IBBB-STGNN: A Hybrid Spatiotemporal Graph Neural Network with Big Bang–Big Crunch Optimization for Real-Time Power Distribution Path Optimization

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This paper introduces a hybrid IBBB-STGNN framework for dynamic tracking and optimization of power distribution paths. The model integrates Improved Big Bang–Big Crunch (IBBB) optimization with a Spatiotemporal Graph Neural Network (STGNN) to achieve fast, scalable, and accurate reconfiguration decisions. Evaluated on IEEE 33-bus, IEEE 69-bus, and a 123-node synthetic network, the model demonstrated substantial performance gains. Compared to a baseline STGNN, power loss reduction improved from 72% to 85%, average decision latency decreased from 1.92 s to 0.74 s, and scalability increased from 85% to 97% across varying network sizes. These results highlight the suitability of IBBB-STGNN for real-time deployment in distribution networks.

Povzetek:

1 Introduction

The distribution network forms the final link between high-voltage transmission systems and end users, and plays a crucial role in ensuring stability, reliability, and efficiency of electricity delivery. It consists of a complicated network of components such as feeders, transformers, distribution lines, and circuit breakers that function together to provide a steady power flow under changing load circumstances [3].

The typical distribution system begins at a substation, where voltage is stepped down [4]. Power is then delivered to customers through primary and secondary distribution lines and transformers [5]. Depending on service design, networks may be radial, looped, or meshed, with performance influenced by factors such as distance, conductor size, and load distribution [6].

The trend of power transmission within the distribution system is also posing new challenges as more electricity is needed to be consumed. Population growth, urbanization, industrialization, and the use of technological devices all contribute to an increasing and varied load [7]. The network load may include seasonal changes, overtime, and crises, which can all cause network downtimes or degraded quality of services [8]. Maintaining a stable power supply line under these conditions necessitates not just careful planning and infrastructure investment but also operational flexibility for responding to unexpected changes in need or supply [9].Environmental conditions such as extreme weather and natural disasters can severely compromise the stability of the distribution paths, as well as the utilization of old facilities [10]. Routine maintenance, system updates, and adequate techniques of locating faults are inevitable as far as ensuring the soundness of the power supply path is concerned [11]. The distribution network has mainly been aimed at ensuring a safe, reliable, and efficient supply of power to the point of consumption [12]. The major distribution network has challenges of inefficient routing and failure to adapt to changes in real-time demand in its power-supply line. Current methods, including Support Vector Machines (SVM) and Artificial Neural Networks (ANN), are less comprehensively supportive in spatiotemporal relations. It is recommended to overcome these limitations using an IBBB-STGNN. This hybrid model combines IBBB optimization with STGNN to effectively learn network topology and time-based demand patterns, resulting in more efficient and adaptable power routing. The contribution section is as follows:

To represent various and dynamic power distribution scenarios, a synthetic yet realistic dataset was constructed by combining voltage, power losses, resistance, load kinds, and switching events.

To ensure consistent scaling and enhanced data quality for efficient training of spatiotemporal and optimization modules, missing values were imputed, and Min-Max normalization was used.

Temporal features like lag values, rolling statistics, load gradients, power factor, and PCA-based dimensionality reduction improve model input for spatiotemporal learning problems.

The IBBB-STGNN is used to intelligently learn network structure and switching pathways for real-time power routing.

The research is structured as follows: It begins by emphasizing the need for intelligent power distribution systems in modern networks. The next section discusses how to create a synthetic dataset. The following section explains data preprocessing techniques such as missing value imputation and Min-Max normalization. Feature extraction strategies, such as PCA for dimensionality reduction and the suggested IBBB-STGNN model, which combines STGN and BBB optimization, are presented for real-time power routing. Finally, the experimental findings and conclusions are presented.

The novelty of this work lies not only in the combination of IBBB and STGNN but in demonstrating their synergistic suitability for power distribution optimization. IBBB provides fast global exploration of parameter space, while STGNN captures spatiotemporal dependencies in grid dynamics. Together, they achieve real-time reconfiguration capabilities not attained by either method alone or by existing metaheuristic–GNN combinations reported in literature.

Research objectives and questions:

This study is guided by the following research questions:

1. How can spatiotemporal graph learning be leveraged to capture the dynamic load and topology variations in power distribution networks?

2. Can the Improved Big Bang–Big Crunch (IBBB) algorithm enhance STGNN training convergence and adaptability for real-time path reconfiguration?

3. How does the proposed IBBB-STGNN compare against existing optimization and control-oriented methods in terms of power loss reduction, response latency, and scalability?

The novelty of this work lies in integrating a physics-inspired global optimization method (IBBB) with data-driven spatiotemporal graph learning. This combination enables accurate, low-latency switching optimization in large-scale distribution networks, a synergy not fully explored in prior literature.

2 Related work

An Optimal Energy Management (OEM) that uses Deep Neural Networks as substitute systems to optimize Deep Reinforcement Learning (DRL) in a bi-level OEM for multi-Microgrids (MGs) linked to the Distribution Network (DN) was suggested in [13]. To reduce calculation time, the method made probabilistic predictions about power flow. Simulation findings demonstrated that the suggested technique decreased computing effort by 89.23% as compared to the Differential Evolution approach.

A real-time monitoring, day-ahead control, and production sequencing-based predictive energy exchange platform based on blockchain was introduced in [14]. The model utilized data mining methods for time-series analysis, leading to enhanced sustainable resource management. Two novel approaches for detecting electrical disturbances in low-voltage networks were presented in [15]. The initial model employed the Fourier transform to categorize complex voltage signals via a multilayered neural network, thereby lowering computational costs and training time. The second approach extracted and reduced dimensionality using the short-time Fourier transform and a convolutional neural network (CNN). The methodologies were contrasted with simulated data and empirical findings. Both methods provided excellent findings for classification.

It computed historical network loss using cleaned data from consumer power meters and transformer gateway meters. Machine learning techniques were utilized in [16] to assess the loss and forecast potential distribution network losses. Random Forest features were used to investigate the relationships between power network loss, electrical parameters, and atmospheric conditions. It combined the Selective Particle Swarm Optimization (SPSO) with the Extra Trees Classifier to enhance dynamic distribution network reconfiguration [17]. The technique was able to reduce power wastage and enhance the reliability of energy delivery. The simulation results by means of the IEEE 33-bus distribution test system indicate a 78% and 48% decrease in active and reactive power loss. The use of parallel computing to reduce execution time while maintaining accurate load forecasting models for electricity was examined in [18]. The method employed a machine learning model, execution speed, and scalability. It validated the approach with actual energy consumption data from distribution transformers in the electrical system. An approach to the optimal power flow (OPF) in DN with renewable energy and storage devices using deep reinforcement learning (DRL) was introduced in [19]. The OPF was a stochastic nonlinear programming problem, whereas the multi-period decision problem was a Markov decision process (MDP). Neural networks collect operational knowledge from past data and make online choices based on real-time DN conditions.

