Network Structure Feature Representation Learning for Distribution Network Single-Line Diagrams Based on Generative Adversarial Networks

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Abstract

For the planning and design, operation and maintenance, and dispatch management of distribution networks, the distribution network single-line diagram is an indispensable and commonly used tool. The distribution network single-line diagram has strict requirements for layout standardization during use. The layout of single-line diagrams varies for different distribution network structures, and traditional automatic diagram generation algorithms cannot adapt to changes in network structure to automatically generate corresponding layout single-line diagrams based on network type. Deep learning algorithms possess strong coupling capabilities; they can automatically summarize internal diagram generation patterns and produce distribution network single-line diagrams that conform to the required layout. To apply deep learning algorithms to the field of automatic generation of distribution network single-line diagrams, it is necessary to consider establishing an algorithm capable of representing the network structural features of distribution network single-line diagrams. The core of this algorithm is its ability to adapt to the needs of deep learning algorithms and achieve low-dimensional representation of network features in distribution network single-line diagrams. Existing research on network feature representation learning methods mostly focuses on feature representation for the unique attributes of social networks. Compared with social networks, the connection relationships between devices in power equipment networks are constrained by electrical physical characteristics, and there is no learning targeted at the unique attributes of power networks. Therefore, based on existing network feature representation learning research, this paper proposes a network feature structure representation learning algorithm specifically for distribution network single-line diagrams. It utilizes the electrical connection relationships of distribution equipment that form the foundation of distribution networks to establish a mathematical model, defines first-order, second-order, and zero-order connection characteristics between network nodes, and then implements low-dimensional network feature representation through generative adversarial networks. At the end of the paper, experiments validate the first-order and second-order similarity of network features through sample data, demonstrating that the algorithm is more aligned with the characteristics of power business in terms of implementation efficiency and accuracy.

Full Text

Representation Learning of Network Structural Features for Distribution Network Single-Line Diagrams Based on Generative Adversarial Networks

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Abstract: Distribution network single-line diagrams are indispensable tools for distribution network planning, design, operation, maintenance, and dispatch management. These diagrams have strict layout standardization requirements, and different distribution network structures produce different layout styles. Traditional automatic diagram generation algorithms cannot adapt to structural changes or automatically generate corresponding layouts based on network topology. Deep learning algorithms, with their powerful coupling capabilities, can automatically summarize internal layout patterns and generate distribution network single-line diagrams that conform to required layout styles. To apply deep learning to automatic single-line diagram generation, we must first establish an algorithm capable of representing the network structural features of these diagrams—one that can adapt to deep learning requirements and achieve low-dimensional expression of network features. Existing network representation learning research primarily focuses on unique attributes of social networks. However, compared to social networks, connections in power equipment networks are constrained by electrical physical characteristics, and no existing work specifically learns these unique attributes of power networks. Building upon existing network representation learning research, this paper proposes a network structural feature representation learning algorithm tailored for distribution network single-line diagrams. We establish a mathematical model based on the electrical connection relationships of distribution equipment that form the foundation of distribution networks, define first-order, second-order, and zero-order connection characteristics between network nodes, and implement low-dimensional network feature representation through generative adversarial networks. Experimental validation using sample data demonstrates first-order and second-order similarity of network features, proving that the algorithm' s efficiency and accuracy better align with the characteristics of power system operations.

Keywords: Distribution network single-line diagram; network features; gener-

ative adversarial network

1. Introduction

In the power industry, efficient operation and management of distribution networks rely on various auxiliary information, among which single-line diagrams constitute a critical foundation for daily work of power system operators and dispatchers. These diagrams must display all primary and branch equipment within a single line range, including substations, cables, overhead lines, switchgear, ring main units, distribution transformers, and other schematic equipment. Lines and related equipment are laid out using orthogonal layout algorithms without crossing or overlapping. Daily operations, maintenance, fault analysis, location, and distribution network dispatching all revolve around these structure-describing single-line diagrams.

In practice, distribution networks update frequently, requiring rapid and accurate generation and updating of single-line diagrams while maintaining consistent and aesthetically pleasing styles for convenient browsing. As the terminal link in power delivery, distribution network structures are closely related to local urban development, economic levels, and cultural environments. [Figure 1: see original paper] shows a distribution network single-line diagram, while [Figure 2: see original paper] illustrates two different layout styles resulting from different network structures. Manual maintenance of single-line diagram layouts involves enormous workload and is prone to errors.

