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APPLIED RESEARCH

PowerX: A Probabilistic Graph Model for Complex Smart Grid Networks

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ABSTRACT Smart grid power networks are essential for addressing the global energy crisis and combating climate change. In the past few decades, information and communication infrastructure have greatly improved. As a result, studying the characteristics of smart grids has become important. To accurately represent the connectivity of different components in power networks, we need precise models. In this study, we introduce a new growth model called PowerX. This model is designed to capture the characteristics of real-world power networks. PowerX is a growth model that is designed to capture the characteristics of real-world power networks by incorporating both random and ordered elements. Specifically, it is designed to accurately capture power networks' degree distribution and clustering coefficient. To assess the effectiveness of PowerX, we compared it with existing growth models such as Watts Strogatz Small World model, Henneberg's model, and Modified Henneberg's model, using the US Western States Power Grid dataset consisting of 4789 nodes and 5571 edges. Our results show that PowerX precisely captures the degree distribution of the real dataset, and its clustering coefficient is close to the actual dataset, outperforming the other comparable models. In addition, we used Gephi to demonstrate the features of the Western States power grid, including identifying the most important node of the network, community structure, and the strongest and weakest nodes. This research provides valuable insights into the characteristics of power networks and demonstrates the effectiveness of PowerX in accurately modeling them. The datasets and codes are publicly available for further research at: github.com/irfan2inform/powerX.

INDEX TERMS Complex networks, Henneberg's model, graph modeling, power networks, power systems, smart grids.

I. INTRODUCTION

Smart grids for power distribution are among the most vital networks in society. Over time, they have developed into complex systems that involve numerous nodes, edges, and communities linking different grid components. These components encompass a range of elements such as electrical, mechanical, and communication nodes, various consumers, generation, and transmission pathways, as well as structural components and complex engineering designs [1]. The interrelated nature of the various components of the modern grid can be efficiently modeled using graph theory and complex networks [2], [3], [4].

While the smart grid facilitates consumers and producers simultaneously, its reliability, stability, robustness, and optimized operation have become challenging due to the enormous interconnections at various points. A modern power grid is a complex network of multiple components cooperating to generate, transmit, and distribute electricity to customers, as shown in Fig. 1. Some of the key

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components of a modern power grid are described as follows:

A. POWER PLANTS

Power plants are facilities designed to generate electricity by harnessing various energy sources, such as solar, wind, water, or fossil fuels. There exist multiple types of power plants, including coal-fired, natural gas-fired, hydroelectric power plants, and renewable energy plants such as solar and wind farms.

B. TRANSMISSION LINES

Transmission lines are like the lifeline of the power grid, responsible for delivering electricity from power plants to substations. These high-voltage wires, often supported by sturdy towers or poles, are typically constructed using materials such as steel or aluminum. The electricity that flows through them packs a punch, with voltages ranging from 115,000 to 765,000 volts.

C. SUBSTATIONS

Substations serve as critical facilities in the power grid, tasked with transforming the high-voltage electricity carried by transmission lines into lower-voltage electricity that can be safely and efficiently distributed to homes and businesses. To accomplish this transformation, substations rely on transformers - devices specially designed to alter the voltage of the electricity passing through them. In this way, substations are essential in ensuring that power is delivered to customers at a voltage level that is both safe and appropriate for their needs.

D. DISTRIBUTION LINES

Distribution lines are wires that carry electricity from substations to homes and businesses. They are made of copper or aluminum and are held up by poles or buried underground. The electricity on these lines is usually less powerful than on transmission lines and is between 4,000 and 35,000 volts.

E. TRANSFORMERS

A transformer is an electrical device that transfers energy from one circuit to another using electromagnetic induction. It consists of two or more coils of wire wrapped around a magnetic core. They transmit and distribute electrical energy efficiently and have other important applications in electronic devices.

F. METERING AND BILLING EQUIPMENT

Metering and billing equipment measures and bills energy consumption, consisting of meters, communication devices, and software that monitor, record, and analyze energy data. Smart meters and advanced infrastructure allow real-time monitoring and remote data collection, promoting accuracy, energy conservation, and waste reduction. This data is used to generate customer bills and provide feedback on energy usage patterns.

G. CONTROL AND COMMUNICATION SYSTEMS

Control and communication systems are the brains of the power grid, ensuring that electricity flows smoothly and safely. These systems are equipped with sensors, control devices, and communication networks that enable operators to monitor the grid's performance in real-time and make adjustments as needed. With these sophisticated systems, the power grid can operate efficiently, and potential problems can be detected and addressed before they become major issues.

The modern smart grid revolutionizes energy transfers from point A to point B. A well-known architecture divides it broadly into four sub-systems: generation, transmission, and distribution for the fourth system, i.e., consumption, as shown in Fig. 2.

Millions of people worldwide have been affected by faulty lines, equipment, and maintenance of smart grids [6]. The complex structure of the power grid makes it difficult to identify the source of most faults. In a centralized power grid, a single station's failure to provide power can cause a domino effect of power outages throughout the system [7], [8]. As a result, modern power grids are evolving towards decentralization and intelligence by implementing structural, monitoring, and topological modifications to prevent cascading failures [9], [10].

Various studies have investigated power grids in different locations, revealing a range of topological structures not captured by existing models. Inaccurate models can lead to inefficient and unreliable power grid operation, with potentially severe consequences for both the environment and society. It is crucial to develop models that can accurately capture the structure and dynamics of power grids in different locations, allowing for more effective planning, management, and control of these critical systems [10]. Watts Strogatz showed the characteristic path length and clustering in a power grid similar to the small-world network model [11], [12]. Other studies have shown the structure of the power grid to be scale-free (power-law) [13], [14] or exponential [15]. However, fully understanding the topological structure remains a relevant research question [16].

The disconnection of a node in power networks is considered a failure because the electricity flow is interrupted, unlike epidemics network [17], where the failure is considered to be the individual death or causing of the disease. The Power grid network relies on the impedance values of the nodes and electric circuit laws, which define the load and response of the network under different conditions [18]. Complex network analysis is applied for the structural vulnerability assessment, cascading failures, and grid synchronization for effective operation and expansion of the modern power grid. Many models are being proposed to predict the topological structure and dynamic behavior of the power grid, but the effectiveness of these models is still an open question [19], [20].