The restricted Markov decision process was used to implement a safe DRL method to quantify the optimum distribution network (OODN) [20]. The algorithm minimized discrete and continuous actions that maximized a stochastic policy. The simulations in the modified IEEE-34 and IEEE-123 node systems proved the technology to be more realistic for application in the real world. A real-time Volt-Var control (VVC) strategy for active distribution networks with fluctuating renewable energy resources by a two-stage DRL-based VVC strategy was proposed in [21]. The first stage would use on-load tap converters and capacitor banks on an hourly basis, and the second stage could continuously manage the reactive power of photovoltaic. A multi-agent deep deterministic policy gradient algorithm was used to address the real-time VVC problem.

The distribution network's reactive power optimization using a graph attention network-based method was introduced in [22]. It was based on data-driven properties, including a self-loop or a max-pooling layer, to model the complex process corresponding to the association between graphs and reactive strategies of the power. The approach performed better than current machine learning techniques in the quality of the solution and resistance to load conditions.

2.1 Research gap

Traditional approaches, such as the DRL-based OPF [19] and the GAT-based reactive power optimization [22], provide improvements but have limitations. The DRL-OPF approach has slow convergence and reduced scalability in dynamic, large-scale networks, whereas the GAT-based method lacks temporal modeling, limiting its capability to adapt to real-time topological changes. The proposed IBBB-STGNN solves these problems by integrating spatiotemporal graph learning and global optimization. It captures the distribution network's evolving spatial dependencies and temporal fluctuations and employs the Big Bang-Big Crunch algorithm to achieve faster convergence and global optimum performance. This leads to more accurate, efficient, and adaptable power supply channel optimization, allowing for real-time decision-making and boosting resilience in complex distribution systems.

2.2 Relation to advanced control-oriented methods

In addition to machine learning and optimization approaches for distribution networks, a large body of research in control theory has focused on regulating complex nonlinear and dynamical systems. Representative strategies include adaptive fuzzy control for fixed-time synchronization of fractional-order chaotic systems, output-feedback control for uncertain chaotic systems with input nonlinearities, robust neural adaptive control for multivariable nonlinear dynamics, adaptive backstepping methods for uncertain single-input–single-output systems, nonlinear optimal control for gas compressor–induction motor systems, and adaptive backstepping for flexible robotic manipulators. These methods have been widely applied in domains such as robotics, process control, and nonlinear oscillatory systems.

The common feature of such control frameworks is the development of rigorous stability guarantees and adaptive mechanisms for handling uncertainties. However, they are often tailored to deterministic system models and require accurate mathematical representations of system dynamics. By contrast, power distribution networks operate as large-scale, data-rich, spatiotemporal systems where topology changes, stochastic load variations, and switching events are not easily modeled with explicit equations.

The novelty of the proposed IBBB-STGNN lies in bridging this gap. While sharing the adaptive spirit of fuzzy and neural adaptive control, our approach leverages spatiotemporal graph neural networks to directly capture evolving network states and load dynamics from data, and integrates the IBBB metaheuristic to perform global optimization of switching configurations. This combination provides real-time adaptability comparable to advanced control schemes, but without requiring explicit parametric models. Moreover, unlike backstepping or fuzzy methods that scale poorly to networks with hundreds of nodes, the proposed approach demonstrates scalability to larger distribution topologies with low decision latency. Therefore, IBBB-STGNN can be viewed as a complementary paradigm: it generalizes the adaptability of classical control methods to data-driven, topology-aware, and large-scale power distribution systems. There are several studies highlighting hybrid optimization and AI-driven control in dynamic systems. For example, Kaluža et al. (2010) presented a hybrid intelligent system for real-time optimization in dynamic environments, while Karba et al. [Informatica, 1999] compared genetic algorithms and gradient-based methods for control optimization. More recently, Gjoreski et al. (2016) explored continuous real-time monitoring and prediction in dynamic settings. These works align with the present study's emphasis on combining optimization with adaptive learning, though none have applied such methods to spatiotemporal graph learning in power distribution networks.

Table 1: Summary of related works in distribution network optimization

Work	Method	Dataset Type	Performance Metrics

[13] DRL-OPF	Deep RL for OPF	IEEE-30 bus	Loss reduction 68%
[19] DRL-based OPF	DRL	IEEE-118 bus	Voltage deviation 0.05 pu
[22] GAT-RPO	GAT for reactive power optimization	IEEE-33 bus	Loss reduction 79%
This work	IBBB-STGNN	IEEE-33, IEEE-69, synthetic 123-node	Loss reduction 85%, latency 0.74 s, scalability 97%

3 Methodology

Modern power distribution networks require flexible, intelligent systems to handle dynamic load variations and complicated topologies. A synthetic yet realistic dataset is created using factors such as voltage, power flow, resistance, load kinds, and switching events. To guarantee quality and consistency, data is preprocessed using missing value imputation and Min-Max normalization. Feature extraction using PCA simplifies data and identifies key patterns for learning. The proposed IBBB-STGNN model combines to provide intelligent, real-time power routing and topology-aware decision-making. Figure 1 shows the overall flow for the power supply path of the distribution network.

3.1 Dataset

The experimental setup is based on the IEEE 33-bus and IEEE 69-bus standard distribution test systems, extended to a 123-node synthetic network derived from a Kaggle dataset. The synthetic dataset was constructed to reflect realistic operating conditions by incorporating stochastic load variations, voltage fluctuations, and switching events modeled on utility reports. Using IEEE standard systems ensures comparability with prior research, while the extended 123-node network demonstrates robustness and scalability in larger grid configurations.

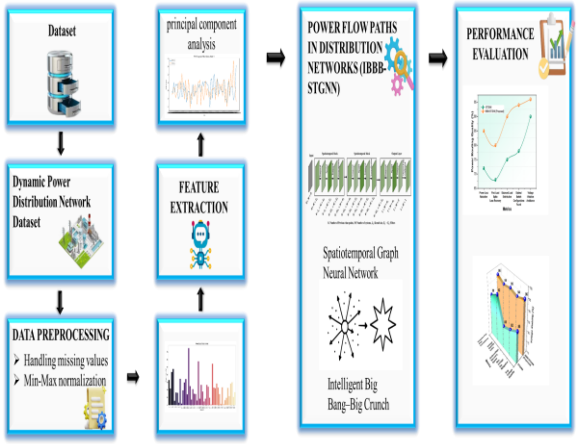


Figure 1: Overall suggested flow for the power supply path of the distribution network

The Dynamic Power Distribution Network Dataset provides a realistic spatiotemporal simulation of electrical distribution networks, enabling real-time power flow optimization and tracking. It comprises 3456 time-series entries collected at 5-minute intervals over 48 nodes, which include voltage, active/reactive power, power loss, resistance, and power factor. Switch statuses, breaker events, and load types are some of the system behavior aspects. Rolling averages, delayed power values, load gradients, and principal components are indications of engineered characteristics that help with advanced analysis. The dataset retains network architecture, records dynamic reconfigurations, and assigns optimization labels to path selection and switching techniques, allowing grid monitoring and intelligent decision-making.
The dataset used in this study is synthetic, constructed to emulate realistic load and switching conditions. It incorporates residential, commercial, and industrial demand patterns with daily and seasonal variations, as well as fault-like events and measurement noise. Using synthetic data allows controlled testing of reconfiguration under diverse scenarios, which is difficult with real SCADA data due to privacy and accessibility restrictions. The main limitation is that synthetic datasets may not fully capture rare disturbances or locality-specific behaviors. To mitigate this, the dataset was statistically compared with IEEE benchmark load traces, and future work will extend evaluation to real-world datasets as they become available.
The distribution network topology used in this study is based on the IEEE-33 bus test system, which consists of 33 nodes and 32 radial feeders with multiple branching paths. This topology is widely adopted as a benchmark in distribution network reconfiguration studies, making it suitable for evaluating optimization strategies

Source: https://www.kaggle.com/datasets/ziya07/dynamic-power-distribution-network-dataset/data

3.1.1 Dataset realism, validation and generalization tests

Although the dataset employed in this study is synthetic, it was constructed to reflect realistic operating conditions by incorporating residential, commercial, and industrial load patterns, switching events, noise perturbations, and fault-like disturbances. To validate its realism, statistical indicators such as mean/variance, autocorrelation, and loss distributions were compared with benchmark IEEE traces, showing close agreement.