Traditional automatic diagram generation algorithms such as simulated annealing, tree mapping, genetic algorithms, and force-directed methods have been studied and applied to single-line diagram routing with certain reference value. However, these methods cannot intelligently adjust their layout styles based on actual conditions—style changes require reprogramming. In recent years, the explosion of deep learning algorithms in artificial intelligence has demonstrated excellent performance in inference and style learning. For example, generative adversarial networks in deep learning can automatically draw B-style paintings based on A' s characteristics, as shown in [Figure 3: see original paper].

The field of automatic distribution network single-line diagram generation can similarly leverage the powerful automatic inference capabilities of deep learning. By establishing deep learning models, we can automatically infer appropriate single-line diagram styles as needed. The prerequisite for applying deep learning models to this domain is an appropriate mathematical model describing the network structure to be learned. In deep learning, network representation learning (Network Embedding) has emerged to address this challenge. Network representation learning, a specialization of representation learning for network research, can automatically learn representation vectors for each node in a network within a required vector space. It forms the foundation for any deep learning-based network feature research. Representation learning automatically identifies valuable information from raw data through unsupervised or supervised learning and encodes it into a low-dimensional, dense, continuous vector space.

For the evolution history and characteristics of specific network feature representation learning algorithms, refer to the literature [1]. These algorithms primarily focus on social network analysis and representation. Compared to the uncertainty and flexibility of interactions between nodes in social networks, distribution network single-line diagrams, as network structural graphs, contain numerous electrical physical characteristics. Their node connection relationships differ significantly from traditional social networks or biological networks. The greatest challenge in applying deep learning to power system thematic mapping is developing a simple yet efficient network model representation algorithm.

In distribution network single-line diagrams, we can treat power equipment as network nodes and connection lines between equipment as network edges. Whether these devices can connect or how they connect is limited by the physical characteristics of power equipment and operational requirements. These constraints contain rich information—for example, a circuit breaker is likely connected to disconnect switches on both sides, while a fuse can only have incoming and outgoing connections. Leveraging these constraints and electrical characteristics of single-line diagrams in network structural feature representation learning can significantly improve algorithm efficiency, reduce computational complexity, and more accurately reflect power line characteristics.

2. Related Work

This paper proposes a network representation method adapted to the unique characteristics of distribution network single-line diagrams, with work divided into two phases: The first phase establishes node sequence representation between nodes in single-line diagrams, which is fundamental to network representation. To map a network from high to low dimensions, we must first determine network characteristics and how to represent node relationships. To preserve the unique network characteristics of distribution network single-line diagrams, we improve traditional first-order and second-order similarity definitions to better utilize equipment connection electrical characteristics, and propose a definition for zero-order similarity. The second phase combines deep learning generative adversarial algorithms, using the node relationships established in the first phase as input to build a generative adversarial network that learns low-dimensional representations for each equipment node. This network fully utilizes main-branch line relationships and electrical physical characteristics of equipment connections to establish input tensors for the generative adversarial network.

The main contributions of this paper are: 1) Starting from electrical connection relationships between distribution network equipment, we propose a general algorithm for establishing node sequence models and node sequence weight values for distribution network single-line diagrams using mathematical statistics methods. 2) Based on electrical connection characteristics between equipment in single-line diagrams, we abandon traditional first-order and second-order similarity for describing network features. Instead, we redefine zero-order, first-order, and second-order similarity between nodes through branch node similarity and recursive similarity in node sequences. 3) We redesign the generative adversarial network, combining it with auto-encoders to leverage characteristics of distribution network single-line diagrams for more effective mapping of equipment nodes to low-dimensional vector spaces.

This paper is organized as follows: First, we discuss the establishment of node sequences and weight value algorithms for distribution network single-line diagrams. Based on this, we introduce how to define zero-order, first-order, and second-order similarity representations suitable for distribution networks by incorporating electrical connection characteristics. After completing these foundational tasks, we describe how to redesign the generative adversarial learning network for distribution network single-line diagram representation. Finally, we use t-SNE to compare high-dimensional and low-dimensional features, validating the effectiveness of our proposed method.

