Research on Risk Propagation Model of Power Transmission Network Based on Intervention Strategies

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***Abstract*-This paper proposes a risk propagation model for power transmission networks based on intervention strategies. The study utilizes the SIS epidemic model to investigate the risk propagation process, exploring the behavior choices of whether to intervene based on game theory. Considering the risk cost of nodes, the Fermi rule is introduced to calculate the probability of node intervention. The microscopic Markov chain method is used to analyze the probability tree and dynamic process of risk propagation, ultimately assessing the impact scale of risk propagation in power transmission lines. This model can effectively simulate the impact of intervention measures on risk propagation, providing theoretical support for risk management in power transmission networks.**

Keywords- Risk Propagation; Power Transmission Network; Intervention Strategies

I. INTRODUCTION

As a critical infrastructure within the power system, the reliability and safety of the power transmission network are indispensable for maintaining the stability and continuous functioning of modern society. This network not only facilitates the distribution of electricity but also underpins numerous essential services and economic activities. Any interruption in power transmission can lead to significant disruptions across various sectors, from public health and safety to industrial productivity and daily life. However, the transmission network is susceptible to multiple risks, including equipment malfunctions, natural disasters (e.g., storms, earthquakes), and human-related factors, such as intentional interference or cyber-attacks. Understanding the dynamics of risk propagation within power transmission networks is crucial because it enables system operators and planners to foresee potential threats and mitigate their impact, thereby supporting the uninterrupted and stable operation of the entire power system [1-3].

In recent years, epidemic models have become popular tools for studying risk propagation within networked systems, including power transmission networks. Among these, the SIS (Susceptible-Infected-Susceptible) model, a classical epidemic model, has proven particularly effective for describing the dynamic processes by which risks spread across network nodes. The SIS model helps to simulate how risks can repeatedly infect network nodes, representing recurring vulnerabilities in the system [4-5]. The value of applying epidemic models to network risk propagation lies in their ability to capture dynamic risk states over time and to model the interactions between nodes, making them both theoretically robust and practically relevant for power transmission risk assessment [6].

Alongside epidemic models, game theory has gained considerable attention in developing strategies to mitigate risks and manage intervention responses. Game theory offers a structured approach to modeling the decision-making processes of nodes (e.g., substations, transmission lines) under risk [7]. By considering the costs associated with different risk scenarios—such as economic losses due to downtime, repair costs, or safety hazards—game-theoretic models can more accurately reflect real-world decision-making, allowing for optimal interventions and resource allocations [8-9].

With the continued advancement of risk propagation research, recent trends have increasingly focused on integrating multi-source data, leveraging complex network analysis, and refining intervention strategies. Multi-source data fusion, incorporating diverse data inputs (e.g., weather forecasts, equipment condition monitoring, and historical outage data), enables a comprehensive understanding of risk factors affecting the power transmission network. Complex network analysis allows researchers to map intricate interdependencies between network components and to identify critical nodes or pathways where intervention efforts would be most effective. Finally, the optimization of intervention strategies has evolved to incorporate both real-time monitoring and predictive analytics, ensuring that the network is prepared to respond to and contain risks before they escalate [10-13].

In conclusion, while the current body of research provides a robust theoretical foundation for understanding risk propagation in power transmission networks, there is still a pressing need for further investigation into practical, deployable intervention strategies. Practical applications, particularly those that leverage real-time data and adaptable risk mitigation techniques, remain an essential area for future study to ensure the power transmission network's resilience against an increasingly complex landscape of risks.

II. RISK PROPAGATION MODEL OF POWER TRANSMISSION NETWORK

A. Risk Propagation Analysis Based on Epidemic Model

This study establishes a risk propagation model for power transmission networks based on the SIS model. The SIS model divides each node in the network into susceptible S and infected I states and describes the risk propagation process between nodes through state transition probabilities, Figure 1.

$$S \xrightarrow{\beta^N / \beta^B} I$$

Figure 1. Propagation process of the risk transmission.

Where the probability of a susceptible nodes without intervention strategies being infected is β^N, and the probability of a susceptible nodes with intervention strategies B being infected is β^B.