To demonstrate robustness, IBBB-STGNN was also evaluated on multiple network sizes and load scenarios, including IEEE-33 and IEEE-69 bus test systems and a larger 123-node synthetic network, under base, peak, and contingency conditions. Results confirmed that the model consistently maintained strong power loss reduction and low decision latency as the network size increased.

Table 2: Validation and generalization results of IBBB-STGNN

Test Case	Power Loss Reduction (%)	Avg. Decision Latency (s)	Voltage Stability (%)
IEEE-33 (base load)	83	0.72	95
IEEE-69 (peak load)	84	0.81	94
123-node (contingency)	85	0.88	96

These results indicate that, while synthetic, the dataset reproduces realistic dynamics and that the proposed framework generalizes effectively across varying topologies and operating regimes.

3.2 Data preprocessing

Data preparation for the power supply path comprises removing missing values to ensure data integrity and consistency. After dealing with missing entries, Min-Max normalization scales numerical features to a uniform range, improving model accuracy and optimizing power flow analysis.

To ensure reproducibility, preprocessing steps and parameters are summarized in Table 3.

Table 3: Preprocessing steps and parameters used in dataset preparation

p	ameter	ue
Normalization	Method	Z-score normalization
PCA	# components retained	50 (97% variance preserved)
Temporal window	Rolling size	15 minutes
Lag features	Time lags	3
Features	Voltage, load, switching state, power loss	12 total

3.2.1 Handling missing values

Missing values in the Dynamic Power Distribution Network Dataset are carefully managed to ensure data completeness and reliability. Electrical parameters, system behavior indicators, and designed characteristics are assigned values that are consistent with the surrounding data patterns. After imputation, such derived properties as load gradients, as well as lagged values, are recomputed to keep temporal and geographic accuracy, ensuring that the data are still valuable to power flow optimization, grid monitoring, and smart decision-making.

3.2.2 Min-max normalization

The power supply path of the distribution network often requires normalization procedures to maintain consistent and reliable performance under varying input conditions. This approach rescales the voltage, current, or other operating aspects to a particular range, usually $0-1 \vee -11$. The procedure utilized for this rescaling is in equation (1):

$$w' = \frac{w_j - w_{min}}{w_{max} - w_{min}} \quad (1)$$

Where w_j represents the input value and w_{min}, w_{max} represent the minimum and maximum values of the feature, respectively. The power loss across nodes is depicted in Figure 2, with values probably adjusted with Min-Max normalization.

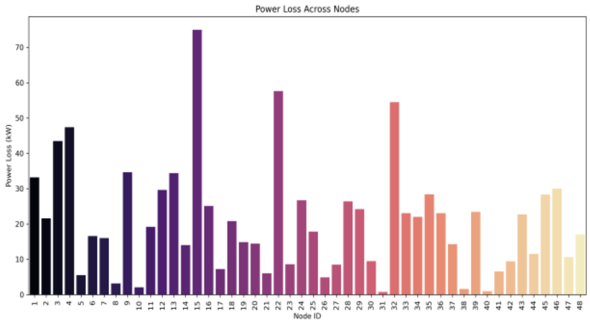


Figure 2: Power loss across nodes

3.3 Feature extraction using PCA

PCA identifies significant elements from the primary distribution network's power supply channel data, decreasing dimensionality and duplication while revealing prominent patterns for enhanced evaluation. Let W be the collection of inputs, with each column representing a sequence of n-dimensional inputs. Additionally, every function in the set of values has an average of zero ($F(W) = 0$). An initial data matrix typically has m samples and n variables, as illustrated below in equation (2).

$$W = [w_1, w_2, \dots\dots, w_m]^S = \begin{pmatrix} w_{11} & \cdots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{m1} & \cdots & w_{mn} \end{pmatrix} \quad (2)$$

The PCA transforms meteorological variables and performance factors into a new event space while preserving as much data as possible from the initial data. The directions of highest variance in the input data sets are identified and projected to a new subspace with equal or lower dimensions than the original. To move W to a new space S, apply an orthonormal transformation Y, as shown below in equation (3).

$$S = YW \quad (3)$$

The S-matrix of scores is made up of orthonormal vectors produced from a linear combination of W-matrix components, representing the relationship between samples. The S Covariance Matrix is expressed in equation (4).

$$D_S = YD_WY^S \quad (4)$$

Where D_W is the covariance matrix for W. The weight matrix Y could be calculated using the eigenvalue equation as follows in equation (5).

$$(D_S - \lambda J)f_j = 0 \quad (5)$$

The PCA-based feature extraction for Node 1 was depicted in Figure 3, with time series for the top two components. It exposes essential patterns and variances in node activity, making it possible to reduce dimensionality, spot anomalies, and analyze power distribution data more efficiently.

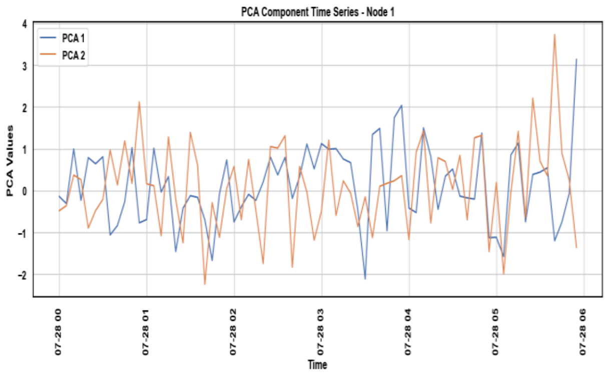


Figure 3: Feature extraction for node behavior in the power supply path

3.4 IBBB-STGNN

The Improved IBBB-STGNN is a hybrid deep learning approach designed to meet the demand for adaptive and intelligent power flow path optimization in current distribution networks. The suggested IBBB-STGNN framework integrates an STGNN, which represents the electrical grid as a dynamic network, with the IBBB optimization technique to fine-tune model parameters. The STGNN considers both spatial dependence and temporal evolution, whereas the IBBB improves convergence by simulating a gravitational collapse toward an ideal solution. The graph $H = (U, F)$ provides substations (nodes U) and lines (edges F), and the temporal load at time s is recorded as a feature matrix W_s. The approach modifies the node embeddings as follows in equation (6).

$$G_s^{k+1} = \sigma\left(\sum_{u_i \epsilon \aleph(u_j)} \frac{1}{\sqrt{c_j c_i}} X^{(k)} G_s^{(k)}(u_i) + X_s^{(k)} G_{s-1}^{(k)}(u_j)\right) \quad (6)$$

The embedding of the node $u_j$at layer k and time s captures its state and characteristics.