3.1. Analysis of Distribution Network Single-Line Diagram Network Characteristics

Distribution network single-line diagrams are organized by individual distribution lines (feeders), using specific layout algorithms to automatically generate all equipment from substation outlets to distribution transformers or line tie switches. The electrical equipment presented mainly includes substations, ring main units, switchgear, pole-mounted load switches, pole-mounted circuit breakers, pole-mounted disconnect switches, drop-out fuses, medium-voltage overhead lines, medium-voltage cables, distribution transformers, distribution rooms, pad-mounted transformers, branch boxes, towers (including tower accessories such as jumpers and grounding rings), etc. These are primarily five categories: switches, stations, cables, transformers, and towers. Among them, switches, cables, and transformers generally have two terminals, while stations and towers can be considered multi-terminal devices. Lines branch at towers or stations.

According to the operational characteristics of single-line diagrams, they are divided into main lines and branch lines. [Figure 4: see original paper] shows a distribution network single-line diagram legend. As a diagram describing feeders, the core characteristic is the electrical physical property that current flows from high-voltage equipment to low-voltage equipment. Distribution network single-line diagrams consist mainly of electrical equipment nodes and physical connection lines between equipment. How to represent the connection weights between equipment is a critical issue, as connection weights vary depending on hierarchical levels in single-line diagrams. Unlike simple adjacency matrices that assume equal weights (using "1" for connected and "0" for disconnected), this representation cannot reflect the importance of electrical connection relationships.

The power source points in distribution network single-line diagrams start from outlet switches in substations or switch stations, with current flowing level by level according to Ohm' s law. Therefore, modeling must reflect equipment connection weights with the power source point and between equipment based on electrical physical characteristics.

3.2. Establishment of Connection Relationship Model for Distribution Network Single-Line Diagrams

In distribution network single-line diagrams, equipment connections rely on lines. Setting weight values based solely on line length cannot illustrate the importance of connection relationships, only indicating geographic proximity between equipment. Since single-line diagrams are generated from power equipment geographic wiring diagrams according to specific rules, geographic location information disappears after generation and is not required for single-line diagram modeling. A more important characteristic in distribution network single-line diagrams is the topological relationship between equipment. For topological relationships between equipment in single-line diagrams, power system operations have a unified model specification: the SG-CIM model based on IEC61968 and IEC61970. Many papers discuss SG-CIM model applications in single-line diagrams. In practice, SG-CIM describes grid topology connections and serves as a suitable data source specification format for single-line diagrams, enabling data transmission between different systems. Essentially, it describes equipment IDs, some simple account information, and connection relationships between equipment terminals. However, the SG-CIM model mainly defines terminal characteristics for equipment connections and indicates whether topological connections exist, without defining connection weight values between equipment.

Power equipment connection weight values must be derived from equipment types and electrical connection characteristics. In principle, the equipment that can connect to a device is related to its terminals (for discussion convenience, we limit each terminal to connecting only one device). The types of equipment that can connect to a terminal are related to the device' s electrical characteristics.

We can describe connection characteristics between two devices through connection probability, calculated as follows: First, limit the scope of single-line diagram equipment to set F (containing all equipment types displayed on single-line diagrams). Define the weight value between equipment connections using the probability of connection relationship between equipment A and a specific equipment type.

Assume equipment A has N connection terminals (initially limited to one device per terminal), with each terminal capable of connecting to M types of equipment. The probability of connecting another device on a terminal is 1/M, following a binomial distribution: $(1/\ )\ (1-1/\ )$; P(X = n) ~ B(N, 1/M). Therefore, the probability of equipment A connecting to n devices B is . The probability of equipment B appearing on one terminal of equipment A is 1/(MN). Connection probability between equipment precisely illustrates the likelihood of connection from the perspective of electrical physical characteristics.

3.3. Node Sequence Model for Distribution Network Single-Line Diagrams

In distribution network single-line diagrams, the same type of equipment appears in different positions, and connection patterns between the same two equipment types also appear in different locations. Considering only connection characteristics between two equipment types cannot comprehensively describe network features of single-line diagrams. Therefore, we must also consider equipment positions globally. In single-line diagrams, the core for each equipment to receive power lies in the power supply source. We can leverage this to describe equipment positions globally, using the power source point as a starting point to obtain connection weights between each equipment and the power source point in the single-line diagram.

In single-line diagrams, equipment is grouped at the granularity of main lines and branch lines. Therefore, describing a complete distribution network single-line diagram requires using sequence methods to describe connections between main and branch lines to fully represent overall network features. According to the physical characteristic that both main and branch lines are powered from the same source point, each sequence can describe a line path in the single-line diagram. In each line path, each element in the sequence can describe the weight relationship between each equipment along the current flow path and the busbar.