A better understanding of the topological characteristics of power smart grids is needed to locate the pattern of failures, better organize the nodes, and intelligently distribute

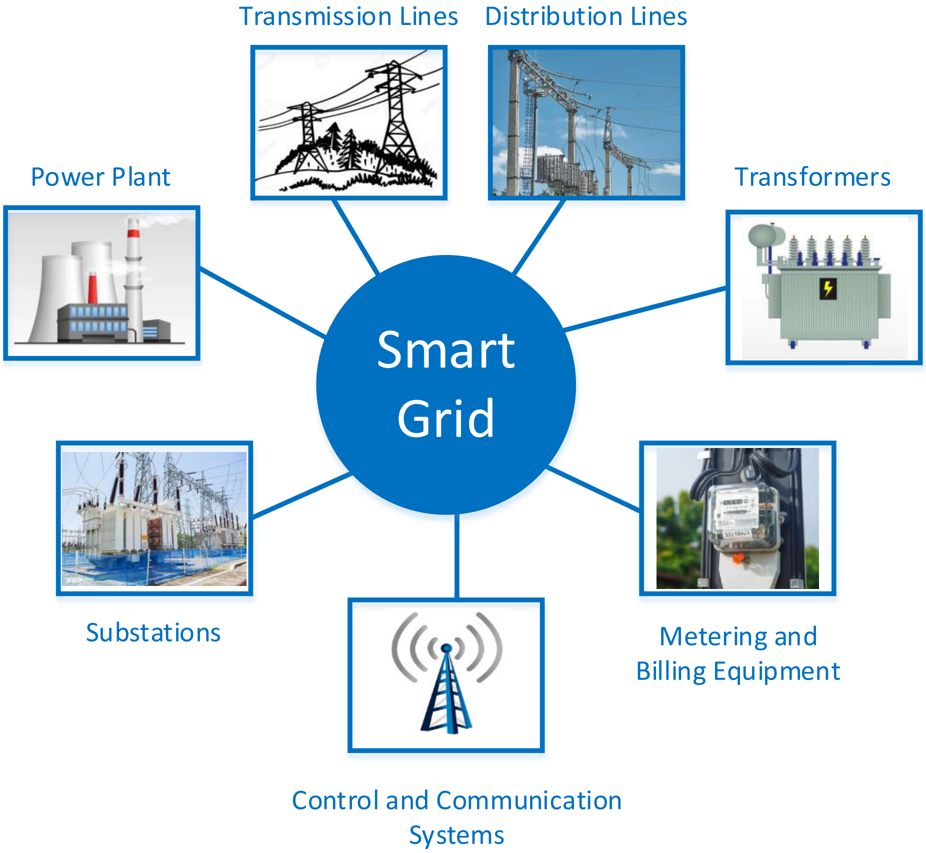

FIGURE 1. Smart grid network with its seven major components.

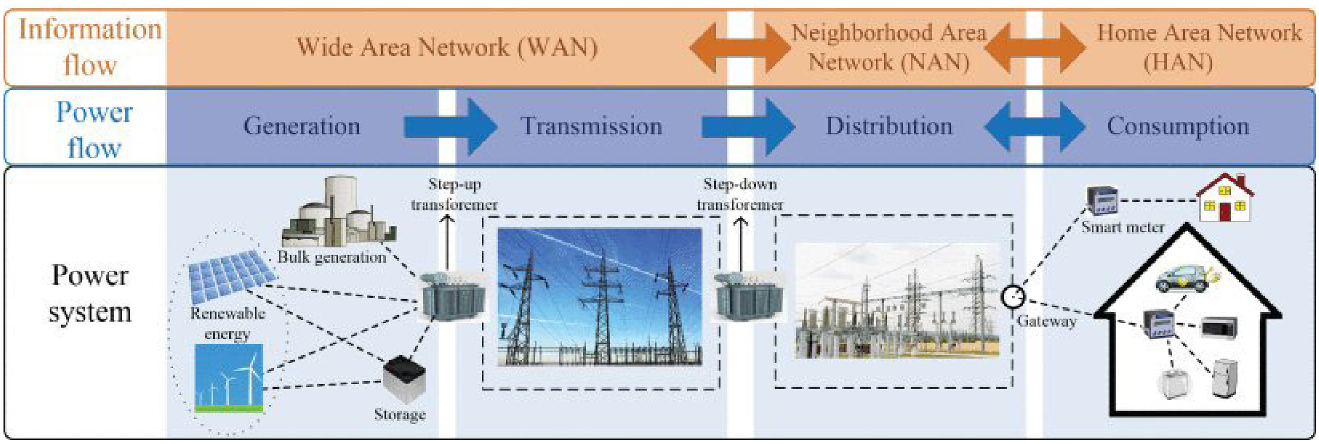

FIGURE 2. Smart grid architecture presenting power systems, power flow, and information flow [5].

the load among different stations. In this work, a novel model named PowerX is proposed to capture the power grid's characteristics by merging randomness and order. Applied to real data from the US Western States Power Grid, the results show that PowerX captures the power grid's characteristics better than benchmark models in terms of degree distribution, clustering coefficient, and other parameters [16].

II. PROBLEM FORMULATION AND PROPOSED MODEL

Real networks are neither totally random nor deterministic. Some extent of randomness is found in every data but yet they are beautifully structured when observed carefully [21]. Many real-world networks exhibit a mixture of randomness and structure, making them more complex and challenging to model accurately. Randomness can arise from various factors, such as noise, errors, and individual preferences or behaviors, while structure can arise from functional constraints, physical constraints, or evolutionary processes. For example, the number of petals in a flower appears to be random, yet they follow a Fibonacci numbers pattern. The small world network represents most of the daily life real networks such as social networks, citation networks, and the 6-degree separation of people in the US experiment performed by Milgram [22]. Fig. 3 shows how a small world network lies between random and regular networks.

The Barabasi-Albert [23] model is a widely used generative model for complex networks in the scientific community. This model generates a scale-free network by sequentially adding new nodes to the network and connecting them to existing nodes with a probability proportional to the degree of the existing node. Here, the degree of a node, represented by k, is defined as the number of connections to other nodes in the network. The probability $P(i)$ that a new node will connect to an existing node i is given as follows:

$$P(i) = \frac{k_i^\alpha}{\sum_j k_j^\alpha} \tag{1}$$

where k_i is the degree of node i, and the summation is over all existing nodes in the network. The parameter α is a constant that controls the network's degree distribution. This simple yet powerful model can generate a wide range of scale-free networks, capturing the key features of many real-world complex networks such as the Internet, social networks, and biological networks.

The present work is motivated by the dual nature of real-world data, which exhibits both randomness and structured patterns. To capture these characteristics, we propose a novel algorithm that combines the Erdos-Renyi random graph model (which incorporates randomness, albeit with a slightly modified connection process), the Barabasi model (which implements preferential attachment), and Henneberg's model (which generates a high clustering coefficient). This new algorithm, named PowerX, aims to provide a more accurate representation of real-world power grid networks [24].

A. MAJOR CONTRIBUTIONS

Following are the major contributions of this work:

- This paper presents PowerX, a unique and innovative model designed to accurately depict the connections and groupings in real-world power networks. PowerX skillfully blends crucial elements from three renowned models, specifically the Erdos-Renyi random graph model, the Barabasi-Albert model, and Henneberg's model. This combination makes PowerX particularly well-suited for power grid applications.
- To thoroughly evaluate PowerX's effectiveness, an extensive comparison is carried out with other widely-used models, such as the Watts-Strogatz Small World model, Henneberg's model, and modified Henneberg's model. The US Western States Power Grid dataset serves as the foundation for this comparison. The results show that PowerX surpasses these other models in capturing the real dataset's characteristics, highlighting its potential for a more accurate representation of power networks.
- The paper not only offers valuable insights into the intrinsic characteristics of power networks but also convincingly demonstrates the superior performance of PowerX in modeling these complex systems. An advanced network analysis tool called Gephi is employed to further analyze the power grid dataset. This tool enables the identification of the most critical parts of the network, the delineation of community structures, and the discernment of the strongest and weakest nodes.

