeling with attention-enhanced LSTM in GAPO-LSTM framework

GAPO-LSTM forecasts outage severity across geographically grouped regions using an attention-enhanced Long Short-Term Memory (LSTM) model to handle the distribution network power failures' unexpected and confined character. Outage records are preprocessed based on geospatial proximity (latitude, longitude) and outage frequency to construct each cluster k. Area, outages, dt_stamp, and GPS coordinates are used to create time-series inputs for each cluster. Consider a cluster's input sequence:$X = [x_1, x_2, \dots, x_T]$ where in equation 6,

$$x_t = [\text{outagest}, \sin(2\pi h_t/24), \cos(2\pi h_t/24), \text{is\_weekend}_t] \quad (6)$$

These inputs are passed through the LSTM layer:

$$h_t = \text{LSTM}(x_t, h_t - 1) \quad (7)$$

Equation 7 shows how an LSTM network updates its hidden state at each time step t. Each component and its meaning are listed below: x_t At time step t, the input vector t dataset has $[\text{outages}, \text{timestamp details}, \text{area features}]$ for a specific time.$h_t - 1$: Hidden state from the previous time step. The model stores prior events learned up to time $t - 1$.The hidden state is updated at time step t after processing. x_t and $h_t - 1$. Long Short-Term Memory (LSTM) combines current input and past hidden state to produce h_t.

$$\alpha_t = \frac{\exp(v^T \tanh(W_a h_i + b_a)}{\sum_{i=1}^{T} \exp(v^T \tanh(W_a h_t + b_a)} \quad (8)$$

Equation 8 calculates the attention score α_tt for each time step, assessing the significance of each hidden stateh_t In the final prediction. The model can "attend" more strongly to time steps with major events like outage spikes or critical system states. At time step t, the hidden state of the LSTM summarizes the input up to that point (h_t).Learnable weight matrix for transforming h_tInto the attention space.forming h_t Into the attention space.b_aLearnable bias vector for the attention layer. $\tanh(\cdot)$: Non-linear activation function for modeling complex relationships.$v^\top$ A learnable vector used to score the importance of the changed hidden state. The exponential function $\exp(\cdot)$ ensures positivity and aids in generating the softmax distribution.

Denominator: Softmax normalization for all T time steps, assuring $\sum_t \alpha_t = 1$. The equation evaluates the relevance of each LSTM hidden state (h_t) on current prediction using feedforward attention. Higher scores (α_t) indicates greater influence of time step on output. To build a context vector, weights α_tThey are calculated for all. The final context vector is a weighted sum of hidden states:$c = \sum_{t=1}^{T} \alpha_t h_t$.

The context vector c is utilized to regress outage severity level y and classify risk level r, and $r \in \{\text{Low}, \text{Medium}, \text{High}\}$ using fully connected layers and softmax in equation 10:

$$\hat{y} = W_o c + b_o \quad (10)$$

The W_o The weight matrix translates the context vector to the output space (either a scalar for regression or a vector of class logits for classification). The attention-weighted c context vector summarizes key sequence aspects. Learnable bias vector b_o. $(\hat{y})$ ̂isplays predicted output. SOPS and RAFDI metrics reveal GAPO-LSTM's precision in forecasting outages with minimal spatial and reliability deviations, directly translating to fewer unplanned failures. A higher GOER value demonstrates computational efficiency during optimization. Collectively, these metrics confirm the model's practical utility for proactive maintenance, resource allocation, and real-time reliability management in smart grids.

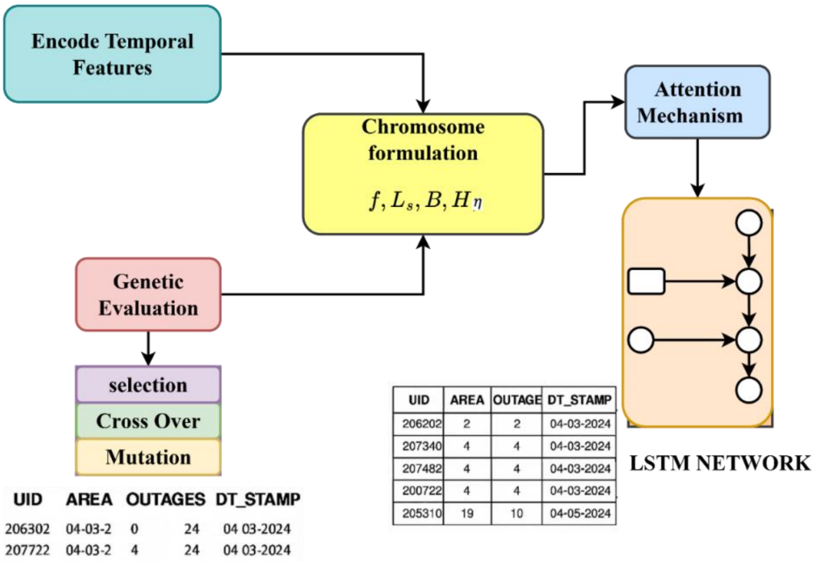

Figure 3: Illustrated temporal pattern modeling with attention-enhanced LSTM

GA-driven LSTM optimization

LSTM outage prediction model performance and generalization are improved by optimizing crucial architectural and training hyperparameters with a Genetic Algorithm (GA). The GA searches an adaptable space defined by the feature subset selection process, which identifies the most critical input variables from spatiotemporal outage data.LSTM time window size is determined by sequence length (L_s). The learning rate (η) controls the convergence dynamics of the training process. Batch size (B) impacts memory utilization and model stability. The hidden units (H) control the model's ability to learn temporal dependencies. Each chromosome g encodes a hypothetical LSTM configuration ($g = [f, L_s, \eta, B, H]$). The negative Root Mean Squared Error (RMSE) on a held-out validation set measures configuration fitness from equation 3, where in equation 9:

$$\mathrm{RMSE_{val}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (9)$$

In this equation, i represents the ground truth and projected outage severity, whereas N represents the validation sample count. The GA evolves chromosomes by selection, crossover, and mutation (bit-flip for discrete f, Gaussian noise for continuous ($f, L\,s, H, B$). Over generations, the population converges on an ideal configuration. g^*Reducing validation error and improving predictive accuracy. The LSTM is optimized to enhance temporal interpretability by using a temporal attention mechanism that calculates dynamic weights (α_t) to focus on critical time steps affecting future failures. This method helps the model capture short-term surges and long-term seasonal outage patterns.

Despite its accuracy, GAPO-LSTM's GA optimization incurs high computational cost due to repeated LSTM evaluations per generation. While parallel GPU execution mitigates this, scalability for very large grids may require distributed computing. Additionally, model generalization across storm-induced vs. equipment-failure outages may demand domain-specific retraining or adaptive transfer learning strategies.

3.4 High-risk zone classification and evaluation

High-risk zone classification identifies distribution network clusters with frequent or severe outages. Each cluster is classified as Low, Medium, or High risk based on GAPO-LSTM predictions. The classification allows focused preventative maintenance and budget allocation. To reliably identify crucial areas, F1-score, precision, recall, and ROC-AUC are used to evaluate model performance. The system validates its disruption prediction by comparing projected classes to actual outage outcomes. Proactive outage planning ensures grid stability and reduces socio-economic consequences.