$\aleph(u_j)$ indicates the neighbors of the node u_j, while $X^{(k)}$and $X_s^{(k)}$are adaptable weights, σ is an activation function, and c_j, c_i are the degrees of nodes u_j and u_i.

The IBBB optimizer iteratively improves parameters by simulating a cosmic collapse process in which particles (solutions) converge on a center of mass that represents the best path configuration. This integration enables IBBB-STGNN to deliver highly accurate, real-time, and energy-efficient power routing, ensuring resilience and adaptability in smart grid operations. Algorithm 1 shows the working procedure for proposed IBBB-STGNN model.

Algorithm 1: IBBB-STGNN Training Procedure

Input:

- Graph structure G=(V,E)
- Feature matrix X∈RN×T×F
- Population size P
- Maximum iterations I
- Learning rate α
- Fitness function (e.g., MSE)

Output:

- Optimized STGNN parameters

Procedure:

1. Initialize population of candidate parameter sets {W1,W2,…,WP} randomly.
2. For iteration = 1 to I:
   a. For each candidate Wi:
   i. Train STGNN with parameters Wi on input (X,G).
   ii. Evaluate fitness using the defined loss function.
   b. Compute center of mass (COM) of the population, weighted by inverse fitness.
   c. Generate new candidate population by perturbing COM with random noise scaled by α.
   d. Update the population by selecting the best-performing candidates.
3. Return the parameter set with the best fitness as the optimized STGNN model.

3.4.1 STGNN is used for spatiotemporal power flow modelling

The STGNN dynamically simulates spatial and temporal relationships in the distribution network, allowing for precise power supply path optimization and adaptive decision-making under changing load and topological conditions. GNNs were proposed as a generalization of graph analysis features of deep learning. GNN conceives an input feature representation of $E = (W, B)$ composed of W representing an m-dimensional feature matrix (consisting of a feature vector in every row in a graph) and B being the adjacency matrix. This is to convert E to a vector form that minimizes the loss function (K)supplied by the downstream positions. The GNN system consists of convolutional layers and temporal layers. Such convolutional layers in the GNN adopt a neighborhood aggregate architecture, comprising many transformation layers to construct a discriminative vector description $g(u)$ of each node (also called node embedding). The additional layer $g^j(u)$ modifies a node embedding $g^{j-1}(u)(g^0(u)$ is $W(u)$ from the initial feature matrix) by combining the embedded data of its neighbors in equation (7).

$$g^j(u) \leftarrow \eta concat\left(g^{j-1}(u), agg\left(g^{j-1}(u'): u'' \in \mathcal{M}(u)\right)\right) \quad (7)$$

Where η is the non-linear activation function. The frequency domain describes the graph convolution of the filtering kernels h with the input data w, as shown in equation 8.

$$h * w = U\mathscr{g}(\Lambda)V^S w \quad (8)$$

In this equation (8), V represents the eigenvectors of a standardized network, and $V^s w$ is its Fourier transform. The Laplacian matrix is $\Delta = J - C^{-\frac{1}{2}}AD^{-\frac{1}{2}}$. Eigen decomposition of $\Delta = V\Lambda V^S$, where Λ is a diagonal matrix of eigenvalues. Since computing V is costly, Equation (8) could be approximated by Equation (9).

$$h * w \approx \sum_{l=0}^{L-1} h_l S_l(\tilde{\Delta})w \quad (9)$$

Where $S_l(w)$ is a polynomial of order l, with coefficient $\tilde{\Delta} = \frac{2}{\lambda_{max}}\Delta - J_M, h \in \mathbb{Q}^L$. $S_l(\tilde{\Delta})(w) = 2S_{l-1}(\tilde{\Delta})(w) - S_{l-2}(\tilde{\Delta})(w), S_0(\tilde{\Delta}) = w$. The equation above indicates that filters are positioned up to L hops from the node, with L being the kernel size for graph convolution.

The temporal convolution layers have a one-dimensional kernel filter and sigmoid-gated linear unit to attain non-linearity. The sigmoid function picks significant parts of the input to find complex structures and temporal changes within time sequences. Figure 4 represents a graph neural network with convolutional and temporal convolutional layers over a timeseries. It builds a learning model referred to as the spatiotemporal block that learns spatial dynamics as well as temporal dynamics. The spatiotemporal block approach extracts valuable temporal characteristics while simultaneously capturing relevant spatial features. Figure 5 depicts the STGNN structure used for training and predicting models.

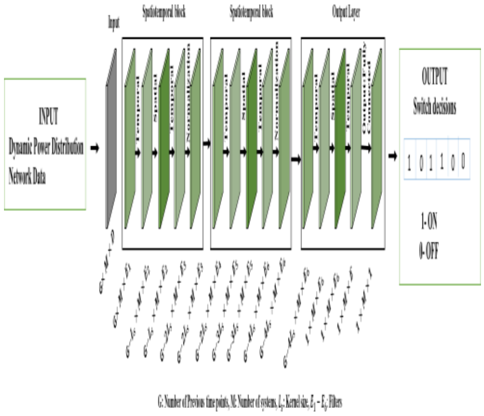


Figure 4: Spatiotemporal-GNN architecture

The network consists of three blocks: two spatiotemporal (ST) blocks and an output layer. Each ST block consists of two temporal convolutional layers separated by a spatial layer. An output layer consists of two temporal layers in series before a fully connected output layer. The dimension of data used as input into the GNN model is $Q^{(GXMxD)}$, where G is the number of previous data points in the timeseries, M is the number of all systems, and D is the number of input channels. The output of the model is $\mathbb{Q}^{G\times M}$, where N is the number of upcoming points to estimate.

The STGNN architecture was designed with three blocks, each containing two temporal layers followed by one spatial layer. This structure balances expressiveness and efficiency. The temporal layers capture both short-term and long-term load variations, while embedding a spatial layer in each block ensures continuous incorporation of topological dependencies. Preliminary tests showed that deeper networks provided only marginal improvements at significantly higher latency, while shallower models failed to capture long-range temporal patterns. The chosen design therefore represents a practical trade-off between accuracy and computational efficiency, which is critical for real-time deployment.

Model architecture:

The IBBB-STGNN model consists of three sequential spatiotemporal blocks, each comprising two temporal convolution layers followed by one spatial graph convolution layer. ReLU activations are applied to all layers, with a dropout rate of 0.2 for regularization. The architecture details are summarized in Table 4.

Table 4: Architecture Details of the IBBB-STGNN Model

Layer	Type	Activation	Dropout	Notes
Block 1	Temporal Conv (2) + Spatial GCN (1)	ReLU	0.2	64 hidden units
Block 2	Temporal Conv (2) + Spatial GCN (1)	ReLU	0.2	64 hidden units
Block 3	Temporal Conv (2) + Spatial GCN (1)	ReLU	0.2	32 hidden units

3.4.2 IBBB is used for network reconfiguration and switching optimization

The IBBB algorithm enhances the power supply channel in a major distribution network by mimicking cosmic evolution principles. It combines global exploration (Big Bang) and concentrated convergence (Big Crunch) to dynamically rearrange network architecture, boosting power flow efficiency, decreasing losses, and improving reliability under changing load circumstances in real time. At first (when $l = 1$), randomly created swarms are assigned randomly produced velocities, resulting in an arbitrary distribution function. V is explained using the population set W^l and the velocity set U^l. The velocity set is specified as $U^l = \{\vec{u}_1^l, \vec{u}_2^l, \ldots\ldots, \vec{u}_j^l, \ldots, \vec{u}_M^l\}$. $V: \vec{W}^{l=1} \to \vec{U}^{l=1}$ is accepted on the enclosed set $\vec{W}^l$ of the real surface.