Next, we describe and present the proposed model in detail.

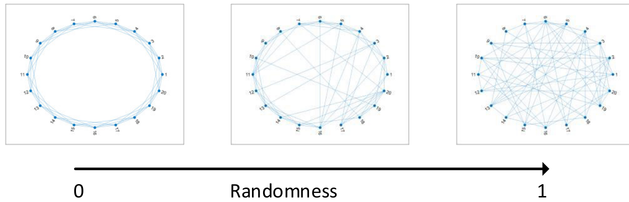

FIGURE 3. Rewiring of a network with probability 0 to 1 by applying the WS Small World Model. The regular network transforms to a random network by increasing the probability from 0 to 1.

B. REAL NETWORK DATASET

The proposed model was applied to a real-world dataset of the US Western States Power Grid, which includes 4789 nodes and 5571 edges, serving approximately 72 million people. The power station network spans from Alberta in the north to Mexico in the south and from California in the west to Texas and Montana. The network is undirected and unweighted, and we used it to evaluate the performance of our algorithm [25]. According to Watts Strogatz, the network has an average degree of 2.669, and its characteristic path length is 18.989, which classifies it as a small world network. A detailed network visualization can be found in Section VII using Gephi software [26].

C. MODEL DESCRIPTION

The proposed powerX model, entails a three step process whereby incoming nodes are able to effectively foster growth within the network, as shown in the Fig. 5.

Let W be the set of incoming words. We can partition W into two subsets, W_{even} and W_{odd}, where W_{even} contains the words that entered the system at even-numbered positions and W_{odd} contains the words that entered at odd-numbered positions.

$N_{odd} = n_i$: where i is odd and n_i represents the tag i+4, for $i = 1, 2, 3, \ldots$

$N_{even} = n_i$: where i is even and n_i represents the tag i+5, for $i = 1, 2, 3, \ldots$

In this way, N_{odd} contains nodes representing tags 5, 7, 9, and so on, while N_{even} contains nodes representing tags 6, 8, 10, and so on.

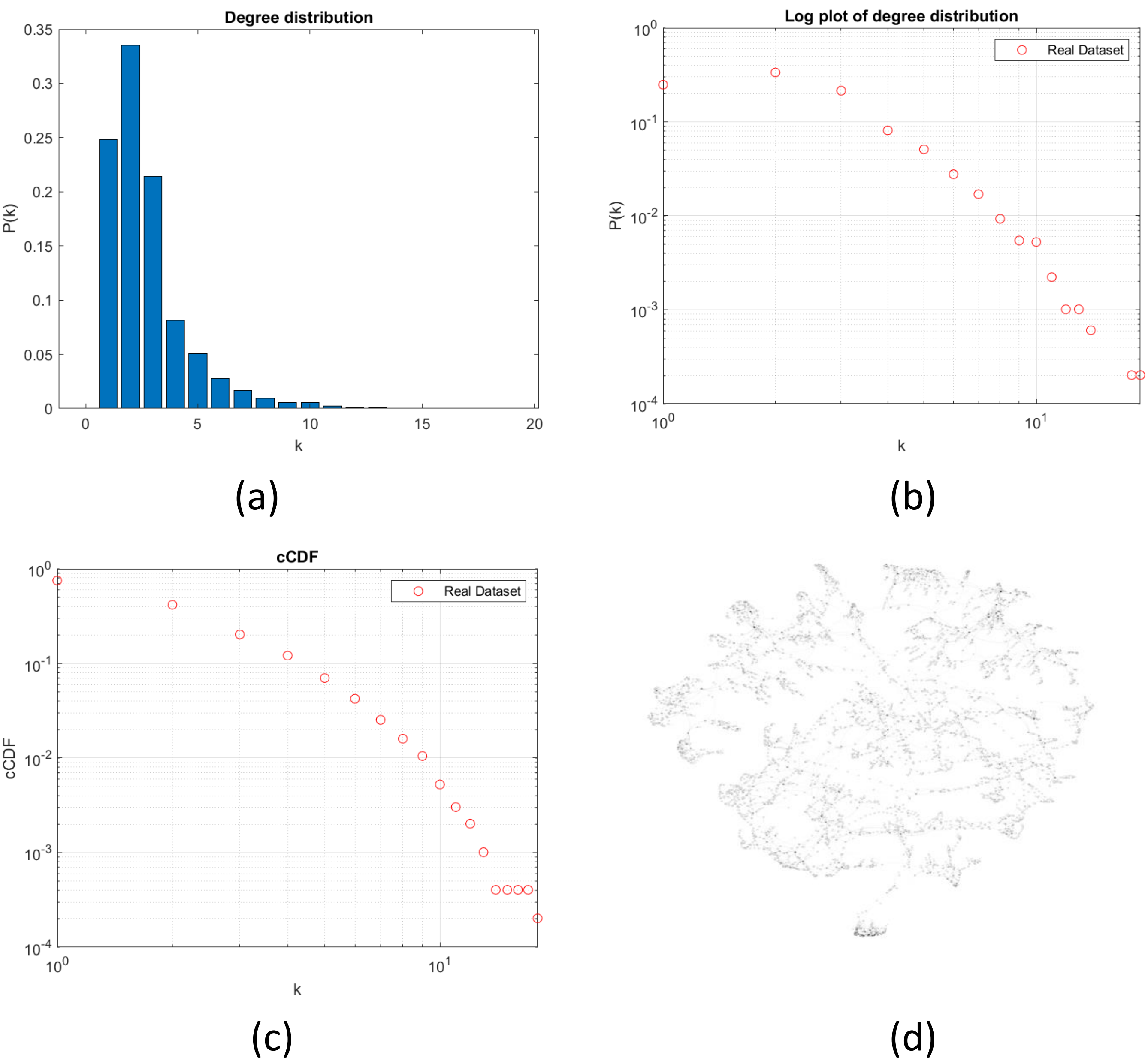

FIGURE 4. Characteristics of the Western States Power Grid network. (a) Degree distribution of the overall network. (b) Log plot of the degree distribution. (c) complementary Cumulative Distribution Function (cCDF). (d) Topological structure of the network constructed using Gephi by the Force Atlas Layout.

Step 0: Initialize a network, denoted by G_0, with four nodes arranged in a triangular structure as illustrated in Fig. 5.

Step 1: [Odd nodes] Add half of the incoming nodes randomly to the network. This is motivated by the observation that real-world networks exhibit random connections. To model this characteristic, we introduce randomness in our model by selecting half of the incoming nodes randomly.

Step 2: [Even nodes] Attach the remaining incoming nodes to two nodes in G_{t-1} using preferential attachment, which is defined by the following equation:

$$P(n_i) = \frac{k_i}{\sum_{j \in G_{t-1}} k_j} \tag{2}$$

where $P(n_i)$ is the probability of selecting node n_i, k_i is the degree of node n_i, and $\sum_{j \in G_{t-1}} k_j$ is the sum of degrees of all nodes in G_{t-1}.

Step 3: If the two nodes selected in Step 2 are not connected to each other, connect them with a probability p. We refer to this edge as the third Henneberg's edge, as it operates on the same principle as in Henneberg's model but with the added probability p.