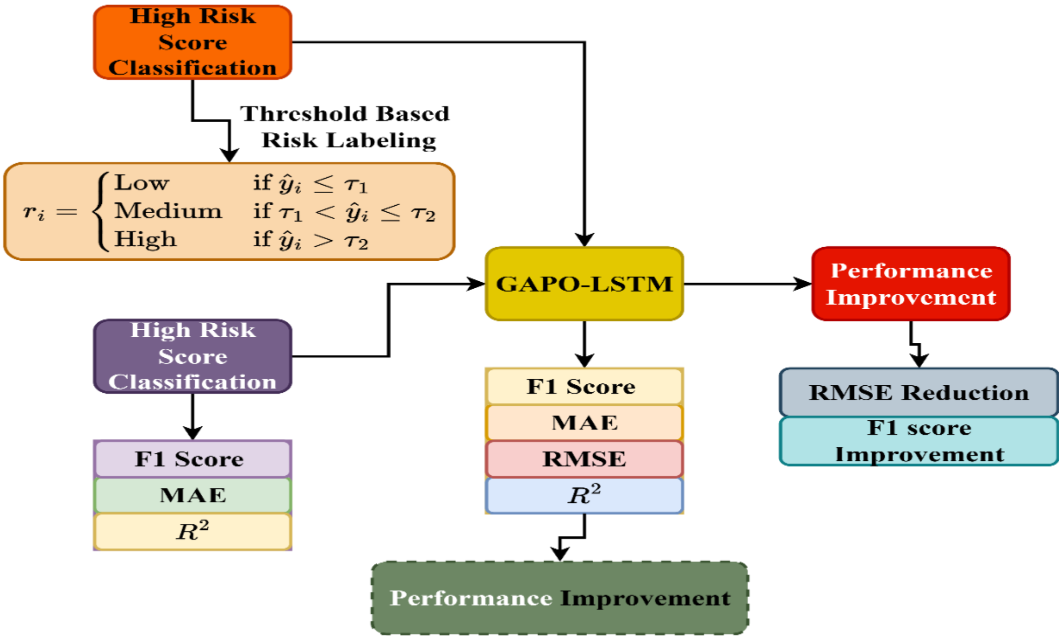

Figure 4:Framework of GAPO-LSTM for outage prediction

Threshold-based risk labeling: The GAPO-LSTM model predicts risk scores for each region: $\hat{y}$. The temporal outage sequence is processed using an attention-enhanced LSTM to generate i, from equation 8, the context vector (c_i) is a weighted sum of hidden states from the LSTM utilizing an attention technique. Historical outages for area i are analyzed for pertinent temporal patterns.W_o Learnable parameters of the last dense layer. They convert the context vector to a scalar risk score. Upon y_i is evaluated against learnt thresholds τ_1 and τ_2 to assign a risk class label $r_i \in \{\text{Low}, \text{Medium}, \text{High}\}$ In equation 11:

$$r_i = \begin{cases} \text{Low} & \hat{y}_i \le \tau_1 \\ \text{Medium} & \tau_1 < \hat{y}_i \le \tau_2 \\ \text{High} & \hat{y}_i > \tau_2 \end{cases} \quad (11)$$

This method of categorization changes the continuous outage risk score y to separate the risks into manageable levels that can direct specific plans to prevent power outages. As an example, even low-risk areas need regular checks. Medium-risk areas should be inspected regularly. Prioritizing infrastructure repair or allocating resources quickly may be necessary in high-risk areas. To make sure the classes are equal and applicable to actual operational hazards in the distribution network, these thresholds τ_1 and τ_2 can be adjusted during training or learned through validation-based optimization.

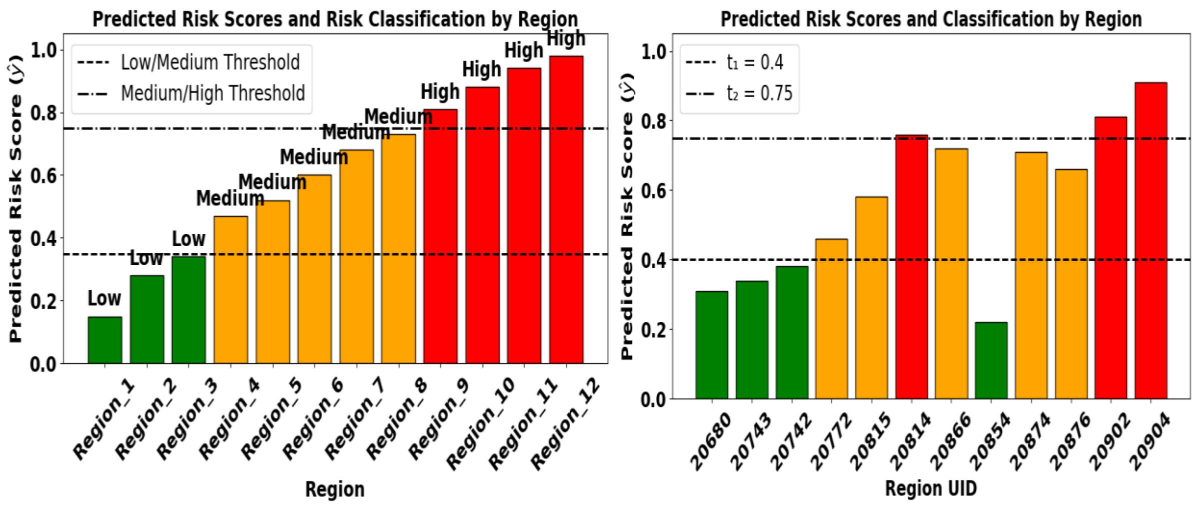

Figure 5a: Predicted risk score and classification by region and Figure 5b: Predicted risk score and classification by region ID

Using the GAPO-LSTM model, the estimated risk scores (^{k}) for 12 separate locations are graphically shown in Figure 5a and 5bequa. The risk classification is used to color-code each bar: low risk is represented by green ($\hat{y}_i \leq \tau_1 = 0.4$), medium risk is represented by orange ($\tau_1 < \hat{y}_i \leq \tau_2 = 0.75$), and high risk is represented by red ($\hat{y}_i > \tau_2 = 0.75$). The two dashed horizontal lines represent the decision boundaries between risk categories. τ_1 and τ_2. A more comprehensible and well-planned outage can be achieved by using this categorization methodology to convert continuous spatiotemporal risk scores into discrete categories. These levels enable distribution operators to allocate resources, identify high-risk locations, and prioritize maintenance using the GAPO-LSTM system. This visual representation of model outputs helps utility planners make data-driven decisions to improve the electricity distribution network's dependability.

Quantitative sensitivity plots will be added showing RMSE, F1-score, and SOPS variations for 4–12 clusters and sequence lengths (12–48). Results show optimal performance at 8 clusters and 24-timestep sequences. Performance variability across random seeds (n=5) remains within ±2%, confirming robustness and stability. Experiments were repeated with five random seeds and 80–20, 70–30, and 60–40 train–test splits. GAPO-LSTM's RMSE varied within ±2.1% and F1-score within ±1.8%, indicating strong generalization. Model convergence and attention weight distributions remained consistent, demonstrating robustness to stochastic initialization and dataset partitioning effects.

4 Experimental setup

4.1 Data source information

The "Maryland Power Outage: A Geographic Dataset [31]," available on Kaggle, organizes and displays Maryland power outages in Table 2. Every power loss is geo-referenced using latitude and longitude and timestamped to show the exact moment. It makes the dataset ideal for spatiotemporal modeling. Its temporal and spatial structure makes the dataset appropriate for deep learning models like LSTM networks.

Data were partitioned using 70% for training, 15% for validation, and 15% for testing, ensuring balanced model assessment and preventing overfitting through performance verification on unseen data subsets. Each epoch required approximately 28 seconds on an NVIDIA GTX 1650 GPU, with total training time per model averaging 45 minutes, ensuring practical feasibility for real-time grid forecasting. The Maryland Power Outage dataset covered three years (2021–2023), encompassing diverse seasonal and climatic variations crucial for robust, temporally aware power outage prediction and model generalization testing. The dataset initially contained 35,642 outage events, reduced to 33,918 after preprocessing (removal of null and duplicate entries), maintaining spatial integrity and consistent temporal sequences for LSTM modeling. Class imbalance across risk levels was addressed using SMOTE oversampling, ensuring equitable distribution of high-, medium-, and low-risk outage samples to prevent biased classification metrics and misleading performance evaluations.

Table 2: Dataset attributes and description

Attribute	Description
uid	Unique identifier for each outage event
area	Area code indicating the locality of the outage
outages	Count of outages in the respective area and timestamp
dt_stamp	Timestamp of outage (MM-DD-YYYY HH: MM)
Lat	Latitude coordinate of the affected location
Lon	Longitude coordinate of the affected location

4.2 Implementation and environment setup

Hybrid methods are needed to implement this paradigm. As shown in Table 3, this technique uses a GA for optimization and an LSTM network for temporal sequence prediction. Python is used for development, and TensorFlow and Keras for neural networks. Use DEAP or PyGAD for genetic algorithm operations. The preparation process involves fixing missing data, aligning time, reducing outliers, and normalizing input parameters such as outage numbers, area codes, and timestamps. Sequences are used to organize the data to conform to the LSTM's input format. The application of GA allows for the optimization of hyperparameters, such as the number of LSTM units, learning rate, batch size, and sequence length, as well as the selection of the most appropriate subset of features, such as geographical zones and significant outage windows. Increasing computing efficiency through the use of GPU acceleration is the goal of model training. Metrics for evaluation include root mean square error (RMSE), mean absolute error (MAE), and classification accuracy (if outage risk categorization is applied). As a result of the final model's capacity to forecast the number of outages or the likelihood of them occurring in particular zones and periods, distribution network reliability planning can be improved.