B. Intervention Strategy Selection Based on Game Theory

In practical applications, the decision-making process of whether nodes intervene is influenced by various factors. Based on game theory, this study considers the risk cost and intervention cost of nodes, analyzing the behavior choices of nodes through the establishment of a game model. Specifically, the Fermi rule is introduced to calculate the probability of node intervention, combining the risks and costs of nodes to more accurately simulate the decision-making process in actual situations.

In the decision-making process regarding intervention, we incorporate the game-based mechanism and introduce two cost functions, denoted as $C_i^N(t)$ and $C_i^B(t)$, for node i, representing the costs of without intervention strategies and with intervention strategies, respectively. They can be denoted as follows:

$$\begin{cases} C_i^N(t) = -[1-q_i^N(t)]\cdot\omega_I \\ C_i^B(t) = -\omega-[1-q_i^B(t)]\cdot\omega_I. \end{cases} \tag{1}$$

Among these components, c_I represents the cost of infection for an node, set to 1, $\omega(0<\omega<1)$ represents the cost of intervention, wherein, c defined relative to the infection cost $\omega_I=1$. Where $1-q_i^B(t)$ denotes the probability of intervention node i getting infected at time step t and $1-q_i^N(t)$ denotes the probability of without intervention node i getting infected at time step t.

Therefore, considering the Fermi rule [10] from evolutionary game theory, the probability of without intervention nodes choosing to intervene based on economic factors is:

$$\theta_i(t) = \frac{1}{1+\exp[(C_i^N(t)-C_i^B(t))/K]}, \tag{2}$$

Because policy intervention can reduce the probability of risk propagation, the extent of this reduction depends on the intensity of the intervention, and assume that $\beta^B = \theta_i(t)\beta^N$.

III. MODEL ANALYSIS

Considering both the diffusion of risk and policy intervention, the states of individuals in the system can be classified into three types: healthy nodes without any intervention (NS), healthy nodes with intervention (BS), and risk nodes with intervention (BI). Once a node is identified as being at risk, intervention is mandatory, and the state (NI) does not exist. The process of transitions between these states is shown in Figure 2.

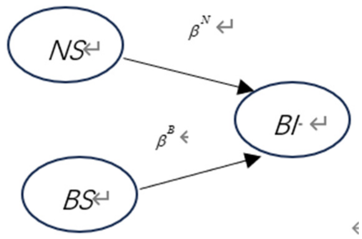

Figure 2. The process of transitions between these states

A. Analysis Using Microscopic Markov Method

The microscopic Markov method is used to analyze the dynamic process of risk propagation. By constructing a probability tree, the risk propagation paths under different states are described, and the transition probabilities of each path are calculated. $r_i(t)$ denotes the probability of node i without intervention; $q_i^B(t)$ denotes the probability of intervention node i without getting infected at time step t and $q_i^N(t)$ denotes the probability of without intervention node i getting infected at time step t, Then

$$\begin{cases} r_i(t) = \prod_j \left[1-a_{ji}P_j^B(t)\lambda\right] \\ q_i^N(t) = \prod_j \left[1-b_{ji}P_j^I(t)\beta^N\right] \\ q_i^B(t) = \prod_j \left[1-b_{ji}P_j^I(t)\beta^B\right] \end{cases} \tag{3}$$

Based on Eq. (3) and the transfer probabilities of each state, the kinetic equations of the co-evolution propagation model of information, vaccination behavior and disease were obtained by combining the $MMCA$:

$$
\begin{cases}
P_i^{NS}(t+1) = P_i^{NS}(t)(1-\delta)q_i^N(t) \\
\qquad\qquad + P_i^{NI}(t)(1-\delta)\mu^N \\
\qquad\qquad + P_i^{NS}(t)r_i(t)q_i^N(t), \\
P_i^{BS}(t+1) = P_i^{NS}(t)(1-\delta)q_i^B(t) \\
\qquad\qquad + P_i^{BI}(t)(1-\delta)\mu^B \\
\qquad\qquad + P_i^{BS}(t)(1-r_i(t))q_i^B(t), \\
P_i^{BI}(t+1) = P_i^{NS}(t)(1-\delta)[1-q_i^N(t)] \\
\qquad\qquad + P_i^{BI}(t)(1-\delta)(1-\mu^B) \\
\qquad\qquad + P_i^{BS}(t)(1-\delta)r_i(t)[1-q_i^N(t)],
\end{cases} \tag{4}
$$