Algorithm 1 generates a complex network with a structure that includes both randomness and preferential attachment, and it is possible to control the degree distribution of the network by adjusting the value of the parameter α and probability p.

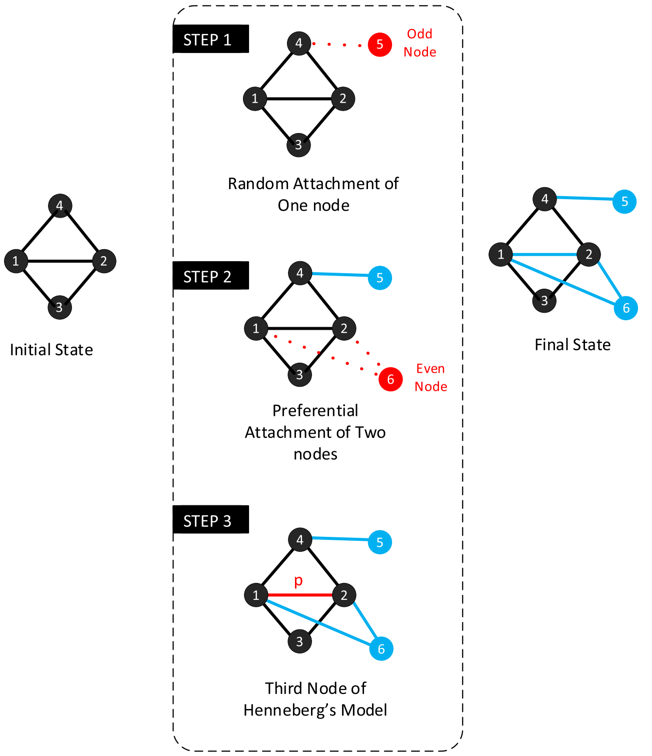

FIGURE 5. **Proposed model for power grid networks, powerX. Addition of Odd and Even nodes are shown in STEP 1 and STEP 2. Step 3 shows the interconnection of the third henneberg's node with probability *p*.**

Algorithm 1 Generation of Complex Network

Initialize a small initial network of four nodes connected in a triangular fashion
for each new "odd" node to be added to the network **do**
  Choose a random existing node, n_i, from the current network, G_t, to connect the new node, n_{t+1}, to:
  Add the edge (n_i, n_{t+1}) to the network G_{t+1}.
end for
for each new even node to be added to the network **do**
  Choose two existing nodes, n_i and n_j, from G_t to connect the new node, n_{t+1}, to using the preferential attachment probability:

$$P(n_i) = \frac{k_i^{\alpha}}{\sum_{j \in G_t} k_j^{\alpha}} \tag{3}$$

  where k_i is the degree of node n_i, α is a parameter that controls the preferential attachment strength.
  Add the edges (n_i, n_{t+1}) and (n_j, n_{t+1}) to G_{t+1}.
end for
for each new "even" node added to the network **do**
  if the nodes chosen in Step 3 are not connected **then**
    Connect them with probability p by adding the edge (n_i, n_j) to G_{t+1}.
  end if
end for
return The generated complex network G_{t+1}

III. SIMULATIONS AND RESULTS

The proposed model is designed as a growing model, where every new incoming node contributes to an increase in the number of edges. The incoming nodes are segregated into odd and even nodes. To ensure the similarity with the real dataset of the US Western States Power Grid, we halt the simulation when the number of nodes in the network reaches 4789. However, as a consequence, the number of edges in the simulated network exceeds that of the real dataset. We conducted 10 simulation runs, and the results consistently showed a similar degree distribution curve, as demonstrated in Fig. 6.

A. THE ADAPTIVE THIRD HENNEBERG'S EDGE

In Fig. 5, STEP 3 of the proposed model depicts the addition of the third Henneberg's edge with a probability p. The addition of the third Henneberg's edge follows two possible scenarios:

- If the two nodes are already connected, then no action is taken.
- If the two nodes are not connected, then they are connected with a probability p. A probability of p=0 implies that the nodes are not connected, while a probability of p=1 means that the nodes are connected. For probabilities of p between 0 and 1, the decision to connect or not depends on the specific value of p.

The following sections demonstrate the simulation results of our proposed model for various probabilities of connecting the two nodes using the third Henneberg's edge.

B. DEGREEE DISTRIBUTION

Fig. 7 presents the degree distribution curves and the average degree distribution of both the real network and the proposed model, with probabilities 0, 0.2, 0.4, 0.6, 0.8, and 1.0 of the third Henneberg's edge. Our observations indicate that when $p = 0$, the average degree distribution of the proposed model is closer to the real data. However, the average degree distribution increases as p increases, which is attributable to the growing nature of the proposed model. Nevertheless, introducing a lower probability into STEP 2 of the proposed model can control the average degree. Notably, it is impossible to introduce the probability into STEP 1 of the proposed model, as this may result in some incoming nodes remaining disconnected from the network.

C. CLUSTERING COEFFICIENT DISTRIBUTION

The clustering coefficient distribution and average clustering coefficient of the proposed model with different probabilities of the third Henneberg's edge are shown in Fig. 8, along with the corresponding values for the real Western States power grid network. Our analysis reveals that a probability of 0.2 results in a clustering coefficient that closely matches the values observed in the real dataset.

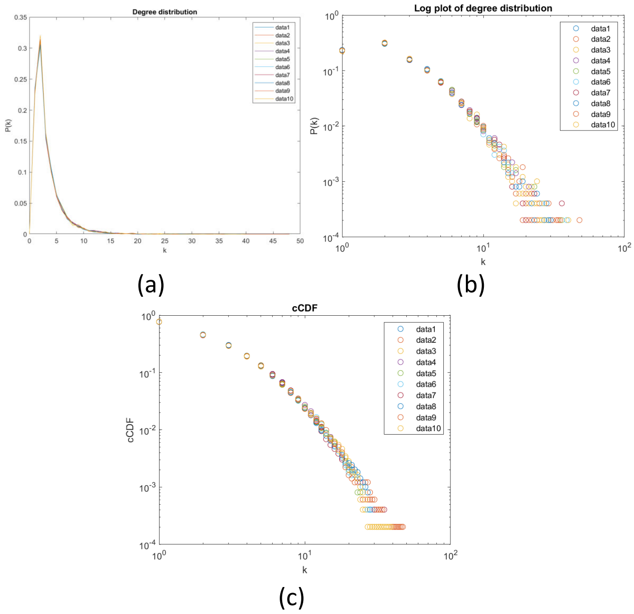

FIGURE 6. Simulation results of the 10 different runs of the proposed model. (a) Degree distribution of the proposed model. (b) Log plot of the Degree Distribution (c) cCDF of the proposed model for 10 different simulation runs.