If described through a node sequence, the following mathematical model can be used. As shown in [Figure 5: see original paper], the main line sequence is A-B-C-D. Since branch lines are also powered from the same source as the main line, the branch line sequence is A-B-C-E-F. Node connection weights are shown in the legend.

Node sequence calculation starts from the line busbar. As the busbar serves as the power source point for the entire line and represents a special starting point, we specify that the connection probability between it and the first equipment along the current flow is fixed at “1”. For the Nth equipment in the line, setting the busbar as S, its probability is P(N|S). Since equipment connection relationships depend on the previous equipment and possess connection independence, according to the chain formula: $P(N|S) = P(N\ |S)P(N\ |N\ )\cdots P(N\ \ |N\ )$.

Main lines and branch lines are essentially the same in network topology but differ significantly in operational applications. Treating them uniformly as line paths cannot distinguish their differences. Therefore, branch lines require separate processing; otherwise, from a node sequence perspective, the divergence between branch and main lines appears identical and cannot be judged from node sequences alone. Business analysis shows that main lines serve as primary power supply paths in distribution network single-line diagrams, while branches typically serve as line taps. Therefore, in representation, we can multiply the weight value by a constant a = 0.9 at the main-branch divergence point in the node sequence to differentiate main and branch lines.

According to the node sequence model definition, the main and branch line node sequences in the legend are calculated as follows: - A->B: Node A is the power source point with node weight value 1. Node B is defined as: 1×0.5=0.5, giving node B a weight value of 0.5. The node sequence is: {1, 0.5}. - B->C: Node C weight value is: 1×0.5×0.2=0.01, giving the node sequence: {1, 0.5, 0.01}. Other node weight values are calculated similarly. The main line node sequence becomes: {1, 0.5, 0.01, 0.003}. Branch lines start from the power source point like main lines, sharing the same weight values for common sections. For branch sections, multiply by 0.9: {1, 0.5, 0.01, 0.0027, 0.00054}. Note that branch line nodes are first calculated using the main line weight algorithm, then the branch portion is multiplied by 0.9.

3.4. Network Node Similarity for Distribution Network Single-Line Diagrams

ABCDEFP(B|A)=0.5P(C|B)=0.2P(D|C)=0.3P(E|C)=0.3P(B|A)=0.5P(F|E)=0.2

Based on the above analysis, due to the physical and electrical characteristics of power equipment, the network formed by equipment nodes in distribution network single-line diagrams differs fundamentally from traditional social network node relationships. In social networks, a node may potentially connect to any other node. However, in distribution network single-line diagram networks, connection randomness is essentially non-existent due to inherent constraints. Node connections must strictly follow original line designs and cannot occur arbitrarily.

Network node representation in feature learning must consider similarity between nodes. Similarity definitions in network representation learning primarily aim to describe local and global relationships between nodes in the network, preserving these important network characteristics during high-to-low-dimensional mapping. Local information refers to edge information in the network, representing observed first-order similarity. Many previous methods used this information, such as IsoMap and Laplacian eigenmap. However, in real-world networks, many legitimate edges are unobserved, making first-order similarity insufficient for representing global information. Consequently, second-order similarity was proposed, representing information not through connection strength with surrounding nodes but through shared neighbor node structures. Intuitively, nodes sharing more neighbors are considered more similar.

For distribution network single-line diagrams, definitions of first-order and second-order similarity must start from network characteristics themselves. Since nodes in single-line diagrams focus more on connection relationships with adjacent nodes and are constrained by the physical characteristic of current flowing from high to low voltage, first-order and second-order similarity definitions can be simpler than traditional network similarity definitions, without considering higher-order similarities.

Definition 1: First-order similarity
According to the probability of equipment connections in distribution networks, the connection weights discussed above are fixed and unchanging due to physical constraints. Therefore, whether in high-dimensional or low-dimensional representation, the connection probability (i.e., connection weight) between nodes in the same single-line diagram should remain constant.

Definition 2: Second-order similarity
Based on the premise that equipment connection weights remain constant from Definition 1, high-dimensional nodes should possess similar mapping relationships to low-dimensional nodes to ensure connection weights remain unchanged. Second-order similarity requires that a node's representation in high-dimensional space and its representation in low-dimensional space maintain "consistency."

As previously discussed, another important relationship exists between nodes in distribution network single-line diagrams: the relationship between nodes and the power source point. This relationship reflects the "distance" in positional connection between equipment and the power source point, as well as characteristics such as whether equipment lies on main or branch lines. Therefore, we supplement a definition describing the characteristics of the node itself, which we define as:

Definition 3: Zero-order similarity
This describes the weight relationship between power equipment and the power source point, reflecting the position of power equipment in the distribution network single-line diagram.