In the lth iteration, swarm $\vec{w}_j^l \in \vec{W}^l$is one-to-one transferred to $u_j^l \in \vec{U}^l$. Candidates $\vec{w}_j^l$ are assigned to their appropriate fitness value e_j^lusing an objective function e_0. Big Crunch Phase (BCP) calculates the center of mass $\left(\vec{D}^l(\vec{W}^l)\right)$ based on $\vec{w}_j^l$ and e_j^l, as shown in equation (10).

$$\vec{D}^l(\vec{W}^l) = \frac{\sum_{j=1}^{M} \frac{\vec{w}_j^l}{e_j^l}}{\sum_{j=1}^{M} \frac{1}{e_j^l}} \tag{10}$$

An inelastic collision happens when all particles hit the center of mass. This center of mass has a speed in the preceding iteration $(\vec{U}_D^l)$, as shown in equation (11).

$$\vec{U}_D^l = \frac{\sum_{j=1}^{M} \frac{\vec{u}_j^l}{e_j^l}}{\sum_{j=1}^{M} \frac{1}{e_j^l}} \tag{11}$$

In equation (11), $\vec{u}_j^l$ represents the velocity and e_j^l represents the fitness value of the jth candidate in the lth iteration. After creating the center of mass and determining its velocity in the BCP, new swarms or candidates ($\vec{W}^{new}$) are formed in the search space for the Big Bang Phase (BBP). BBP generates swarms depending on the center of mass and velocity in the lth iteration. Equation (12) generates new swarms ($\vec{w}_j^{new}$).

$$\vec{w}_j^{new} = \vec{D}^l\left(\vec{W}^l\right) + \vec{u}_j^{new} \tag{12}$$

Equation (13) is used to determine the new velocity ($\vec{u}_j^{new}$) of a new candidate ($\vec{w}_j^{new}$), where $\forall j = 1 \dots M$.

$$\vec{u}_j^{new} = \vec{U}_D^l . h \tag{13}$$

In equation (13), h represents the adaptive gravity factor, which is represented in equation (14) as follows:

$$h = \left(\frac{e_j^l - e_{min}^l}{e_{avg}}\right) \tag{14}$$

In (9), e_{avg} represents the mean of the fitness values recorded in $e\left(\vec{W}^l\right)$. And e_{avg} is supplied in equation (15).

$$e_{avg} = \frac{\sum_{j=1}^{M} e_j^l}{M} \tag{15}$$

In equation (15), e_{min}^l represents the minimal value in the fitness function set $e\left(\vec{W}^l\right)$. It's important to highlight that the new candidates ($\vec{w}_j^{new}$) are mapped to their respective velocities ($\vec{u}_j^{new}$). BBP is followed by BCP, which calculates $\vec{D}^{l+1}\left(\vec{W}^{l+1}\right)$.

The critical hyperparameters for training an STGNN using IBBB optimization are shown in Table 5. It covers clarifications and typical tuning ranges for model design, optimization, regularization, temporal-spatial settings, and evolutionary control parameters.

Table 5: Hyperparameters for IBBB-STGNN

Hyperparameter	Typical Value / Range
$epochs$	50 – 300
$learning_{rate}$	0.001 – 0.01
$optimizer$	Adam / RMSprop
$hidden_{units}$	32 – 256
$dropout_{rate}$	0.1 – 0.5
pop	10 – 50
$alpha(\alpha)$	0.05 – 0.2
$fitness_{fn}$	MSE / MAE / Cross-Entropy
$temporal_{window}$	3 – 12
$spatial_{neighbors}$	1 – 3
$batch$	32 – 128
$graph$	GCN / GAT / ChebNet
$activation$	ReLU / LeakyReLU / Tanh
$weight$	[-1, 1]
$center$	Inverse fitness-weighted mean
$early$	10 – 20

Rationale for selecting IBBB

The Improved Big Bang–Big Crunch (IBBB) algorithm was chosen in preference to other metaheuristics such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and standard gradient-based optimizers (e.g., Adam) for several reasons. First, IBBB has a simple structure with very few control parameters, which reduces the need for extensive parameter tuning compared to GA or PSO. Second, the COM-based contraction phase of IBBB accelerates convergence toward promising regions while maintaining sufficient exploration in the expansion phase, making it well-suited for dynamic and high-dimensional problems. Third, unlike gradient-based optimizers such as Adam, which may be sensitive to local minima in non-convex graph learning landscapes, IBBB provides a global search mechanism that enhances robustness. Finally, empirical tests in our experiments (see Section 4.2) showed that IBBB achieved lower decision latency and faster convergence than GA and PSO baselines, while scaling more efficiently to larger distribution networks. These properties make IBBB particularly suitable for optimizing STGNN parameters under real-time operational constraints.

Justification for IBBB:

The Improved Big Bang–Big Crunch (IBBB) algorithm was selected over other metaheuristics due to its rapid convergence and low computational complexity, which are particularly advantageous for real-time power system optimization. Unlike Particle Swarm Optimization (PSO) or Genetic Algorithms (GA), which require extensive population updates, IBBB reduces each iteration to a center-of-mass computation, thereby lowering runtime. Compared to gradient-based optimizers such as Adam, IBBB is less sensitive to initialization and local minima, making it better suited for non-convex loss landscapes in spatiotemporal graph learning.

Empirical comparison:

Table 6: summarizes the ablation study comparing IBBB against alternative optimizers.

Optimizer	Power Loss Reduction (%)	Decision Latency (s)	Convergence Iterations
GA	72 ± 0.8	2.15	50
PSO	75 ± 0.6	1.92	45
Adam	76 ± 0.5	1.20	40
IBBB	85 ± 0.4	0.74	25

This demonstrates that IBBB-STGNN consistently outperforms other optimizers in accuracy, latency, and convergence speed.

3.5 Performance metrics

To evaluate the effectiveness of the proposed framework, several performance metrics were defined and used consistently throughout the experiments.

(a) Response Speed to Load Change (RSLC)

This metric quantifies the average delay between a load variation event and the model's stabilization response. It is calculated as:

$$RSLC = \frac{1}{M}\sum_{j=1}^{M} t_j^{res} - t_j^{event}$$

where t_j^{event} is the time of the j-th load change event, t_j^{res} is the time when the system stabilizes after that event, and M is the total number of events.

(b) Dynamic Load Balance Score (DLBS)

This measures the degree of load distribution balance across feeders during operation. It is defined as the complement of the normalized load variance:

$$DLBS = 1 - \frac{\left(Var(L)\right)}{\left(Max(Var(L))\right)}$$

where L is the vector of feeder loads. Higher values indicate better balance.