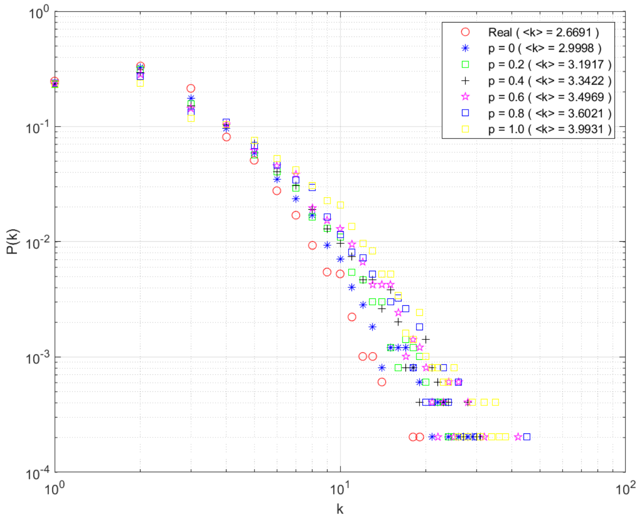

FIGURE 7. Adaptive Degree distribution of the proposed model with varying probabilities of the third Henneberg's edge. The legend in the graph shows the average degree of each network.

D. DISTANCE DISTRIBUTION

Figure 9 displays the distance distribution and average distance of the real network and proposed model for probabilities 0, 0.2, 0.4, 0.6, 0.8, and 1.0 of the third Henneberg's edge.

We observe that decreasing the probability from 1.0 to 0 results in the proposed model's average distance becoming closer to the real data. However, the real data's large average distance value could be addressed in the future by introducing a lower probability value in STEP 2 of the proposed model.

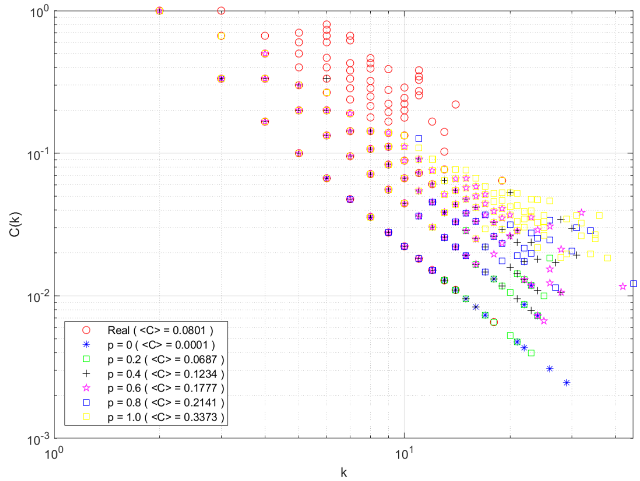

FIGURE 8. Adaptive Clustering Coefficient of the proposed model with varying probabilities of the third Henneberg's edge. The legend in the graph shows the average clustering coefficient of each network.

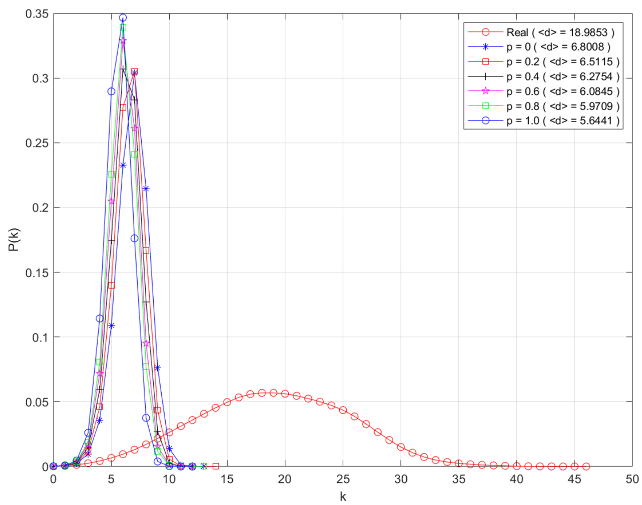

FIGURE 9. Adaptive Distance distribution of the proposed model with varying probabilities of the third Henneberg's edge. The legend in the graph shows the average distance of each network.

E. ADAPTIVE AVERAGE VALUES

The impact of the probability p of the third Henneberg's edge on several network parameters, including the average degree, maximum degree, average clustering coefficient, density, and average path length, is evident. Fig. 10 illustrates the variation of these parameters as the probability is increased or decreased from 0 to 1, providing a clear visual representation of the observed increasing/decreasing pattern. This suggests that the probability of the third Henneberg's edge has a significant impact on the network topology and should be carefully considered in network modeling and analysis.

F. COMPARISON WITH STATE-OF-THE-ART MODELS

The proposed model is inspired by Henneberg's model, which describes the growth of connectivity among incoming nodes.

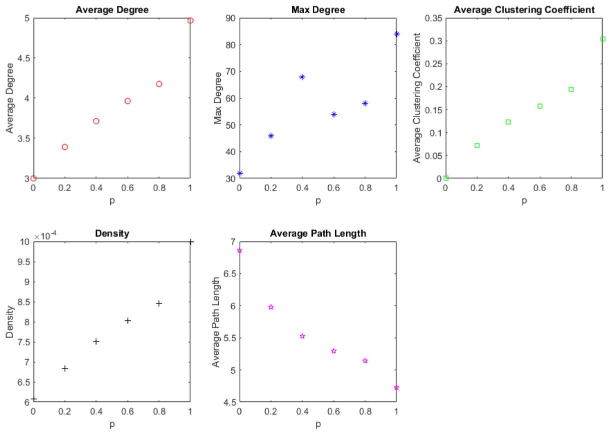

FIGURE 10. **Adaptive parameters of the proposed model by changing the probability of the Henneberg's edge.**

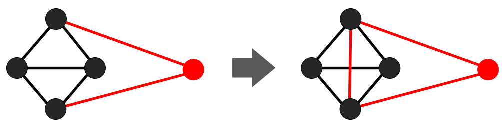

FIGURE 11. **Henneberg's Model.**

In the proposed model, new nodes connect to existing nodes in a triangular fashion, as illustrated in Fig. 11.

The US Western States Power Grid, studied in Section III, has been previously described as a small world network in its original paper [11]. In order to make the power-law distribution more prominent, our henneberg's modified model incorporates preferential attachment. Specifically, in STEP 2 of our proposed model, incoming nodes are connected to existing nodes using preferential attachment. Therefore, we compare the proposed PowerX model with three different networks, including the original Henneberg's Model, the modified Henneberg's Model, and the Watts Strogatz Small World Model.