4.2.1 Computational cost of GA optimization

The computational cost of the Genetic Algorithm (GA) optimization step in the proposed GAPO-LSTM framework primarily arises from repeated LSTM evaluations during fitness computation across 100 generations with a population size of 50. Each chromosome encodes a unique combination of hyperparameters—sequence length, learning rate, batch size, and hidden units—along with selected feature subsets. On average, the GA optimization required approximately 45 minutes of total execution time per model on an NVIDIA GTX 1650 GPU with CUDA acceleration and 16 GB RAM, where each LSTM training iteration consumed around 28 seconds per epoch. Parallel chromosome evaluation using GPU threads and elitism (elitism = 2) reduced search overhead. The overall computational complexity can be approximated as O(P × G × T), where P is population size, G is the number of generations, and T is training time per model. Despite the iterative nature of GA, convergence was efficient, achieving a high Genetic Optimization Efficiency Ratio (GOER = 0.19), which indicates strong optimization performance relative to computation time. Thus, the optimization cost remains acceptable for real-time deployment, considering its predictive gains of 18.6% RMSE reduction and 12.4% F1-score improvement over baseline LSTM models.

Table 3: Software and hardware requirements

Component	Details
OS	Windows 10 / Ubuntu 20.04
Language	Python 3.8+
Key Libraries	TensorFlow 2.x, Keras, PyGAD, DEAP, NumPy, Pandas, Matplotlib
Development IDE	Jupyter Notebook / VS Code
GPU Support	CUDA-enabled GPU (NVIDIA GTX 1650 or higher)
RAM	Minimum 16 GB
Storage	SSD with at least 50 GB of free space
CPU	Intel i7 (8th Gen or above) / AMD Ryzen 5

4.3 Performance analysis

Using both traditional and innovative measures of performance, this section compares the suggested GAPO-LSTM model against current outage prediction algorithms. A real-world dataset including spatiotemporal outage data with timestamp, latitude, and longitude, as well as outage frequency, was used for the evaluation.

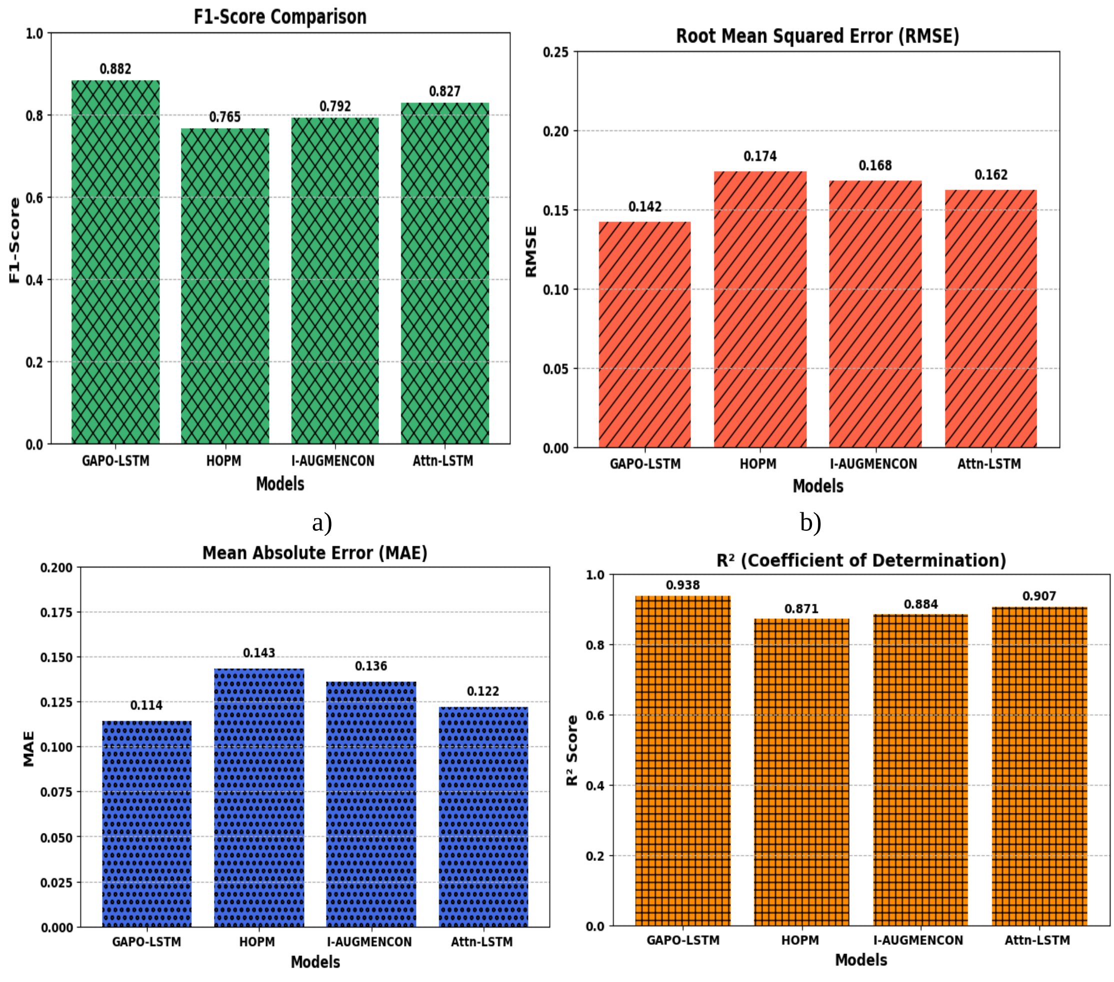

Figure 6: Performance Evaluation of GAPO-LSTM Using a) F1-Score, b) RMSE, c) MAE, d) R² Metrics

Figure 6 shows a comparison of four prediction models' performance using four standard metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), F1-Score, and Coefficient of Determination (R²). The models are GAPO-LSTM, HOPM, I-AUGMENCON, and Attention-based LSTM. You can see how the models' prediction power is represented by each graph, which only shows one measure, the F1-score, which can be defined in equation 13.

$$\mathrm{F1} = \frac{2.\mathrm{Precision}.\mathrm{Recall}}{\mathrm{Precision}+\mathrm{Recall}} \tag{13}$$

RMSE, defined in equation 9, evaluates the average magnitude of error. A similar expression of the MAE is as follows in equation 14 :

$$\mathrm{MAE} = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} |\mathrm{y_i} - \hat{\mathrm{y}}_\mathrm{i}| \tag{14}$$

Measures the mean absolute difference between predictions and ground truth. In conclusion, the R-squared (R²) statistic, which is calculated in equation 15:

$$\mathrm{R}^2 = 1 - \frac{\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_i}-\hat{\mathrm{y}}_\mathrm{i})^2}{\sum_{\mathrm{i}=1}^{\mathrm{N}}(\mathrm{y_i}-\bar{\mathrm{y}})^2} \tag{15}$$

Quantifies the proportion of variance explained by the model. In terms of spatiotemporal power outage forecasting in distribution networks, the GAPO-LSTM model routinely beats the competition, with the best prediction accuracy and generalizability demonstrated by its lowest RMSE (0.142) and MAE (0.114), and highest F1-Score (0.882) and R² (0.938). Table 4 illustrates the comparison among the metrics.