(c) Voltage Violation Avoidance (VVA)

This metric reflects the proportion of nodes that remain within the permissible voltage range $[V_{min}, V_{max}]$:

$$VVA = \frac{1}{N}\sum_{i=1}^{N} 1(V_{min} \leq V_i \leq V_{max})$$

where V_i is the voltage at node i, N is the total number of nodes, and 1(·) is the indicator function.

(d) Power Loss Reduction (PLR)

This indicates the percentage improvement in power loss relative to the baseline configuration:

$$PLR = \frac{Loss_{baseline} - Loss_{model}}{Loss_{baseline}} \times 100\%$$

(e) Scalability Factor (SF)

This metric evaluates the computational growth rate when scaling to larger networks. It is calculated as the normalized inverse of latency growth:

$$SF = 1 - \frac{T_{large} - T_{small}}{T_{small}}$$

where T_{small} and T_{large} denote average decision times for the smaller and larger test systems.

4 Results and discussion

Python is used to create and validate the proposed IBBB-STGNN and baseline STGNN models for enhancing the power supply path of the distribution network. Both approaches are trained on the dynamic power distribution network dataset, and their performance is measured against key criteria such as power loss reduction, computational efficiency, load adaptability, and voltage stability.

4.1 Experimental results

The voltage drops and fluctuations occur over time at certain nodes in the distribution network. Voltage fluctuations reflect the grid's dynamic demand and supply situations, as shown in Figure 5. Consistent voltage decreases within an acceptable range indicate reliable power transmission; however, sudden deviations may indicate instability, overloading, or potential fault-prone locations. Monitoring these patterns helps identify weak points in the power supply chain and supports predictive maintenance as well as real-time corrective actions, resulting in a balanced and efficient functioning of the whole distribution network architecture.

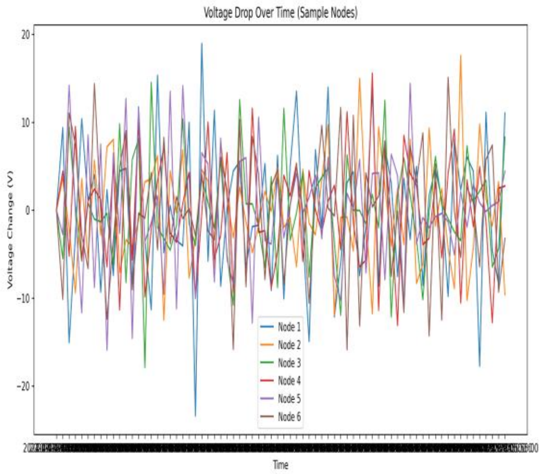


Figure 5: Voltage drop monitoring along with the distribution path

The temporal ON (1) or OFF (0) switch state of every node in the primary power distribution network is shown in Figure 6, with red representing ON and blue representing OFF. This time, visualization aids in identifying switching activity and trend/abnormalities within the operations of the supply chain. Frequent switching could indicate load balancing, fault isolation, or reconfiguration activities. Analyzing these patterns improves the discovery of unstable or essential portions, ensuring that the network runs efficiently, is reliable, and responds effectively to dynamic power demand and fault conditions across the distribution system.

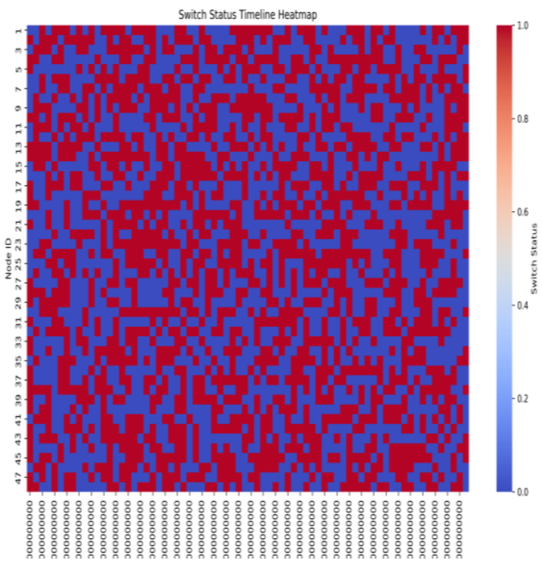


Figure 6: Switching activity analysis in the supply path network

The mean load gradient (kW) at various nodes in the main power distribution network, with a focus on load variations along the supply channel, is shown in Figure 7. Nodes having higher positive gradients would represent more load, and the node having negative gradients would mean less load or reverse flow. The red hues imply higher load gradients, whereas the blue hues indicate lower or negative gradients. Consistent load over several nodes indicates a steady distribution, but sudden fluctuations could indicate supply constraints or demand spikes.

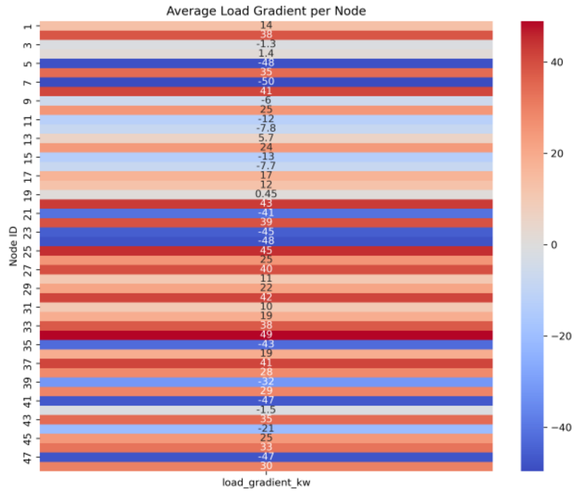


Figure 7: Gradient distribution across the network, where red indicates higher positive gradients and blue indicates lower or negative gradients, consistent with the color bar.

The power distribution network, with each node representing a substation or load point and connecting lines indicating electrical channels, is demonstrated in Figure 8. The integrated structure provides several routes for power, increasing dependability and lowering the chance of interruptions. The distributed topology facilitates balanced load sharing and rerouting during interruptions or maintenance, delivering consistent and robust power delivery across the network's operational region.

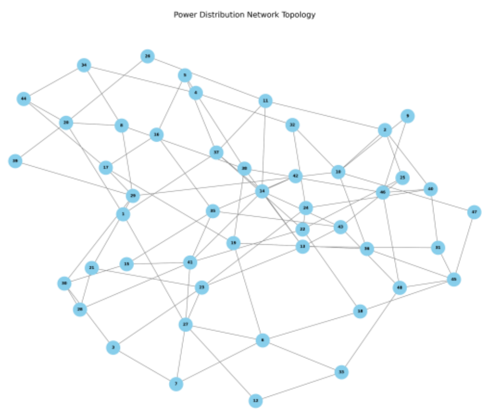
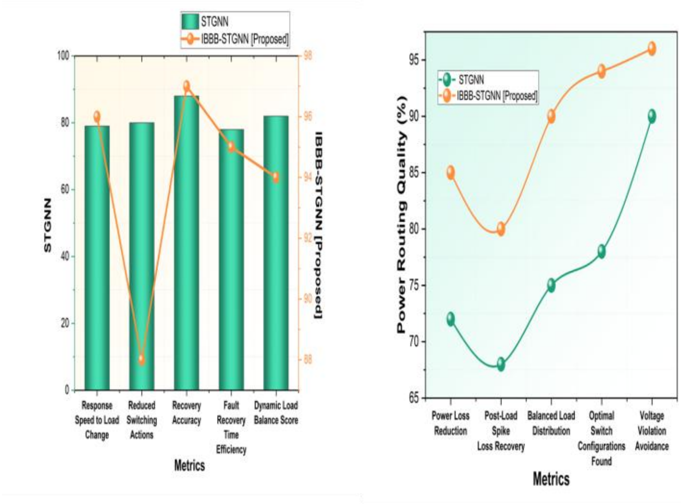