IV. VISUALIZATION USING GEPHI

Gephi is a powerful open-source software tool that facilitates the analysis and visualization of complex networks. The tool offers an interactive platform that enables users to explore and interpret network data in a user-friendly manner, helping them discover patterns and insights that might be concealed in the underlying data. Gephi offers a suite of robust features for importing, manipulating, and visualizing network data, such as a range of layout algorithms for organizing nodes and edges, dynamic filtering tools for exploring different facets of the network, and statistical measures for studying network properties like centrality, clustering, and modularity. With a high degree of customization, the software allows users to enhance its capabilities with various plugins and extensions. Gephi is an indispensable tool for researchers, analysts, and practitioners working with complex network data, providing an intuitive and powerful platform for

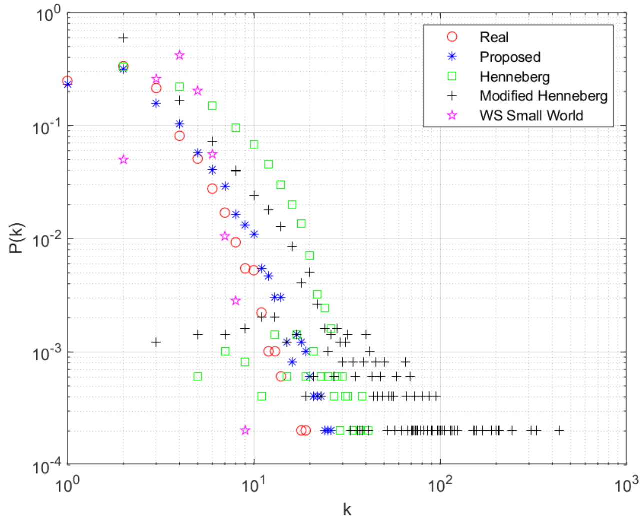

FIGURE 12. **Degree Distribution of the real dataset (US Western States Power Grid), the proposed model, Henneberg's Model, Modified Henneberg's Model, and WS Small World Model.**

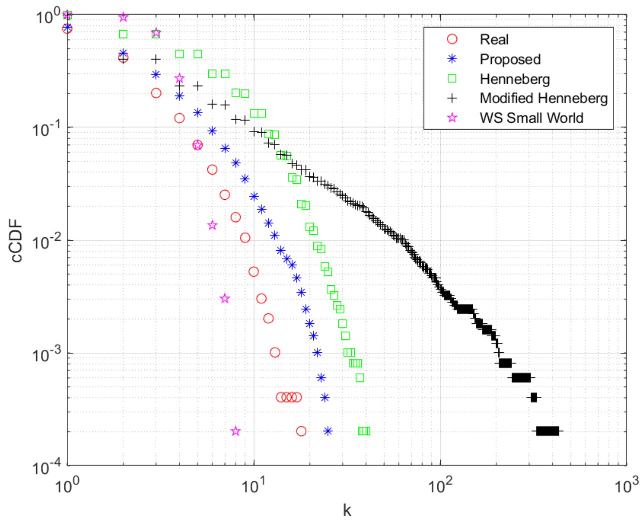

FIGURE 13. **Complementary Cumulative Distribution function (cCDF) of the real dataset (US Western States Power Grid), the proposed model, Henneberg's Model, Modified Henneberg's Model, and WS Small World Model.**

exploring and visualizing network structures and dynamics across diverse domains and applications.

A. MODULAR STRUCTURE

The proposed model has a modular structure with a modularity value of 0.918, and it forms a total of 21 communities. The detailed results are as follows:

- Modularity: 0.918
- Modularity with resolution: 2.873
- Number of communities: 21

Given this network, we can analyze its properties and answer questions such as:

- What is the strongest node in the network?

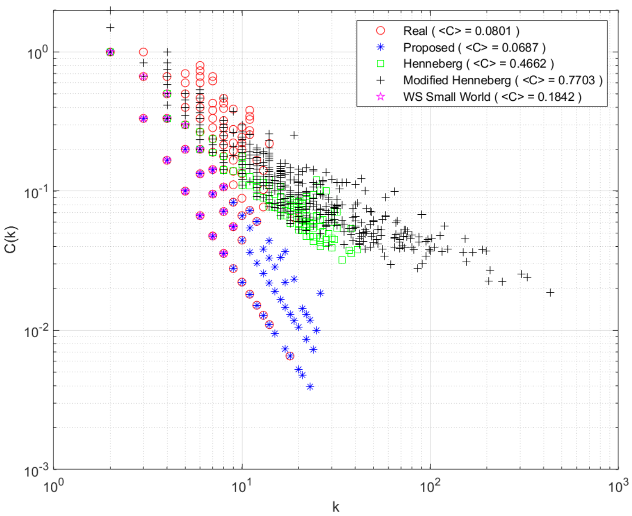

FIGURE 14. Clustering Coefficient of the real dataset (US Western States Power Grid), the proposed model, Henneberg's Model, Modified Henneberg's Model, and WS Small World Model. The legend in the graph shows the average clustering coefficient of each network.

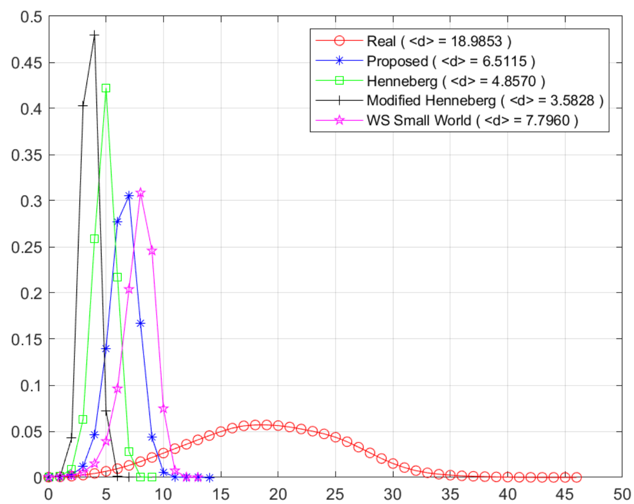

FIGURE 15. Distance Distribution of the real dataset (US Western States Power Grid), the proposed model, Henneberg's Model, Modified Henneberg's Model, and WS Small World Model. The legend in the graph shows the average path length of each network.

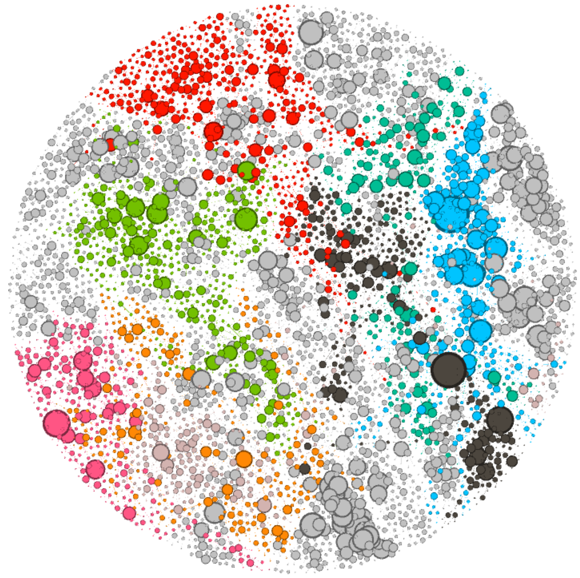

FIGURE 16. The network of Western States Power Grid drawn using Gephi and running a community structure algorithm.