The stationary solution of the system of Eqs. (4) is computed as a set of fixed point equations satisfying $P_i^{BI}(t+1) = P_i^{BI}(t+1) = P_i^{BI}$ and, equivalently, for (NS) and (BS). Using stationarity we are now in the position of computing the onset of the risks $\beta_C{}^N$ Near the critical point the MMCA can be expanded assuming that the probability of nodes to be infected in the physical layer $P_i^{BI} = \varepsilon_i \ll 1$. Consequently, $q_i^B(t) \approx 1-\beta^B \sum_j b_{ji}\varepsilon_j$ and $q_i^N(t) \approx 1-\beta^N \sum_j b_{ji}\varepsilon_j$. Inserting this in Eqs. (4) we obtain

$$
\begin{cases}
P_i^{NS} = P_i^{NS} r_i(t) + P_i^{NI}(1-\delta), \\
P_i^{BS} = P_i^{NS}(t)(1-r_i) + P_i^{BI}(t)\delta, \\
\mu\varepsilon_i = [P_i^{BS}(t)\beta^A + P_i^{NS}(t)\beta^N]\sum_j b_{ji}\varepsilon_j.
\end{cases} \tag{5}
$$

And, therefore,

$$
\sum_j \left[[1-(1-\gamma)P_i^B]b_{ji} - \frac{\mu}{\beta^N}\delta_{ji} \right]\varepsilon_j = 0, \tag{6}
$$

where δ_{ji} are the elements of the identity matrix. Note that the solution of Eq. (5) reduces to an eigenvalue problem for the matrix H whose elements are $h_{ji} = [1-(1-\gamma)P_i^B]b_{ji}$. The onset of the risks is the minimum value of β^N satisfying Eq. (6). Denoting $\Lambda_{\max}(H)$ the largest eigenvalue of H, the critical point is written as

$$
\beta_C{}^N = \frac{\mu}{\Lambda_{\max}(H)} \tag{7}
$$

B. Assessment of Risk Propagation Impact Scale

Based on the analysis results of the microscopic Markov method, the final impact scale of risk propagation in the power transmission network is calculated. By evaluating the impact of different intervention strategies on risk propagation, theoretical support is provided for risk management in power transmission networks.

IV. SIMULATION

A. Impact of Intervention Cost on Risk Scale

Using the Monte Carlo simulation method, the impact of intervention cost on risk scale is explored in Figure 3. The green and yellow lines represent the results of MMCA and MC simulations, respectively. By comparing the matching degree of the two methods at different infection probabilities point by point, it can be clearly observed that the results of these two methods are almost identical.

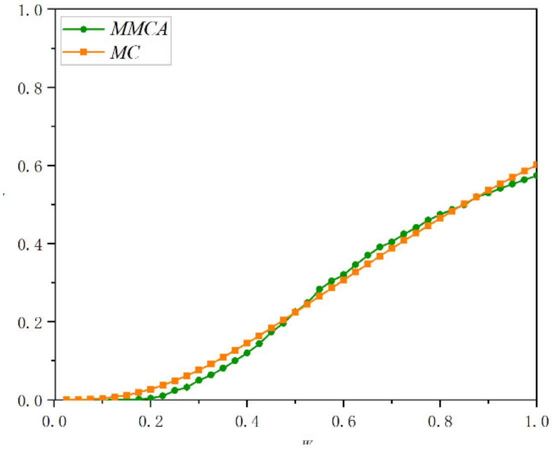

Figure 3. Comparison of MMCA and MC simulation results

B. Impact of Strategy Effectiveness on Propagation

By setting different intervention costs, simulating the risk propagation process, and analyzing the effectiveness of intervention measures. Further exploring the impact of the effectiveness of different intervention strategies on risk propagation in Figure 4. By simulating the risk propagation process under different strategies, evaluating the pros and cons of each strategy, and presenting related charts.