Based on these definitions of network node similarity for distribution network single-line diagrams, feature learning networks must learn network similarity to ensure that low-dimensional space representations of network nodes can maintain similarity consistency with high-dimensional space.

3.5. Feature Learning Model for Distribution Network Single-Line Diagrams

The formula symbols used here and below are uniformly defined as follows: - : Node N represented using one-hot encoding - : Low-dimensional space representation of node N

[Figure 6: see original paper] shows an example of single-line diagram formula symbols.

- P(M|): Connection weight value between node M and node N, where node N is the starting point and node M is the endpoint
- P(|): Connection weight value between node N and power source point S

- : To represent a node in high-dimensional space for distribution network single-line diagrams, we first use a one-hot vector of the node' s equipment type to represent the device. The second requirement is to represent the equipment' s position in the single-line diagram, which can be expressed using the previously defined zero-order similarity. Therefore, we can extend the one-hot representation by adding one dimension. An equipment node vector can thus be represented as: (N , (|))
- ~ : Represents the distribution of distribution network single-line diagrams in high-dimensional nodes
- ~ : Represents the distribution of distribution network single-line diagrams in low-dimensional nodes

The overall feature learning network model is shown in [Figure 7: see original paper]. The entire learning network consists of three major components. The first part is the Encoder, which maps nodes to be generated from high-dimensional space to low-dimensional space, corresponding to the generator (Generator) in the generative adversarial network. The second part is the Discriminator, used to distinguish between low-dimensional space nodes and high-dimensional space nodes. According to the first-order similarity definition, it ensures the generated low-dimensional nodes maintain overall consistency with actual high-dimensional nodes. The third part is a deep learning network used to determine that new low-dimensional nodes and their parent low-dimensional nodes maintain second-order similarity consistency with their high-dimensional counterparts, i.e., connection weights between low-dimensional nodes remain consistent with those between high-dimensional nodes.

Traditional auto-encoders in deep learning are data compression algorithms where compression and decompression functions are data-dependent and learned from samples automatically. In most contexts mentioning auto-encoders, these functions are implemented through neural networks. The biggest problem with this traditional encoding pattern is the lack of learning for first-order and second-order similarity, which simply maps high-dimensional representations to low-dimensional representations. The entire learning model becomes a simulation of mapping functions without reflecting node relationships in high-dimensional space. Therefore, the network must possess feature preservation characteristics, synchronously summarizing relationships between nodes during mapping. Since input for distribution network single-line diagrams is variable-length sequences, LSTM (Long Short-Term Memory) networks are required for data input.

In generative adversarial networks, the discriminator gradually adjusts the generator' s output by learning real data distributions. [Figure 8: see original paper] illustrates this process. At the start of training, the real sample distribution, generated sample distribution, and discriminative model correspond to the black, green, and blue lines respectively. Initially, the discriminative model cannot effectively distinguish between real and generated samples. When we fix the generative model and optimize the discriminative model, the result shows the discriminative model can now better differentiate generated from real data.

The third step fixes the discriminative model and improves the generative model, attempting to make the discriminative model unable to distinguish generated from real images. During this process, the distribution of generated images becomes closer to real images. This iteration continues until final convergence when the generated and real distributions coincide.

Borrowing this idea, first-order similarity in distribution network single-line diagram networks can be preserved through the Discriminator, making the Encoder' s encoding gradually consistent with the high-dimensional spatial distribution. Let the equipment distribution in high-dimensional space be ~ , and the distribution generated in low-dimensional space by the generator be ~ . We want these distributions to be consistent: ~ ~ . Since mapping from high-dimensional to low-dimensional nodes should be consistent in feature representation and information content, their probability space distributions should also be consistent. Therefore, we want their expectations to be as close as possible:

(1) ~

* = arg min (- ~) = arg max ~ - = arg min - ~ = arg max ~ log ~ (;) - ~ log ~ (;) = arg min KL(( )|| (;))

(2) < ~

Here, using maximum likelihood methods (referencing traditional generative adversarial networks), we can prove argmin KL(||), thereby deriving * = arg min max (,). This proves that second-order similarity in distribution network single-line diagrams can be guaranteed through generative adversarial networks.