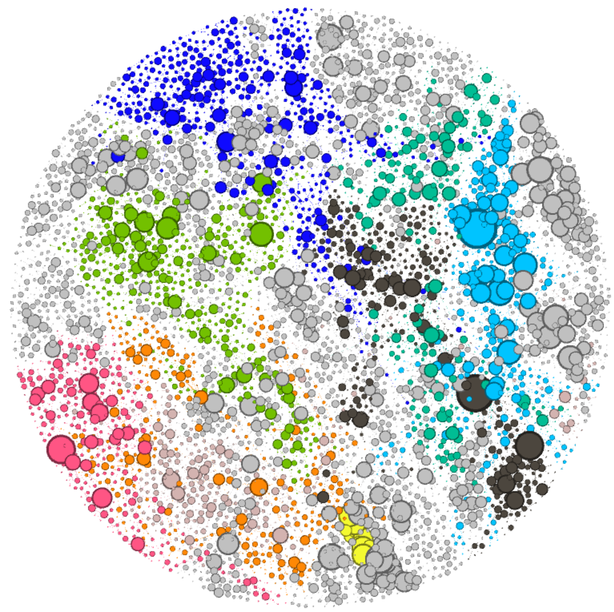

FIGURE 17. Visualization of the US Power Grid Network showing the strongest nodes.

- What is the weakest node in the network?
- What is the strongest edge in the network?
- What is the weakest edge in the network?

B. STRONGEST NODE OF THE NETWORK

The coreness of a network is a metric that characterizes the resilience of its nodes. Specifically, it quantifies the number of nodes that must be removed or traversed to reach a given node, providing insights into the robustness of the network [24]. In this study, the graph's coreness is calculated to be 5, and the corresponding nodes belonging to the 5-core are visualized in Fig. 17.

The strongest nodes are colored Yellow as shown. They are 12 nodes as shown in Fig. 18.

C. WEAKEST NODE OF THE NETWORK

In a network, the weakest points are usually 1-core nodes, known for their low connectivity. Each of these nodes has just one connection to another node in the network. As a result, they don't play a significant role in the overall network since they don't act as bridges or help with communication between other nodes. Their impact on the network's overall unity and function is quite limited.

The main issue with 1-core nodes is their risk of disconnection or isolation. With only one connection, losing

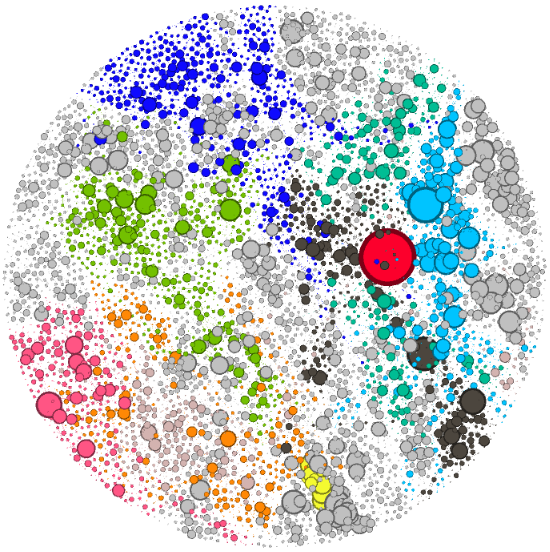

FIGURE 18. strongest nodes with their charactestics.

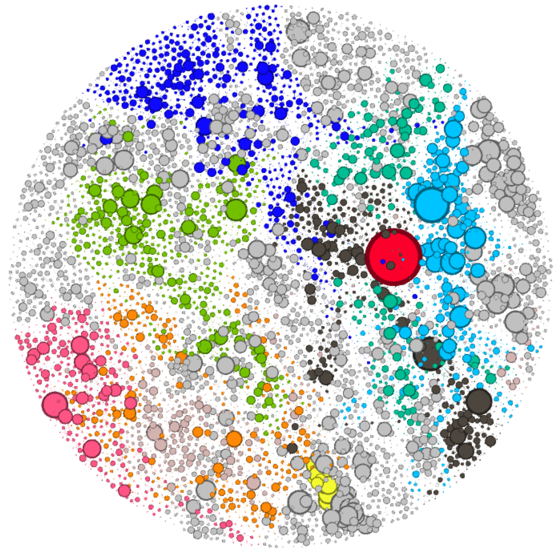

FIGURE 19. Visualization of the US Power Grid Network showing the most important node of the network.

or breaking that connection can lead to complete separation from the rest of the network. These weak nodes are more likely to cause disruptions, negatively affecting the network's overall strength. Recognizing and strengthening these weak nodes, when possible, can be an important step in improving the stability and performance of a network, especially when the nodes represent essential components or resources.

D. MOST IMPORTANT NODE OF THE NETWORK

Betweenness centrality is a key metric in network analysis, employed to quantify the prominence of a node within a network based on the shortest paths between all pairs of nodes. This measure specifically evaluates the frequency at which a node appears on these paths, thereby providing insights into the node's influence over the network's overall connectivity. Nodes exhibiting high betweenness centrality are considered vital, as they often serve as communication bridges or network connectors, effectively controlling the flow of information or resources across the network.

Calculating the betweenness centrality for a node involves determining the sum of the ratio of the shortest paths between all pairs of nodes that traverse the node in question. This calculation facilitates the identification of crucial intermediary nodes or brokers, which are typically situated in strategically advantageous positions within the network. Consequently, such nodes are able to regulate access to information and resources, potentially manipulating other nodes' connectivity. In real-world applications, betweenness centrality has proven effective in various contexts, including social networks, transportation networks, communication networks, and biological networks, by highlighting key nodes or individuals in each scenario.

The most important node, indicated in red in Fig. 19, has the highest betweenness centrality score of 3518477.

V. FINAL ANALYSIS

The largest node in a network may serve as the backbone, but it is also vulnerable to attacks, making the security of the entire network more critical. Therefore, understanding the characteristics of the network is essential to preventing significant losses, such as fatal breakdowns of the smart grid. In this study, the WS model indicates that the US Western States power grid possesses a small-world network property, evidenced by its low characteristic path length. However, the proposed model has a lower characteristic path length of 6.8, suggesting that it will be more efficient in terms of network communication. The degree distribution of the real power grid remains a topic of debate, with some suggesting it follows a power-law distribution, exponential distribution, or other types. Additionally, different power grids exhibit distinct topological structures, such as scale-free (power-law) or exponential, depending on factors such as power distribution, Ohm's law, Kirchhoff's laws, among others, contributing to the complexity of the power grid network.

Our proposed model has accurately captured the degree distribution of the US Western States Power Station network, enabling the study of synthetic networks for future analyses. The clustering coefficient is a critical parameter that varies across different networks, providing insights into essential features such as robustness, safety, and vulnerability. We have made our clustering coefficient adaptable, with values ranging from 0.000616 to 0.3036, depending on the probability of Henneberg's edge. The closest clustering coefficient to the real data of the Western States Power Grid, 0.0801, is achieved at a probability of 0.2, with a clustering coefficient of 0.0710.

The Western States power grid network exhibits a scale-free structure, with high-degree nodes (hubs) having a disproportionately significant influence. However, this structure makes the network vulnerable to targeted attacks, as evidenced by the highest degree node having only one neighbor edge out of its 18 total edges.

Gephi facilitates visualization of networks, simplifying and accelerating their study. The most important node, with the highest degree, is easily identifiable in the graph produced by Gephi.