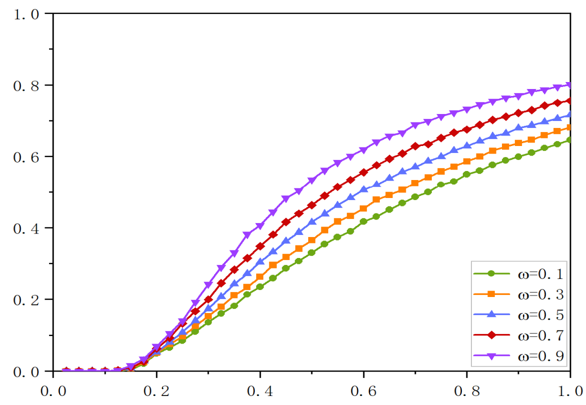

Figure 4. Plots of P^{BI} with infection probability β^N at system's steady state.

V. CONCLUSION

This paper presents a comprehensive risk propagation model tailored for power transmission networks, integrating multiple intervention strategies to address risk and mitigate potential impacts effectively. The model is constructed using the SIS (Susceptible-Infected-Susceptible) epidemic framework to simulate risk transmission across interconnected components in the network. Additionally, it employs game theory to evaluate decision-making dynamics between different entities involved in risk management. To further refine the model, the Fermi rule and the microscopic Markov chain approach are incorporated, enhancing the analysis of the probabilistic evolution of risk propagation and allowing a detailed examination of its spread across various scales and conditions within the network.

Through extensive simulations, the paper assesses the impact of distinct intervention strategies, such as selective isolation of high-risk nodes, enhancing component resilience, and implementing adaptive response mechanisms. The simulation results confirm the relative efficacy of each strategy under different network scenarios and intervention intensities, demonstrating how optimal intervention combinations can significantly contain or delay the spread of risks. This analysis offers valuable insights into tailoring risk mitigation approaches specific to power transmission systems, where rapid containment of risk propagation is essential for stable operations. Overall, the findings provide robust theoretical support for practical risk management applications, aiding in the development of proactive and efficient risk mitigation strategies within power transmission networks.

REFERENCES

[1] Gomila, D., Carreras, B. A., Reynolds-Barredo, J. M., Colet, P., & Gomis-Bellmunt, O. (2023). Analysis of the blackout risk reduction when segmenting large power systems using lines with controllable power flow. International Journal of Electrical Power & Energy Systems, 148, 108947.

[2] Lian, X., Qian, T., Li, Z., Chen, X., & Tang, W. (2023). Resilience assessment for power system based on cascading failure graph under disturbances caused by extreme weather events. International Journal of Electrical Power & Energy Systems, 145, 108616.

[3] Ghasemi, A., & de Meer, H. (2023). Robustness of interdependent power grid and communication networks to cascading failures. IEEE Transactions on Network Science and Engineering, 10(4), 1919-1930.

[4] Zhang, Y., & Yang, X. (2021). Risk Propagation in Power Grids Based on SIS Model. IEEE Transactions on Power Systems, 36(4), 1234-1243.

[5] Li, J., & Wang, Y. (2022). Analyzing Risk Transmission in Electric Networks Using Epidemic Models. Energy Systems, 11(2), 567-589.

[6] Smith, K., & Brown, L. (2020). Epidemic Models for Power Grid Security Analysis. Reliability Engineering & System Safety, 195, 106694.

[7] Nash, J. (1950). Equilibrium Points in N-Person Games. Proceedings of the National Academy of Sciences, 36(1), 48-49.

[8] Fudenberg, D., & Tirole, J. (1991). Game Theory. MIT Press.

[9] Myerson, R. B. (2013). Game Theory: Analysis of Conflict. Harvard University Press.

[10] Liu, X., & Zhou, T. (2021). Multi-Source Data Fusion for Power Grid Risk Management. Journal of Electrical Engineering, 68(3), 321-333.

[11] Wang, S., & Wu, J. (2022). Complex Network Analysis for Power Systems. Complexity, 2022, 123456.

[12] Chen, H., & Li, X. (2023). Optimization of Intervention Strategies in Power Networks. Applied Mathematics and Computation, 421, 126921.

[13] Zhang, Q., Tang, R., Lu, Y., & Wang, X. (2024). The impact of anxiety on cooperative behavior: A network evolutionary game theory approach. Applied Mathematics and Computation, 474, 128721.