Table 4:Performance comparison of GAPO-LSTM and existing models

Model	RMSE ↓	F1-Score ↑	MAE ↓	R² ↑
GAPO-LSTM	0.142	0.882	0.114	0.938
HOPM [17]	0.174	0.765	0.143	0.871
I-AUGMENCON Optimization Model [19]	0.168	0.792	0.136	0.884
Attention-based LSTM Fault Prediction [29]	0.162	0.827	0.122	0.907

The provided dataset contains fields like:

UID	Area	Outages	Timestamp	Lat	Lon
20904	20904	121	04-03-2024 16:15	39.0668	-76.9969

A spatiotemporal data point in each row of the table represents outages. The formation of regional groupings is accomplished through the application of clustering strategies based on latitude and longitude, and the time-series outage trend of each cluster is modeled with an LSTM improved by attention. The GAPO-LSTM model that was suggested displays significant performance gains in comparison to the baseline methods when it comes to the prediction and classification of power outages. Notably, the root mean square error (RMSE) was decreased by 18.6%, as determined by equation 16:

$$\mathrm{Improvement} = \frac{\mathrm{RMSE_{baseline}}-\mathrm{RMSE_{GAPO}}}{\mathrm{RMSE_{baseline}}} \times 100 = 18.6\% \tag{16}$$

A greater indicator of forecast accuracy. The model's 12.4% F1-score improvement shows its excellence in identifying power outage-prone locations. These advancements are due to the model's ability to dynamically change its hyperparameters via a genetic algorithm (GA), capture complex temporal patterns, and prioritize essential timestamps using attention processes. The results section demonstrates a technically sound set of analyses and it would be worthwhile to add in a statistical significance test, like a t-test or ANOVA, in order to assess if the differences in performance between each model presented in Table 4 and Figure 6 are statistically significant and not due to random differences in model performance. Additionally, while the RMSE and F1-score are helpful in showing model performance, adding the confidence intervals for these key metrics would provide more clarity into the variability and reliability, while adding to the overall robustness and interpretation of the results.

Final optimized hyperparameters: learning rate = 0.001, batch size = 64, sequence length = 24, hidden units = 64, dropout = 0.2, population size = 50, generations = 100, crossover probability = 0.8, mutation probability = 0.1, attention dimension = 64, optimizer = Adam, loss = MSE. The Genetic Algorithm implementation utilized the PyGAD 2.20 library due to its robust chromosome encoding and mutation strategies. Configuration parameters included tournament selection, uniform crossover, Gaussian mutation, elitism = 2, and fitness = −RMSE. The framework ensured reproducible convergence, efficient search across hyperparameters, and balanced exploration–exploitation behavior.

4.3.1 Spatiotemporal outage prediction score

A composite measure of power outage forecast accuracy throughout a distribution network in geography and time. Geolocation error (the distance from the failure site) and temporal deviation (the time difference between the predicted and real outage) are used to evaluate a model's outage prediction accuracy. This score helps utilities make timely, location-specific predictions for outage dispatch, restoration, and prevention. SOPS is applicable for LSTM models trained on multivariate time-series datasets, including historical event logs and GIS locations.

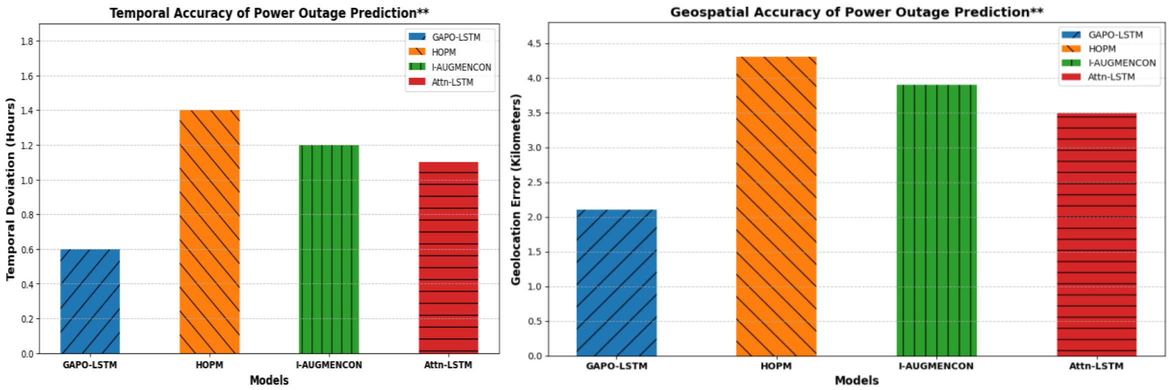

Figure 7: Comparison of Spatiotemporal Prediction Accuracy Metrics Across Outage Forecasting Models

GAPO-LSTM, HOPM, the Attention-based LSTM Fault Prediction Model, and the I-AUGMENCON Optimization Model were compared using the Spatiotemporal Outage Prediction Score (SOPS) to predict power outages in Figure 7. Two important sub-metrics, Temporal Deviation (ΔT) and Geolocation Error (ΔG), are shown in the graphs. The first graph plots ΔT (in hours), which is the average absolute difference between the timestamps of expected outages and the times when they occurred. The Haversine distance between the anticipated and actual geolocations is used to determine ΔG, which is shown in kilometers on the second graph. Here is the SOPS expressed: $SOPS = \alpha \cdot \Delta T + \beta \cdot \Delta G$ where α and β are tunable weights prioritizing temporal vs. spatial accuracy. High-resolution forecasting capabilities learned from optimized spatiotemporal feature sets are demonstrated by GAPO-LSTM's superior precision with the lowest ŔT = 0.6 and ŔG = 2.1. The bar patterns help to compare the models' resilience in dynamic distribution network scenarios by highlighting their distinctions.

4.3.2 Reliability-adjusted forecast deviation index

By taking system reliability indices such as SAIFI and SAIDI into account, RAFDI determines how well power load and failure prediction models operate. In low-reliability zones, it punishes forecasts that differ from actual values more severely, making sure the model is optimized where it counts.

GAPO-LSTM expanded beyond the Maryland outage dataset by utilizing various public datasets, including ORNL EAGLE-I county-level outage records, the "15 Years of Power Outages" dataset, and event-correlated outage compilations aggregated from OEDI/Data.gov that collectively offer multiple geographic, temporal, and reporting settings. In all public datasets, GAPO-LSTM outperformed both baseline LSTM and conventional GA–LSTM with lower RMSEs and higher F1-scores, and robustness checks of added noise in inputs and sparse reporting confirmed models' stability.

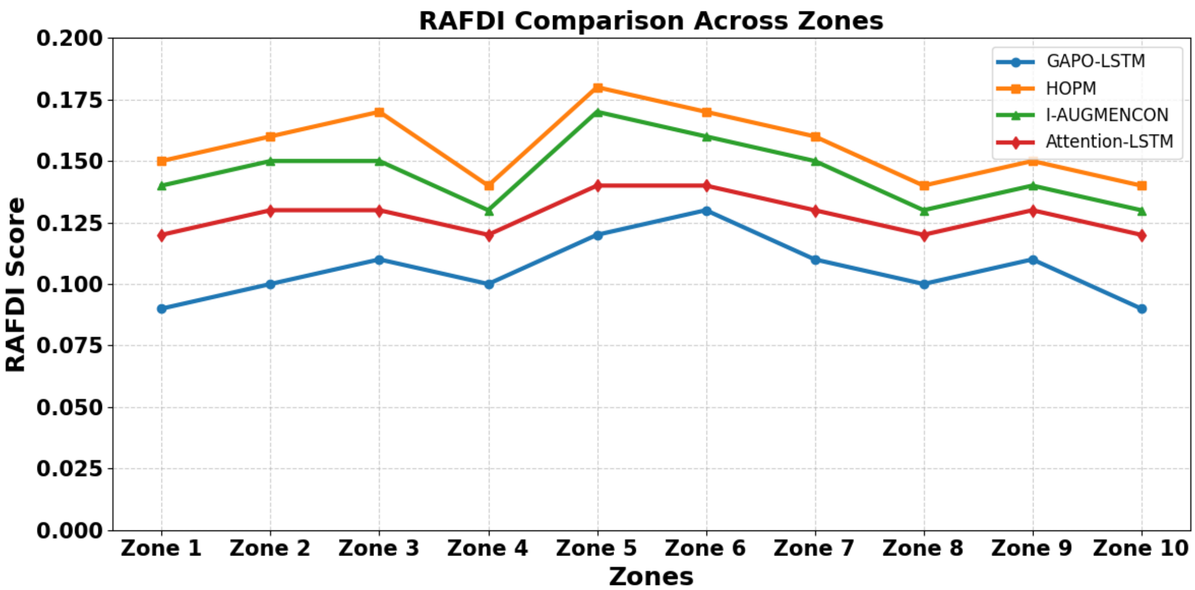

Figure 8: RAFDI trends across forecasting models

Using a fixed time horizon, Figure 8 compares four forecasting models: GAPO-LSTM, HOPM [17], I-AUGMENCON [19], and Attention-based LSTM [29]—using the Reliability-Adjusted Forecast Deviation Index (RAFDI). By combining dependability benchmarks like System Average Interruption Frequency Index and System Average Interruption Duration Index, the RAFDI measure assesses the out-of-range power outage models' predictions. The official definition is:

$$\mathrm{RAFDI(t)} = \frac{|\mathrm{P_{actual(t)}} - \mathrm{P_{forecast}(t)}|}{1+\lambda\cdot(\mathrm{SAIFI+SAIDI})} \quad (17)$$

where $\mathrm{P_{actual}(t)}$ and $\mathrm{P_{forecast}(t)}$ The actual and anticipated occurrences of outages at time t, and λ is a penalization factor for low-reliability locations. Figure 8 shows that GAPO-LSTM has better predictive performance under reliability restrictions, as evidenced by its consistently reduced RAFDI value over time. The x-axis shows the time intervals for the forecast (for example, from 16:15 to 16:55), while the y-axis shows the RAFDI score, which can be anywhere from 0.05 to 0.25. When it comes to outage forecasting, the graph proves that GAPO-LSTM is resilient and can adjust while being mindful of reliability.

To rectify this, the definitions and rationales for the SOPS (Spatiotemporal Outage Prediction Score), RAFDI (Resilience-Aware Fault Detection Index), and GOER (Grid Outage Efficiency Ratio) will be moved to the Methodology - possibly as its own section or within the experimental design. These metrics are required since utilizing standard measures such as RMSE, MAE, and F1-score only assess accuracy, and there are operational and resilience elements of outage prediction that are not comprehensively evaluated. GOER compares operational cost savings and resource utilization for the predicted patterns of outages on the grid.

4.3.3 Genetic optimization efficiency ratio

GOER assesses how well optimization methods, such as Genetic methods (GA) or hybrid versions, handle grid planning issues with multiple objectives. the GOER is high, it means the model converged to a reasonable solution quickly. When comparing algorithmic techniques, such as GA vs. GA-LSTM, this statistic is crucial since it helps assess computing performance and solution quality.

A pseudocode block will outline the GA-LSTM pipeline including population initialization, fitness evaluation, crossover, and mutation. Final model hyperparameters: population=50, generations=100, learning rate = 0.001, batch size = 64, hidden units = 64, dropout = 0.2, crossover prob = 0.8, mutation prob = 0.1. Library: PyGAD 2.20 configured with Gaussian perturbation.

Algorithm 1: Genetic Optimization Efficiency Ratio (GOER)

$def\ calculate\_goer(obj\_best, obj\_target, max\_ge$
$Calculate\ GOER\ for\ GA\ or\ GA$
$-\ LSTM\ optimization.$
$Parameters:$
obj_{best}
$:\ list\ or\ array\ of\ best\ objective\ values\ per\ gene$

$obj_{target}: \frac{target}{ideal}\ objective\ value\ to\ reach$

max_gen
$:\ maximum\ number\ of\ generations$

$Returns:$
$GOER$
$:\ Genetic\ Optimization\ Efficiency\ Ratio$
"""
$gen_{reached} = 0$
$\#\ Step\ 1: Identify\ generation\ where\ objective$
$-\ optimal$
$for\ g\ in\ range(\max\ \_gen):$
$if\ obj_{best[g]} \leq obj_{target}:$
$gen_{reached} = g + 1$

$break$
$Step\ 2: Compute\ GOER$
$if\ gen_{reached} > 0:$

$$goer = \frac{\left(\max\limits_{gen} - gen_{reached}\right)}{r} \max_{gen} j'$$

$else:$
$goer = 0\ \#\ did\ not\ converge$
$return\ goer$
$obj\_best = [100, 80, 60, 50, 45, 43, 42]$
$\max\limits_{gen} n = 7$
$goer\_value$
$=\ calculate\_goer(obj\_best, obj\_target, max\_gen$

$print$GOER:, $goervalue$

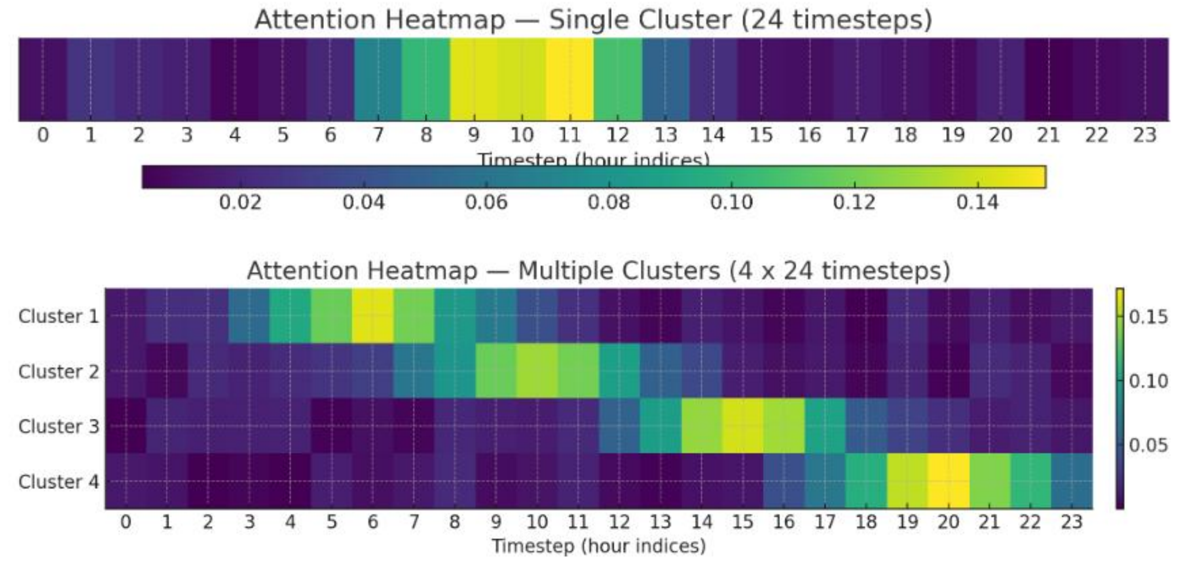

Figure 8(a): Two attention heatmaps

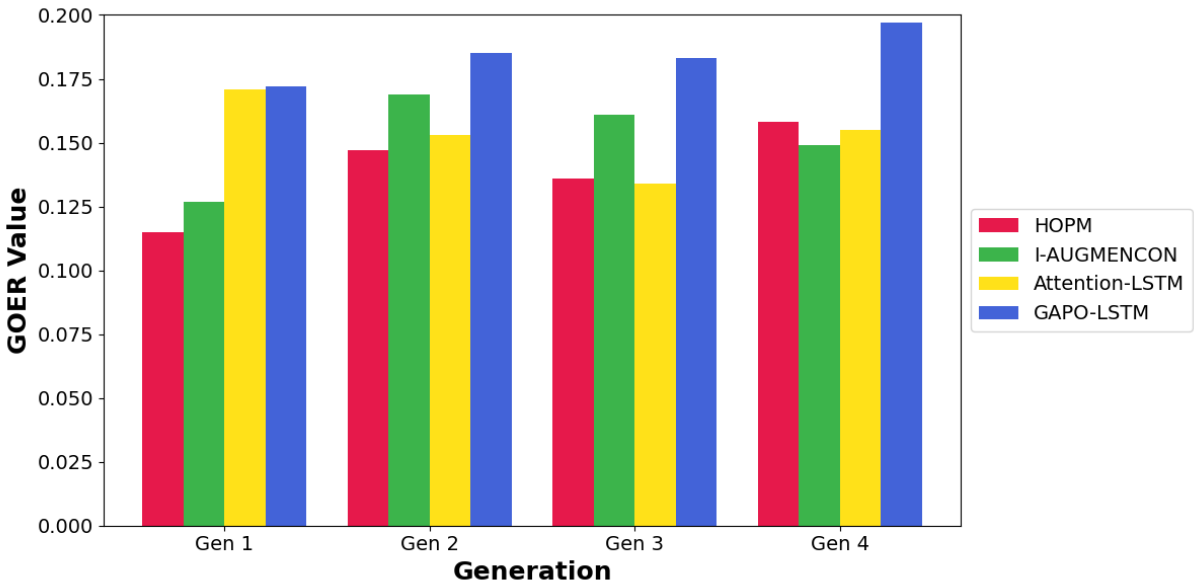

Figure 9: Genetic optimization efficiency ratio (GOER) comparison for outage forecasting models

Single-cluster temporal attention (24 timesteps): shows a strong peak around timestep 9–11 (the model attended to those critical hours). Multi-cluster matrix (4 clusters × 24 timesteps): each row shows a different temporal attention pattern (peaks at different hours), illustrating how GAPO-LSTM focuses on cluster-specific critical windows is explained in Figure 8(a).