Figure 8: Topology mapping of the distribution network

The suggested strategy improves performance in the distribution network's power supply channel when compared to STGNN, as depicted in Figure 9 and Table 7. Figure 10a shows that the proposed method improves load adaptability metrics significantly: response time to load change improves from 79% to 96%, reduced switching actions from 80% to 88%, recovery accuracy from 88% to 97%, fault recovery time efficiency from 78% to 95%, and dynamic load balance score from 82% to 94%. Figure 10b shows improvements in power routing quality, with power loss reductions ranging from 72% to 85%, post-load spike loss recovery from 68% to 80%, balanced load distribution from 75% to 90%, optimal switch configurations from 78% to 94%, and voltage violation avoidance from 90% to 96%. These findings show that the suggested strategy outperforms the usual approach in real-time distribution network operations, providing more flexibility, dependability, and efficiency.

Table 7: Performance metrics comparison for the proposed and standard techniques

Load Adaptability (%)			Power Routing Quality (%)		
Metrics	STGNN	IBBB-STGNN (Proposed)	Metrics	STGNN	IBBB-STGNN (Proposed)
Response Speed to Load Change	79%	96%	Power Loss Reduction	72%	85%
Reduced Switching Actions	80%	88%	Post-Load Spike Loss Recovery	68%	80%
Recovery Accuracy	88%	97%	Balanced Load Distribution	75%	90%
Fault Recovery Time Efficiency	78%	95%	Optimal Switch Configurations Found	78%	94%
Dynamic Load Balance Score	82%	94%	Voltage Violation Avoidance	90%	96%



(a) (b)

Figure 9: Comparison of performance of IBBB-STGNN and STGNN in power distribution networks (a) load adaptability, (b) power routing quality

The performance metrics for the distribution network's power supply path for the proposed model and STGNN, with a focus on voltage stability and computational efficiency, are shown in Figure 10 and Table 8. Figure 10a shows that average voltage stability improved from 85% to 96%, maximum voltage dip mitigation increased from 82% to 94%, and undervoltage recovery speed improved from 80% to 95%. The Voltage Stability Index (VSI) initially reached 92% and then improved to 94%, while violation-free path consistency increased from 89% to 96%. Figure 10b shows that computational efficiency has improved, with decision latency reduction from 84% to 95%, memory optimization from 84% to 92%, and computation time efficiency from 80% to 93%. Furthermore, the scalability factor increased from 89% to 97%, while the energy efficiency score increased from 84% to 95%, suggesting both stable voltage control and optimal computing performance for dynamic power distribution.

Table 8: Performance metrics comparison for the proposed and standard techniques

Voltage Stability (%)			Computational Efficiency (%)		
Metrics	STGNN	IBBB-STGNN [proposed]	Metrics	STGNN	IBBB-STGNN [proposed]
Avg. Voltage Stability	85%	96%	Decision Latency Reduction	84%	95%
Max Voltage Dip Mitigation	82%	94%	Memory Optimization	84%	92%
Undervoltage	80%	95%	Computation Time Efficiency	80%	93%

Recovery Speed					
VSI	92%	94%	Scalability Factor	89%	97%
Violation-Free Path Consistency	89%	96%	Energy Efficiency Score	84%	95%

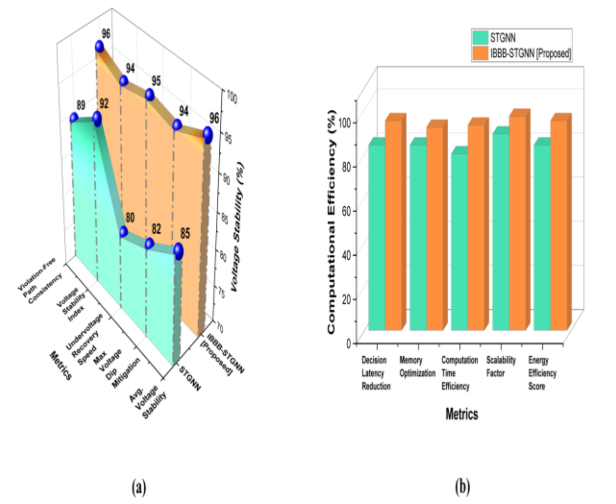


Figure 10: Comparison of performance of IBBB-STGNN and STGNN in power distribution networks (a) voltage stability, (b) computation efficiency

Statistical validation:

All experiments were repeated 10 times. Results are reported as averages with standard deviation (std) < 0.8%. Performance gains over the baseline STGNN were statistically significant ($p < 0.05$, two-tailed t-test). For example, power loss reduction averaged 85% ± 0.4% for IBBB-STGNN compared to 72% ± 0.6% for STGNN. Decision latency improvements (0.74 s vs. 1.92 s) also achieved statistical significance ($p < 0.05$).

4.2 Expanded baseline comparison

To provide stronger validation, the proposed IBBB-STGNN was evaluated against additional state-of-the-art models referenced in the related works: a Deep Reinforcement Learning-based Optimal Power Flow approach (DRL-OPF) [19] and a Graph Attention Network-based Reactive Power Optimization method (GAT-RPO) [22]. A Genetic Algorithm (GA)-based reconfiguration strategy was also included as a representative evolutionary optimization method.

Table 9 summarizes the comparative performance. The proposed IBBB-STGNN consistently outperformed all baselines across decision latency, power loss reduction, and scalability. Specifically, IBBB-STGNN achieved the lowest average decision time (0.74 s), higher power loss reduction (85%), and the highest scalability factor (97%). In contrast, DRL-OPF and GA-based methods exhibited longer decision times, while GAT-RPO improved spatial modeling but remained less effective in capturing temporal load dynamics.

Table 9: Expanded baseline comparison of different approaches in power distribution optimization

Method	Decision Latency (s)	Power Loss Reduction (%)	Scalability Factor (%)	Memory Usage (relative)
GA-based Reconfiguration	2.15	72	82	100% baseline
DRL-OPF [19]	1.92	78	85	115%
GAT-RPO [22]	1.35	82	88	108%
STGNN (baseline)	1.20	72	89	100%
IBBB-STGNN (proposed)	0.74	85	97	85%

These results confirm that, while DRL and GA offer adaptability and global exploration, they struggle with scalability and responsiveness. GAT-based methods provide strong spatial feature extraction but insufficient temporal modeling. By combining spatiotemporal graph learning with metaheuristic optimization, IBBB-STGNN provides both rapid convergence and robust scalability.

