A Rapid Monte Carlo Reliability Evaluation Method for Integrated Energy Systems Based on Transformer

Yu Liu¹*, Jianfeng Li², Tao Jiang², Zixin Zhang³, Zhe Shi³, Bo Yang³

1State Grid Shenyang Power Supply Company, Shenyang, Liaoning, 110811, China.
2State Grid Liaoning Electric Power supply Co., Ltd., Shenyang, Liaoning, 110811, China
3State Grid Liaoning Electric Power Company Limited Economic Research Institute, Shenyang, Liaoning, 110811, China.
*Corresponding author’s e-mail: zsrfkl@ncepu.edu.cn

Abstract. In this paper, a Transformer-based fast Monte Carlo reliability evaluation method for integrated energy systems is proposed. First, the faults of the system components are sampled and the corresponding minimum cut load amounts are calculated to obtain the sample data for training the machine learning model. Then, Transformer is used as a machine learning algorithm for mining the nonlinear mapping relationship between system component faults and the minimum cut load, and the estimation model of the minimum cut load under different faults is trained. Finally, the model is combined with Monte Carlo simulation method to randomly sample component states, and for each state, the minimum cut load amount is directly given by the trained estimation model, thus realizing fast evaluation of integrated energy system fast reliability. The proposed method is applied to the integrated energy system test case, which verifies its effectiveness.

1. Introduction

To achieve energy saving and emission reduction, and to relieve energy pressure, countries all over the world are developing Integrated Energy System (IES), which can not only break the institutional, technical, and market barriers of the traditional energy supply system, but also enhance the overall interaction of source, network and load under multiple energy flows, and the substitutability and complementarity between energy flows will improve the system's energy supply reliability of the system[1]. For this reason, the study of reliability assessment methods has become an urgent need for planning and operation, taking into account the differences in the impact of different energy supply interruptions on users, the characteristics of each energy system's operating state changes, and the complementarity of multiple energy sources under faults.

Monte Carlo simulation-based generation/transmission system reliability evaluation usually includes reliability modeling, state selection, state correction, and consequence evaluation, and index calculation, among which state selection, state correction, and consequence evaluation are the core of reliability evaluation. The state selection, state correction, and consequence evaluation are the core elements of reliability evaluation and usually take up most of the computation time. At present, there are some improvements for The efficiency of state selection has been improved by mature research results. Various variance reduction techniques[2], state-space truncation methods[3], or fast sorting algorithms[4] are designed to select important and representative systems to reduce the computational
complexity in terms of reducing the number of system states to be evaluated. The computational complexity is reduced by reducing the number of system states to be evaluated. In the system state analysis, the core is to solve the optimal tide optimization problem with the objective of optimal load cutting. Most of the existing studies are based on model linearization and optimization of the solution algorithm to reduce the computation time[5].

With the development of artificial intelligence, deep learning algorithms are widely used in finance, security, medical, and other industry fields. Because of its strong ability to extract features from high-dimensional nonlinear data, the use of machine learning and other information technologies to solve practical problems in power systems has become a research hotspot in related fields. At present, scholars have started to explore The literature [6] proposed that the support vector machine (SVM) model can be used to obtain the correspondence between different system faults and the consequences of faults. The literature [7] proposed a new state classification method using a multi-label radial basis function (MLRBF) network and importance sampling (IS) to calculate power system reliability metrics. Based on this, the literature [8] proposes a systematic framework for dynamically analyzing the real-time reliability of the system by integrating different machine learning methods and statistical data, and simulating the dynamic behavior of the system by stacking autoencoders. However, the problem of "dimensional catastrophe" is faced for the reliability evaluation of integrated energy systems, and the lack of effective feature extraction capability affects the subsequent reliability analysis calculation.

Therefore, this paper implements the reliability evaluation of integrated energy system based on Transformer, traverses the system component faults and calculates the minimum cut load amount of the system, extracts the key features in the data by the attention mechanism, and trains the Transformer model as the sample, and gives the minimum cut load amount of the system under the state directly by the trained model, which avoids the calculation of the optimal tide after each sampling to get the system state, thus realizing the fast reliability of the integrated energy system.

2. Transformer-based fast monte carlo reliability evaluation method
The flow chart of the Transformer-based fast Monte Carlo reliability evaluation method proposed in this paper is shown in Figure 1, which mainly includes three main steps: sample data generation, Transformer model training, and fast Monte Carlo reliability evaluation.
2.1. Sample Data Generation

In an integrated energy system, when a component failure occurs, such as a generator machine or line failure, load shedding operation can be performed to solve the system problems caused by node voltage and line current overruns cause system problems and maintain system. In a power system, when a component failure occurs, such as a generator or line failure, load shedding can be performed to solve system problems caused by nodal voltage and line current overruns, and to maintain system frequency, power angle, and voltage stability. The topology of the literature [9] is used as an example to model the optimal cut load of the system. The objective function is

\[
\min F = \sum_{i=1}^{n_e} c_i R_{i}^e + \sum_{j=1}^{n_g} c_g R_{j}^g + \sum_{k=1}^{n_h} c_k R_{k}^h
\]  

In the formula, \(n_e, n_g, n_h\) is the number of electric, gas, and thermal load nodes respectively; \(R_{i}^e, R_{j}^g, R_{k}^h\) is the load reduction of node \(i\) electrical load, node \(j\) gas load, and node \(k\) thermal load, respectively, \(t \in T, T\) is the system fault state duration, \(c_e, c_g, c_h\) is the cost of electricity, gas and heat load reduction.