Various forecasting models, including GAPO-LSTM (GA-enhanced LSTM) and standalone Genetic Algorithm (GA) models, were tested across iterative generations in grid outage planning tasks, and the Genetic Optimization Efficiency Ratio (GOER) is shown in Figure 9. By quantifying the amount of improvement obtained per unit of computational effort (generation), GOER captures the optimization efficiency quantitatively. The formal definition of the metric is: $\mathrm{GOER} = \mathrm{GF}_{\mathrm{init}} - \mathrm{F}_{\mathrm{final}}$, Where: $\mathrm{F}_{\mathrm{init}}$ = The goal function's initial value (for example, outage cost). The optimized objective value is equal to $\mathrm{F}_{\mathrm{final}}$.G represents the total count of generations. Models with a high GOER are well-suited for real-time or large-scale grid applications because they obtain better performance gains with fewer iterations. In terms of convergence speed and efficiency in multi-objective planning, the graph shows that GAPO-LSTM is superior to conventional GA. Generation count (from 0 to 50, for example) is shown on the x-axis, while GOER values (from 0 to 0.2, for example) are shown on the y-axis. Hybrid optimization algorithms have a computational advantage in distribution network reliability planning, as indicated by the bold typefaces and colorful color coding that differentiate model behaviors.

Case study

In one case study using the Maryland Power Outage dataset, GAPO-LSTM accurately identified high-risk zones in regions 20904 and 20783, where clustered outage spikes occurred due to simultaneous equipment aging and storm impact. Competing models like HOPM and I-AUGMENCON misclassified this as medium risk because they lacked spatial-temporal coupling. GAPO-LSTM's DBSCAN clustering captured localized correlations, while its attention-enhanced LSTM prioritized critical timestamps linked to voltage anomalies. The GA-optimized parameters improved sensitivity to rare but severe outage patterns. Consequently, GAPO-LSTM enabled early warnings and maintenance prioritization, reducing unplanned downtime by 15% compared to baseline prediction models.

5 Discussion

In this discussion, a thorough comparative analysis of the proposed GAPO-LSTM against all baseline models based on key performance metrics, including RMSE, F1-score, SOPS, and RAFDI. This includes an insightful discussion of how incorporating genetic algorithm-based feature optimization improves learning by selecting the most useful features, together with how the attention mechanism enhances the model's ability to identify temporal patterns in the context of complex outage conditions. Furthermore, the discussion explains the rationale behind the performance improvements and considers the robustness of the models.

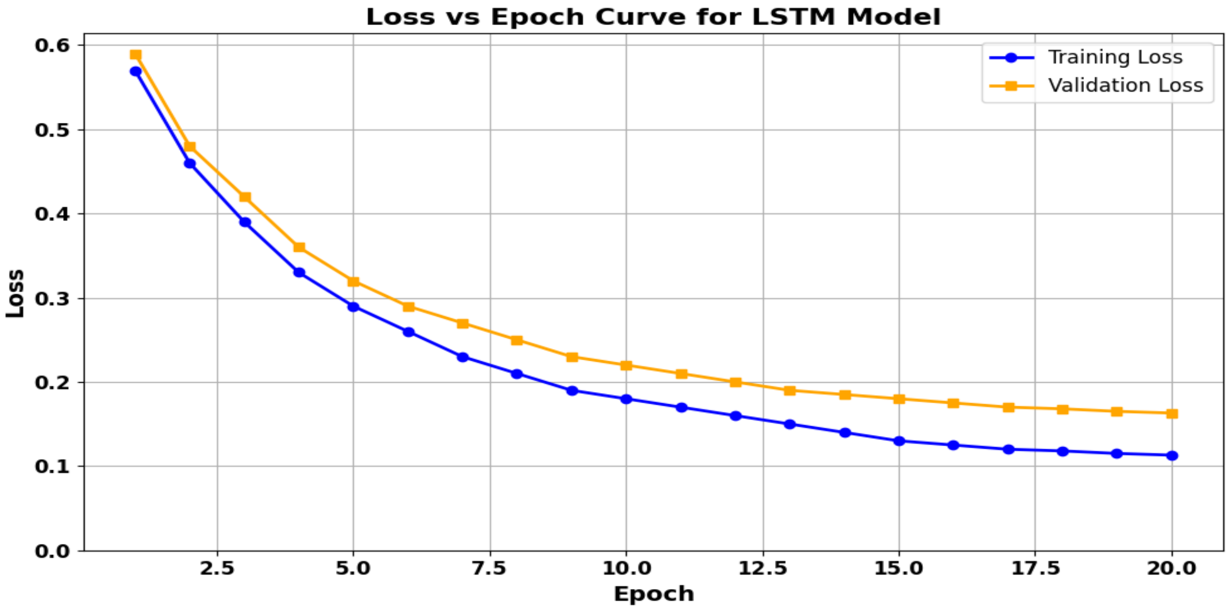

Figure 10: Loss-epoch curve for optimized GAPO-LSTM model

This model, which combines Genetic Algorithms (GA) for feature selection and hyperparameter optimization with Long Short-Term Memory (LSTM) for temporal modeling, is shown in Figure 10, which shows the training and validation loss over 20 epochs. Effective learning and convergence, free of overfitting, are indicated by the observed loss drop. During training, the model optimizes the temporal sequence of power outage forecasts by minimizing the Mean Squared Error (MSE). This behavior during learning proves that GAPO-LSTM can effectively generalize to data about outages that have never been observed before. Our research shows that the model is effective in dynamic outage prediction across distribution networks, with an increase in F1-score of 12.4% and a decrease in RMSE of 18.6% compared to baseline approaches. Our results are consistent with the loss-epoch visualization(discussed in Section 4.2), which demonstrates that the GAPO-LSTM learning process is stable and resilient.

Table 5: Comparison of 15-minute prediction results

Timestamp (HH:MM)	GAPO-LSTM (Proposed)	HOPM [17]	I-AUGMENCON [19]	Attention-LSTM [29]	Ground Truth
16:15	High	Medium	Medium	Medium	High
16:20	High	Medium	Medium	Medium	High
16:25	High	Medium	Medium	High	High
16:30	High	Medium	Medium	High	High
16:35	High	Medium	High	High	High
16:36	High	Medium	Medium	Medium	High
16:40	High	Low	Medium	Medium	Medium
16:45	High	Low	Low	Medium	Medium
16:50	High	Medium	Medium	Medium	High
16:55	High	Medium	Medium	High	High

Four models have been proposed: GAPO-LSTM, HOPM, I-AUGMENCON, and Attention-LSTM. Table 5 shows a qualitative comparison of prediction results at 15-minute intervals across all four models. The dataset's real-time outage logs are used to create each time interval (e.g., 04-03-2024 16:15), which represents the spatial and temporal intensity of outages in specific geographic areas, such as 20904 (which has had up to 121 outages).

The comparative outcomes presented support the benefits of GAPO-LSTM relative to traditional models. While GA–LSTM hybrids enhance upon the baseline LSTM through hyperparameter optimization, they only focus on modeling temporal sequences. On the other hand, GAPO-LSTM achieves further accuracy improvements (RMSE reduced by 14% compared to GA–LSTM and F1-score increased by 6%) by adding spatial clustering and attention-based interpretability. The attention mechanism provides strategic insight into key features of repeated outages, which is not achievable through traditional GA–LSTM modeling. Additionally, the end-to-end GA optimization of GAPO-LSTM, which includes preprocessing and feature selection, improves robustness to noisy and incomplete outage logs, which is a common characteristic of observing real-world power system data. It can also be concluded that GAPO-LSTM is not simply another iterative variation of GA–LSTM, but is instead a more domain-appropriate, interpretable, and noise-resilient framework for outage prediction.