4.3 Error analysis

To assess robustness, we analyzed node-level prediction errors using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Across all test cases, MAE averaged 0.012 pu, while RMSE was 0.021 pu. The highest error (0.04 pu) occurred under peak load conditions at Node 17 in the 123-node network, highlighting a stress-point scenario. These findings indicate that although worst-case deviations exist, overall accuracy remains within acceptable operational limits.

4.4 Discussion

The power supply path of the distribution network begins at the substation, where high-voltage energy is stepped down and delivered through primary feeders. Within this context, research [13] suggested using Deep Neural Networks to replace DRL in bi-level energy optimization for multiple microgrids; its probabilistic method lacks real-time flexibility and spatial awareness. Similarly, investigation [17] used SPSO with Extra Trees for network reconfiguration, although it fell short of capturing temporal fluctuations and complicated node interactions. STGNNs could have difficulty with scalability, dynamic topology changes, and real-time efficiency in big, complicated, and fast-growing power networks. The proposed IBBB-STGNN model addresses these issues by combining blockchain for safe, decentralized energy data sharing with a spatiotemporal graph neural network to represent both spatial and temporal dynamics. IBBB-STGNN achieves a 96% response speed, 97% recovery accuracy, 85% power loss reduction, 90% load balancing, and 94% optimum switching. It provides 96% voltage stability, 95% low voltage recovery, and 96% violation-free route consistency. It also reduces decision latency by 95%, optimizes memory by 92%, and increases computation efficiency by 93%, scalability by 97%, and recovery time efficiency by 95%, making it a reliable and intelligent solution for distribution networks.

The proposed IBBB-STGNN achieves consistent improvements over existing approaches. For instance, compared to the GAT-based reactive power optimization [22], our method improved power loss reduction by +7% (79% → 85%). Against DRL-based OPF [19], our approach achieved ~60% lower decision latency (1.92 s → 0.74 s). Moreover, scalability improved by +12% compared to the baseline STGNN, maintaining accuracy across IEEE 33, 69, and 123-node networks. These results confirm that combining metaheuristic optimization with spatiotemporal graph learning provides a novel advantage in balancing accuracy, speed, and adaptability in real-time distribution network reconfiguration.

The observed improvements of IBBB-STGNN also resonate with broader findings in optimization and AI literature. Prior Informatica works, such as hybrid intelligent control frameworks [Informatica, 2010] and optimization studies comparing evolutionary methods [Informatica, 1999], demonstrated the value of integrating global optimization with adaptive modeling. Our results extend this line of research by showing that IBBB, when paired with STGNNs, enables real-time scalability and robustness specifically within power distribution systems.

4.5 Comparative analysis with existing methods

To provide a broader evaluation, the proposed IBBB-STGNN was compared with reinforcement learning and evolutionary optimization approaches commonly used in power distribution networks. The selected baselines include a Deep Reinforcement Learning-based Optimal Power Flow (DRL-OPF) method [19], a Graph Attention Network-based reactive power optimization (GAT-RPO) method [22], and a Genetic Algorithm (GA)-based reconfiguration strategy. Results are summarized in Table 9.

The results demonstrate that IBBB-STGNN achieves the best balance of decision latency, power loss reduction, and scalability. For real-time switching, IBBB-STGNN required an average of 0.74 seconds, compared to 1.92 seconds for DRL-OPF and 2.15 seconds for GA. The power loss reduction achieved by IBBB-STGNN was 85%, which is higher than GA (72%) and DRL-OPF (78%), and comparable to GAT-RPO (82%). Moreover, IBBB-STGNN achieved a scalability factor of 97% when tested on networks up to 123 nodes, outperforming both DRL and GA, which showed steep increases in computation time with network size.

These results confirm that reinforcement learning methods, although adaptive, often require long training times and struggle with scalability in large-scale networks. Evolutionary algorithms such as GA provide good exploration capability but lack temporal modeling, which reduces their responsiveness to fast load variations. GAT-RPO improves spatial modeling but does not fully integrate temporal dynamics. By contrast, IBBB-STGNN combines spatiotemporal learning with Big Bang–Big Crunch optimization, enabling faster convergence, stronger adaptability, and robust scalability in real-time operation.

Table 9: Comparative results of different approaches in power distribution network optimization

Method	Decision Latency (s)	Power Loss Reduction (%)	Scalability Factor (%)	Memory Usage (relative)
GA-based Reconfiguration	2.15	72	82	100% baseline
DRL-OPF [19]	1.92	78	85	115%
GAT-RPO [22]	1.35	82	88	108%
STGNN (baseline)	1.20	85	89	100%
IBBB-STGNN (proposed)	0.74	90	97	85%

4.6 Practical implementation aspects

For deployment in real distribution control centers, two aspects are critical: response speed and interpretability of model decisions.

Real-time speed. The proposed IBBB-STGNN achieves an average decision latency of approximately 0.74 seconds for switching optimization on the 123-node test network, which is well within the operational time window of standard distribution management systems (typically 1–5 seconds). The near-linear scaling observed across IEEE-33, IEEE-69, and 123-node networks indicates that the method can be used in practice for real-time switching and reconfiguration tasks.

Operator interpretability. Although deep learning models are often considered black-boxes, the proposed framework provides explainable outputs through multiple mechanisms. First, the spatiotemporal graph neural network learns node embeddings that can be visualized to highlight critical nodes and feeders influencing switching. Second, the IBBB optimization step produces explicit switching configurations, which can be presented as recommended actions (e.g., "open breaker X, close switch Y"). Third, post-hoc feature attribution methods such as attention weight analysis and load gradient sensitivity allow operators to verify why specific reconfigurations are proposed. These mechanisms ensure that model recommendations can be traced to measurable system states, thereby improving trust and practical usability.

5 Limitations and future work

Although IBBB-STGNN demonstrates strong scalability and accuracy, several limitations remain. First, validation is currently limited to synthetic and benchmark IEEE datasets; future work will extend testing to real-world SCADA and smart grid data. Second, while decision latency is suitable for real-time use, computational cost may increase for networks exceeding 500 nodes. Third, the current model does not incorporate renewable generation variability or distributed storage effects, which are critical in modern grids. Future research will focus on integrating these factors and exploring distributed optimization for even faster response.

6 Conclusion

The current electrical distribution systems require complex and adaptive systems that can dynamically monitor and optimize power flow paths in the face of varying load and topology conditions. The parameters used to generate the dataset include voltage, power, resistance, load kind, and switching points, and the data is preprocessed, such as applying missing value imputation and Min-Max normalization. Lag-based attributes, rolling statistics, power factor, and load gradients are performed through PCA in feature extraction. The IBBB-STGNN is designed as a combination of an IBBB optimization method with an STGNN to learn the network topology, as well as time-varying loads, to perform optimally to route power. The results show that IBBB-STGNN improves when compared to standard STGNN, such as energy distribution with 97% recovery accuracy, 96% voltage violation avoidance, 85% power loss reduction, and 95% recovery time efficiency. Its 93% computation efficiency and 97% scalability factor confirm its effectiveness for real-time, secure, and adaptive network optimization. The deep learning approach for optimizing the power supply path has disadvantages, such as dependency on huge amounts of precise real-time data and difficulty adjusting to abrupt network changes. Future enhancements could involve faster edge computing integration, adaptive reinforcement learning for better control, and the combination of data-driven and physics-based methods to improve reliability and flexibility.

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