VI. CONCLUSION

The power smart grid network is a highly complex system that has evolved over many years and significantly impacts human life in terms of safety, communication, transportation, and more. Any unknown fault in the power grid can have a disastrous effect on these vital processes and result in chaos. In the past, most power grid failures have caused cascading effects, leading to power outages over large areas. To address these challenges, we have developed a novel network model, powerX, that precisely describes the power grid network. By simulating our model on real data from the US Western States Power Station, we have perfectly matched the actual data regarding degree distribution and clustering coefficient. Our proposed model presents a promising approach for future research on power grid network analysis, contributing to developing more effective approaches to ensure the reliability and security of power grid networks.

VII. FUTURE WORK

Some potential future directions of this work could include exploring further applications of the powerX network model to investigate the vulnerability and robustness of power grid networks. Additionally, the average path length difference between the proposed model and real data is quite high, so future work could focus on tuning this parameter to better match real-world data. One potential approach to improving the model would be introducing a probability into STEP 1 and STEP 2, although this may lead to the problem of unconnected nodes. One solution would be to continue adding new nodes to the proposed model until the required number of nodes are connected. It would also be interesting to investigate the effects of targeted attacks on the network, and the role of highly connected nodes (i.e., hubs) in maintaining the network's stability. Finally, incorporating real-time data streams into the powerX model could enhance its predictive capabilities, enabling more accurate predictions of potential faults and fast responses to prevent outages.

CODE AVAILABILITY

MATLAB code files used to simulate the proposed model and for visualization are publicly available at github. https://github.com/irfan2inform/powerX

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REFERENCES

[1] G. Dileep, "A survey on smart grid technologies and applications," *Renew. Energy*, vol. 146, pp. 2589–2625, Feb. 2020.

[2] N. K. Singh and V. Mahajan, "Detection of cyber cascade failure in smart grid substation using advance grey wolf optimization," *J. Interdiscipl. Math.*, vol. 23, no. 1, pp. 69–79, Jan. 2020.

[3] G. A. Pagani and M. Aiello, "The power grid as a complex network: A survey," *Phys. A, Stat. Mech. Appl.*, vol. 392, no. 11, pp. 2688–2700, Jun. 2013.

[4] G. A. Pagani and M. Aiello, "Power grid complex network evolutions for the smart grid," *Phys. A, Stat. Mech. Appl.*, vol. 396, pp. 248–266, Feb. 2014.

[5] Y. Saleem, N. Crespi, M. H. Rehmani, and R. Copeland, "Internet of Things-aided smart grid: Technologies, architectures, applications, prototypes, and future research directions," *IEEE Access*, vol. 7, pp. 62962–63003, 2019.

[6] Q. Li, Y. Deng, X. Liu, W. Sun, W. Li, J. Li, and Z. Liu, "Autonomous smart grid fault detection," *IEEE Commun. Standards Mag.*, vol. 7, no. 2, pp. 40–47, Jun. 2023.

[7] D. Fan, Y. Ren, Q. Feng, Y. Liu, Z. Wang, and J. Lin, "Restoration of smart grids: Current status, challenges, and opportunities," *Renew. Sustain. Energy Rev.*, vol. 143, Jun. 2021, Art. no. 110909.

[8] R. Ghanbari, M. Jalili, and X. Yu, "Correlation of cascade failures and centrality measures in complex networks," *Future Gener. Comput. Syst.*, vol. 83, pp. 390–400, Jun. 2018.

[9] M. Adnan, M. Ali, and M. Tariq, "A probabilistic approach for power network stability in smart grids," in *Proc. 15th Int. Conf. Emerg. Technol. (ICET)*, Dec. 2019, pp. 8138–8143.

[10] M. Ghorbanian, S. H. Dolatabadi, and P. Siano, "Big data issues in smart grids: A survey," *IEEE Syst. J.*, vol. 13, no. 4, pp. 4158–4168, Dec. 2019.

[11] D. J. Watts and S. H. Strogatz, "Collective dynamics of 'small-world'networks," *Nature*, vol. 393, no. 6684, pp. 440–442, 1998.

[12] G. Cimini, T. Squartini, F. Saracco, D. Garlaschelli, A. Gabrielli, and G. Caldarelli, "The statistical physics of real-world networks," *Nature Rev. Phys.*, vol. 1, no. 1, pp. 58–71, 2019.

[13] D. P. Chassin and C. Posse, "Evaluating North American electric grid reliability using the BarabáSi–Albert network model," *Phys. A, Stat. Mech. Appl.*, vol. 355, nos. 2–4, pp. 667–677, Sep. 2005.

[14] H. Karimipour, A. Dehghantanha, R. M. Parizi, K. R. Choo, and H. Leung, "A deep and scalable unsupervised machine learning system for cyber-attack detection in large-scale smart grids," *IEEE Access*, vol. 7, pp. 80778–80788, 2019.

[15] P. Crucitti, V. Latora, and M. Marchiori, "A topological analysis of the Italian electric power grid," *Phys. A, Stat. Mech. Appl.*, vol. 338, nos. 1–2, pp. 92–97, Jul. 2004.

[16] S. Karmich, E. M. Ziani, and J. Bouchnaif, "Evaluating national electric grid reliability by 2030 using the BarabáSi–Albert network model," *Mater. Today, Proc.*, vol. 72, pp. 3238–3243, Jan. 2030.

[17] I. Z. Kiss, J. C. Miller, and P. L. Simon, *Mathematics of Epidemics on Networks*, vol. 598. Cham, Switzerland: Springer, 2017, p. 31.

[18] A. Torres and G. Anders, "Spectral graph theory and network dependability," in *Proc. 4th Int. Conf. Dependability Comput. Syst.*, 2009, pp. 356–363.

[19] C.-C. Chu and H. H. Iu, "Complex networks theory for modern smart grid applications: A survey," *IEEE J. Emerg. Sel. Topics Circuits Syst.*, vol. 7, no. 2, pp. 177–191, Jun. 2017.

[20] Y. Ruan, J. Tang, Y. Hu, H. Wang, and L. Bai, "Efficient algorithm for the identification of node significance in complex network," *IEEE Access*, vol. 8, pp. 28947–28955, 2020.

[21] A. Abedi, L. Gaudard, and F. Romerio, "Review of major approaches to analyze vulnerability in power system," *Rel. Eng. Syst. Saf.*, vol. 183, pp. 153–172, Mar. 2019.

[22] X. Fan Wang and G. Chen, "Complex networks: Small-world, scale-free and beyond," *IEEE Circuits Syst. Mag.*, vol. 3, no. 1, pp. 6–20, Sep. 2003.

[23] R. Albert and A.-L. Barabási, "Statistical mechanics of complex networks," *Rev. Mod. Phys.*, vol. 74, no. 1, p. 47, 2002.

[24] S. Wandelt, X. Sun, M. Zanin, and S. Havlin, "QRE: Quick robustness estimation for large complex networks," *Future Gener. Comput. Syst.*, vol. 83, pp. 413–424, Jun. 2018.

[25] Å. J. Holmgren, "Using graph models to analyze the vulnerability of electric power networks," *Risk Anal.*, vol. 26, no. 4, pp. 955–969, Aug. 2006.
[26] M. Bastian, S. Heymann, and M. Jacomy, "Gephi: An open source software for exploring and manipulating networks," in *Proc. Int. AAAI Conf. Web Social Media*, 2009, vol. 3, no. 1, pp. 361–362.

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