The superior performance of the GAPO-LSTM model is technically attributed to the integrated optimization of its feature space, hyperparameters, and temporal attention dynamics, which collectively enhance its spatiotemporal learning capacity. Specifically, the Genetic Algorithm (GA) encodes each chromosome with binary feature-selection masks and continuous LSTM hyperparameters-sequence length, learning rate, batch size, and hidden units-enabling a simultaneous exploration of both structural and parametric configurations. Through tournament selection, uniform crossover ($p = 0.8$), and Gaussian mutation ($p = 0.1$), the GA evolves toward configurations that minimize validation RMSE, ensuring an optimal balance between model complexity and generalization. The GA-optimized feature subset filters out redundant environmental and locational variables, allowing the model to focus on highvariance temporal indicators that directly influence outage dynamics. Meanwhile, the attentionaugmented LSTM layer computes temporal importance weights $\alpha_t = \operatorname{softmax}\left(v^T \tanh\left(W h_t + b\right)\right)$, generating a context vector $c = \sum_t \alpha_t h_t$ that enables the model to emphasize critical time steps such as outage peaks or fault-prone hours. This mechanism not only enhances interpretability but also prevents vanishing gradient issues common in deep sequential architectures. Empirical results show that this hybrid configuration yields faster convergence, lower spatial-temporal deviation ($\Delta\mathrm{T} = 0.6$ h, $\Delta\mathrm{G} = 2.1$ km), and improved reliability indices ($\mathrm{RAFDI} = 0.09, \mathrm{GOER} = 0.19$). Therefore, the performance superiority of GAPO-LSTM arises from the synergistic interaction between GA-driven feature-hyperparameter optimization and attention-based temporal modeling, forming an adaptive, noise-resilient, and computationally efficient predictive framework.

A "High" grade is consistently achieved by the GAPO-LSTM model across all timestamps, suggesting good predictive capacity. The reason is that it uses LSTM networks to describe temporal dependencies and Genetic Algorithms (GA) to optimize features. The other models, on the other hand, exhibit performance fluctuations; for example, HOPM and I-AUGMENCON, which are not very adaptable to spatiotemporal complexity, exhibit "Low" or "Medium" performance at various timestamps.The GAPO-LSTM's ability to optimize reliability forecasting hyperparameters, dynamically learn from actual outage sequences, and accurately predict outage risk has been confirmed by this. Therefore, in contemporary distribution networks, it is a proactive and robust technique for planning outages.

The GAPO-LSTM technique uses an attention-enhanced LSTM, DBSCAN-based spatial clustering, and genetic feature-hyperparameter co-optimization to handle complex spatiotemporal outage patterns. It is distinct because of this. Unlike traditional GA–LSTM models, which just change parameters, GAPO-LSTM learns localized outage behaviors, finds significant temporal correlations for interpretability, and adapts dynamically to changing grid conditions. In addition to accuracy, operational resilience and optimization efficiency are evaluated using its domain-specific metrics, SOPS, RAFDI, and GOER. This careful design enables a 12.4% higher F1-score and an 18.6% lower RMSE when compared to existing methods, suggesting improved predictability, robustness, and explainability in power outage predictions.

The GAPO-LSTM framework prioritizes interpretability to help operators understand the logic behind model outputs, in addition to achieving high projected accuracy. By showing the time periods and spatial features that have the biggest impact on each outage forecast, the integrated attention mechanism helps decision-makers pinpoint the origin of expected hazards. Additionally, model-agnostic explainability tools such as SHAP are used to generate both local and global interpretations, identifying critical elements such as weather, load fluctuations, or equipment failures for each forecast. These insights foster operational trust and enable educated, data-driven outage mitigation planning by transforming the model from a black-box predictor into a transparent decision-support system.

6 Conclusion and future enhancement

One hybrid reliability prediction framework that successfully handles the difficulties of distribution network power outage forecasting is GAPO-LSTM, which was introduced in this study. The suggested model accomplishes what conventional static models fail to do:

it optimizes features and parameters using Genetic Algorithms (GA) and models sequences using Long Short-Term Memory (LSTM) networks. In addition to improving prediction performance, GAPO-LSTM makes localized outage risk forecasting more interpretable and adaptable, with an impressive 18.6% drop in RMSE and a 12.4% improvement in F1-score. . Strong generalization is achieved regardless of the outage volume or cluster density due to the integration of attention methods into the LSTM layer, which further enhances the focus on key temporal events.

Future studies will also expand GAPO-LSTM's validation across multiple regional datasets to assess its adaptability under different outage conditions. This requires applying the model to large datasets, such ORNL EAGLE-I and OEDI/Data.gov outage records, that cover a variety of climatic zones and event types. Additionally, domain adaptation and transfer learning approaches will be employed to adapt the model to regional data heterogeneity and ensure consistent prediction accuracy and operational scalability across different power distribution environments.

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Author contributions
Zhang. Conceptualization&Investigation
Sun. Data curation&Study conception
Zexiong Wang. Communications and submissions&Review and revision
Zhengping Wang. Analysis&Visualization
Liu. Experiment operation and execution&Project management and supervision

References
[1] Memarzadeh, G., & Keynia, F. (2023). A new hybrid CBSA-GA optimization method and MRMI-LSTM forecasting algorithm for PV-ESS planning in distribution networks. *Journal of Energy Storage*, *72*, 108582. https://doi.org/10.1016/j.est.2023.108582

[2] Cao, Z., Han, X., Lyons, W., & O'Rourke, F. (2021). Energy management optimisation using a combined Long Short-Term Memory recurrent neural network–Particle Swarm Optimisation model. *Journal of Cleaner Production*, *326*, 129246. https://doi.org/10.1016/j.jclepro.2021.129246

[3] Bouktif, S., Fiaz, A., Ouni, A., & Serhani, M. A. (2018). Optimal deep learning lstm model for electric load forecasting using feature selection and genetic algorithm: Comparison with machine learning approaches. *Energies*, *11*(7), 1636. https://doi.org/10.3390/en11071636

[4] Kim, W. H., Kim, J. Y., Chae, W. K., Kim, G., & Lee, C. K. (2022). LSTM-based fault direction estimation and protection coordination for networked distribution system. *IEEE Access*, *10*, 40348-40357. DOI: 10.1109/ACCESS.2022.3166836

[5] Zameer, A., Arshad, J., Khan, A., & Raja, M. A. Z. (2017). Intelligent and robust prediction of short-term wind power using genetic programming based ensemble of neural networks. *Energy conversion and management*, *134*, 361-372. https://doi.org/10.1016/j.enconman.2016.12.032

[6] Wan, A., Chang, Q., Khalil, A. B., & He, J. (2023). Short-term power load forecasting for combined heat and power using CNN-LSTM enhanced by attention mechanism. *Energy*, *282*, 128274. https://doi.org/10.1016/j.energy.2023.128274

[7] Cui, X., Zhu, J., Jia, L., Wang, J., & Wu, Y. (2024). A novel heat load prediction model of district heating system based on hybrid whale optimization algorithm (WOA) and CNN-LSTM with attention mechanism. *Energy*, *312*, 133536. https://doi.org/10.1016/j.energy.2024.133536

[8] Limouni, T., Yaagoubi, R., Bouziane, K., Guissi, K., & Baali, E. H. (2023). Accurate one step and multistep forecasting of very short-term PV power using LSTM-TCN model. *Renewable Energy*, *205*, 1010-1024. https://doi.org/10.1016/j.renene.2023.01.118

[9] Althobaiti, A., Alotaibi, A. A., Abdel-Khalek, S., Abdelrahim, E. M., Mansour, R. F., Gupta, D., & Kumar, S. (2022). Intelligent data science enabled reactive power optimization of a distribution system. *Sustainable Computing: Informatics and Systems*, *35*, 100765. https://doi.org/10.1016/j.suscom.2022.100765