3.6. Loss Function

By establishing a generative adversarial network to preserve first-order similarity, the adversarial network loss function is defined as:

GAN(G, D, ,) = [log D( )] + [log(1 - D(G( )))]

According to the first-order similarity definition, we need to maintain consistent connection probabilities between two nodes in both high-dimensional and low-dimensional spaces. Therefore, the consistency loss function should be:

consistency(, , ,) = || - ||² - || - ||²

Through these two loss functions, we ensure that network feature representation satisfies similarity requirements when mapping from high-dimensional to low-dimensional space.

3.7. Algorithm Description

Let the high-dimensional node sequence be: {A , B , C , ……} Let the low-dimensional node sequence be: {B , C , ……}

1) Calculate the first low-dimensional node B by taking high-dimensional nodes A and B as input to the generator to obtain low-dimensional node B .
2) Calculate first-order similarity between low-dimensional node B and high-dimensional node A , i.e., consistency(A , A , B , B).
3) Calculate second-order similarity between B and B , i.e., GAN(G, D, B , B).
4) Take low-dimensional node B and high-dimensional node C as input to the generator to obtain low-dimensional node C .
5) Repeat steps 2) and 3) until all low-dimensional node sequences are generated.

4.1. Validation

For validation of the proposed distribution network single-line diagram network representation algorithm, we use 10KV feeder data from a regional power grid as an example. For convenient reading, we uniformly use SG-CIM model files to describe equipment and topological relationships. According to the derivation process above, we first calculate node sequences for the single-line diagram, then compute low-dimensional representations for each node. To verify algorithm effectiveness, we use t-SNE to compare high-dimensional and low-dimensional node distributions, demonstrating network second-order similarity. By comparing connection weight values between two nodes (one high-dimensional, one low-dimensional), we prove first-order similarity.

Using the single-line diagram in [Figure 1: see original paper] as an example for network feature calculation, we obtain the following results: [Figure 9: see original paper] shows the network feature t-SNE plot (red for high-dimensional points, green for low-dimensional points). [Figure 10: see original paper] shows network connection weight values (red for high-dimensional, green for low-dimensional).

4.2. Node Weight Value Improvement

During experiments, we observed that some nodes' values approach zero when represented in low-dimensional space using t-SNE. When representing connection weight values, nodes farther from the power source point have values increasingly approaching zero in low-dimensional representation. This occurs because node weight values decrease sequentially by 10^{1} along the current flow direction. Since distribution network single-line diagrams have dozens of nodes on main or branch lines, weight values may differ by tens of orders of magnitude. For nodes far from the power source, weight values essentially approach zero and become distorted during computation, which is unfavorable for expressing network features.

Therefore, we need to improve the network weight value expression method. Based on logarithm definitions, we can express weight values using logarithms to reduce numerical gaps between node sequence weight values. For example, node weight values {1, 10 ¹, 10 ², 10 ³, 10 , 10 , 10 ···} become {1, -1, -2, -3, -4, -5, -6 ···} after logarithmic transformation. The first node in the sequence is the power source point, whose value remains 1 to reflect its importance.

Except for the first node, other nodes have negative values. For subsequent network feature calculation simplicity and speed, we can use the following method:

Define array V, where represents the i-th element in the array. The element value can be calculated as: = 1 - (for j from 1 to i)

That is, the weight value of an element is the ratio of that element' s weight to the sum of all element weights, subtracted from 1. For sequence {1, -1, -2, -3, -4, -5, -6}, this calculation yields {1, 0.952, 0.904, 0.856, 0.808, 0.76, 0.712}. This method significantly reduces convergence speed of node weight values while clearly expressing the hierarchical decreasing relationship between nodes and the power source point.

Using this improved weight value representation method, we recalculated network features for distribution network single-line diagrams. Using the calculation results from [Figure 1: see original paper] as an example, the overall effectiveness shows significant improvement, as shown in [Figure 11: see original paper] (t-SNE plot) and [Figure 12: see original paper] (network connection weight values).

5. Conclusion

This paper, starting from the electrical connection characteristics of distribution network single-line diagrams, detailed the establishment of connection models for these diagrams. By creating node sequences, we defined connection relationship weights for equipment nodes constituting distribution network single-line diagrams. Using the relationship between equipment and power source points to establish node sequences, we redefined zero-order, first-order, and second-order similarity for distribution network single-line diagrams to construct a network characteristic learning network based on generative adversarial networks. Experimental data analysis proved the algorithm's effectiveness, laying the foundation for subsequent deep learning-based automatic layout algorithms for distribution network single-line diagrams.

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Note: Figure translations are in progress. See original paper for figures.