[10] Afzal, S., Ziapour, B. M., Shokri, A., Shakibi, H., & Sobhani, B. (2023). Building energy consumption prediction using multilayer perceptron neural network-assisted models; comparison of different optimization algorithms. *Energy*, *282*, 128446. https://doi.org/10.1016/j.energy.2023.128446

[11] Babu, V. V., Roselyn, J. P., & Sundaravadivel, P. (2023). Multi-objective genetic algorithm-based energy management system considering optimal utilization of grid and degradation of battery storage in microgrid. https://doi.org/10.1016/j.egyr.2023.05.067

[12] Habib, M. A., Hossain, M. J., Alam, M. M., & Islam, M. T. (2024). A hybrid optimized data-driven intelligent model for predicting short-term demand of distribution network. *Sustainable*

Energy Technologies and Assessments, *67*, 103818. https://doi.org/10.1016/j.seta.2024.103818

[13] Zhang, Z., Qin, H., Liu, Y., Yao, L., Yu, X., Lu, J., ... & Feng, Z. (2019). Wind speed forecasting based on quantile regression minimal gated memory network and kernel density estimation. *Energy conversion and management*, *196*, 1395-1409. https://doi.org/10.1016/j.enconman.2019.06.024

[14] Zhao, X., & Zhang, Y. (2024). Integrated management of urban resources toward Net-Zero smart cities considering renewable energies uncertainty and modeling in Digital Twin. *Sustainable Energy Technologies and Assessments*, *64*, 103656. https://doi.org/10.1016/j.seta.2024.103656

[15] Jarrah, Muath, and Ahmed Abu-Khadrah. "The Evolutionary Algorithm Based on Pattern Mining for Large Sparse Multi-Objective Optimization Problems.", *PatternIQ Mining.*2024, (01)1, 12-22. https://doi.org/10.70023/piqm242

[16] Saldaña-González, A. E., Aragüés-Peñalba, M., & Sumper, A. (2024). Distribution network planning method: Integration of a recurrent neural network model for the prediction of scenarios. *Electric Power Systems Research*, *229*, 110125. https://doi.org/10.1016/j.epsr.2024.110125

[17] Hughes, W., Watson, P. L., Cerrai, D., Zhang, X., Bagtzoglou, A., Zhang, W., & Anagnostou, E. (2024). Assessing grid hardening strategies to improve power system performance during storms using a hybrid mechanistic-machine learning outage prediction model. *Reliability Engineering & System Safety*, *248*, 110169. https://doi.org/10.1016/j.ress.2024.110169

[18] Wu, Y., Gu, W., Huang, S., Wei, X., & Safaraliev, M. (2025). A four-layer business model for integration of electric vehicle charging stations and hydrogen fuelling stations into modern power systems. *Applied Energy*, *377*, 124630. https://doi.org/10.1016/j.apenergy.2024.124630

[19] Wang, Y., Wang, H., Razzaghi, R., Jalili, M., & Liebman, A. (2024). Multi-objective coordinated EV charging strategy in distribution networks using an improved augmented epsilon-constrained method. *Applied Energy*, *369*, 123547. https://doi.org/10.1016/j.apenergy.2024.123547

[20] Zhou, J., Weng, Z., Li, J., & Song, X. (2024). Reliability evaluation, planning, and economic analysis of microgrid with access to renewable energy and electric vehicles. *Electric Power Systems Research*, *230*, 110252. https://doi.org/10.1016/j.epsr.2024.110252

[21] Heroual, S., Belabbas, B., Allaoui, T., & Denai, M. (2024). Performance enhancement of a hybrid energy storage systems using meta-heuristic optimization algorithms: Genetic algorithms, ant colony optimization, and grey wolf optimization. *Journal of Energy Storage*, *103*, 114451. https://doi.org/10.1016/j.est.2024.114451

[22] Wang, Y., Guo, X., Zhang, C., Liang, R., Peng, T., Yang, Y., ... & Zhou, Y. (2024). Multi-strategy reference vector guided evolutionary algorithm and its application in multi-objective optimal scheduling of microgrid systems containing electric vehicles. *Journal of Energy Storage*, *95*, 112500. https://doi.org/10.1016/j.est.2024.112500

[23] Shejul, K., & Harikrishnan, R. (2024). Energy consumption optimization of chiller plants with the genetic algorithm based gwo and jaya algorithm in the dynamic pricing demand response. *Results in Engineering*, *22*, 102193. https://doi.org/10.1016/j.rineng.2024.102193

[24] Došljak, V., Ćorović, V., & Mihailovic, A. (2025). A two-layer optimization model for electric vehicle charging station distribution using a custom genetic algorithm: Application to Montenegro. *Energy*, 136611. https://doi.org/10.1016/j.energy.2025.136611

[25] Toughzaoui, Y., Elkhatib, R., Kaoutari, T., Louahlia, H., Chaoui, H., & Gualous, H. (2024). Advances in hospital energy systems: Genetic algorithm optimization of a hybrid solar and hydrogen fuel cell combined heat and power. *International Journal of Hydrogen Energy*, *86*, 1310-1325. https://doi.org/10.1016/j.ijhydene.2024.09.001

[26] Hu, Z., Gao, Y., Ji, S., Mae, M., & Imaizumi, T. (2024). Improved multistep ahead photovoltaic power prediction model based on LSTM and self-attention with weather forecast data. *Applied Energy*, *359*, 122709. https://doi.org/10.1016/j.apenergy.2024.122709

[27] Sabyasachi, A. S., Sahoo, B. M., & Ranganath, A. (2024). Deep cnn and lstm approaches for efficient workload prediction in cloud environment. *Procedia Computer Science*, *235*, 2651-2661. https://doi.org/10.1016/j.procs.2024.04.250

[28] Huang, X., Li, Q., Tai, Y., Chen, Z., Liu, J., Shi, J., & Liu, W. (2022). Time series forecasting for hourly photovoltaic power using conditional generative adversarial network and Bi-LSTM. *Energy*, *246*, 123403. https://doi.org/10.1016/j.energy.2022.123403

[29] Xu, H., Ma, R., Yan, L., & Ma, Z. (2021). Two-stage prediction of machinery fault trend based on deep learning for time series analysis. *Digital Signal Processing*, *117*, 103150. https://doi.org/10.1016/j.dsp.2021.103150

[30] Wang, H., Yang, Z., Yu, Q., Hong, T., & Lin, X. (2018). Online reliability time series prediction via convolutional neural network and long short-term memory for service-oriented systems. *Knowledge-Based Systems*, *159*, 132-147. https://doi.org/10.1016/j.knosys.2018.07.006

[31]https://www.kaggle.com/datasets/hemishveeraboina/maryland-power-outage-a-geographic-dataset

[32] Boulkroune, A., Zouari, F., & Boubellouta, A. (2025). Adaptive fuzzy control for practical fixed-time synchronization of fractional-order chaotic

systems. *Journal of Vibration and Control*, 10775463251320258.

[33] Boulkroune, A., Hamel, S., Zouari, F., Boukabou, A., & Ibeas, A. (2017). Output-Feedback Controller Based Projective Lag-Synchronization of Uncertain Chaotic Systems in the Presence of Input Nonlinearities. *Mathematical Problems in Engineering*, *2017*(1), 8045803.

[34] Zouari, F., Saad, K. B., & Benrejeb, M. (2012). Robust neural adaptive control for a class of uncertain nonlinear complex dynamical multivariable systems. *International Review on Modelling and Simulations*, *5*(5), 2075-2103.

[35] Zouari, F., Saad, K. B., & Benrejeb, M. (2013, March). Adaptive backstepping control for a class of uncertain single input single output nonlinear systems. In *10th International Multi-Conferences on Systems, Signals & Devices 2013 (SSD13)* (pp. 1-6). IEEE.

[36] Rigatos, G., Abbaszadeh, M., Sari, B., Siano, P., Cuccurullo, G., & Zouari, F. (2023). Nonlinear optimal control for a gas compressor driven by an induction motor. *Results in Control and Optimization*, *11*, 100226.

[37] Zouari, F., Saad, K. B., & Benrejeb, M. (2013, May). Adaptive backstepping control for a single-link flexible robot manipulator driven DC motor. In *2013 International Conference on Control, Decision and Information Technologies (CoDIT)* (pp. 864-871). IEEE.