By generating a large number of system states, the system state space \(X\) is obtained, and the cut load quantity \(Y\) corresponding to each system state in \(X\) can be obtained by the above minimum cut load calculation method. Therefore, \(X\) and \(Y\) constitute the feature vectors and labels for training the Transformer model, which can be used to train the Transformer model for quickly evaluating the cut load quantity of the system in different states, and the following describes the training of the Transformer model is described below.
2.2. The structure of Transformer
Transformer achieves feature extraction of high-dimensional nonlinear data by using a stacked attention mechanism and a fully connected layer of the dot product, based on encoder and decoder structures, as shown in Figure 2.

2.3. Reliability index calculation
In order to quantify the reliability performance of IES, a series of reliability indices for the different agents and whole integrated system should be established. They mainly include loss of load probability (LOLP) and expected energy not supplied (EENS).

\[
LOEP = P \left( \sum_{i=1}^{n_i} C_i^e > 0 \right) \cup \left( \sum_{j=1}^{n_j} C_j^g > 0 \right) \cup \left( \sum_{k=1}^{n_k} C_k^h > 0 \right)
\]  

(2)

\[
EEGHNS = 8760 \times \left( \sum_{i=1}^{n_i} C_i^e \cdot LOLP_i + \sum_{j=1}^{n_j} C_j^g \cdot LOGP_j + \sum_{k=1}^{n_k} C_k^h \cdot LOHP_k \right)
\]

(3)

In the formula, \( C_i^e \), \( C_j^g \), and \( C_k^h \) denotes the load reduction of electric, gas, and thermal subsystems at nodes \( i \), \( j \), and \( k \), respectively.

3. Case studies and results analysis
Before training, the input data and the corresponding labels are first normalized, while 20,000 samples are generated by adding appropriate random fluctuations to the load. The samples are divided into 18,000 training samples and 2,000 test samples. After training, the model training accuracy reached 95.23% and the reliability index is shown in Table 1.

| Class            | LOLP(Transformer) | EENS(Transformer) | LOLP[9]    | EENS[9]   |
|------------------|-------------------|-------------------|------------|-----------|
| Electricity system | 0.0784            | 373.9428          | 0.0754     | 351.6804  |
| Gas system       | 0.0203            | 403.0334          | 0.0213     | 418.0192  |
| Heat system      | 0.0223            | 207.1471          | 0.0255     | 222.3246  |
| IES              | 0.0946            | 994.6214          | 0.0948     | 992.0242  |
From Table 1, it can be seen that the Transformer-based reliability evaluation method proposed in this paper can effectively achieve the reliability evaluation of IES compared with reference [9]. From the analysis of the results, it can be seen that using the Transformer method, the model between the system state and the minimum system cut load is first trained, and then the system state is sampled by the Monte Carlo method then the minimum system cut load is directly derived from the model, from which the reliability index can be calculated, and the deviation is found to be small when comparing the index calculated by conventional Monte Carlo with the index obtained by this method. It can be seen that the method has excellent characteristics, which provides a new system state evaluation model for subsequent IES reliability evaluation, and it helps to conduct reliability evaluation in a data-driven and empirical manner.

4. Conclusion
This paper combines the Transformer method with the Monte Carlo method to calculate the reliability index, which is efficient in time and avoids the complex optimal tide calculation after each sampling, while transformer predicts the system load cut accurately, maintains high accuracy in calculation precision, and the calculation process is easier to understand. The method is reasonable and feasible as shown by the analysis of the example.

References
[1] Zhang X, Shahidehpour M, Alabdulwahab A, et al. (2015) Optimal expansion planning of energy hub with multiple energy infrastructures. J. IEEE Transactions on Smart Grid, 6: 2302-2311.
[2] BIE Z H, WANG J H, WANG X F. (1999) A new method for reducing monte carlo analog variance. J. China Electric Power, 12: 43-46.
[3] ZAN G L, WANG Z D, LI Q Y, et al. (2017) High voltage distribution network reliability evaluation based on state space truncation and isolation scope derivation. J. Automation of Electric Power Systems, 41: 79-85.
[4] JIA Y B, YAN Z. (2010) Reliability evaluation of generation system based on improved quick sorting method. J. Power Grid Technology, 34: 144-148.
[5] Fu X, Sun H, Guo Q, et al. (2017) Probabilistic power flow analysis considering the dependence between power and heat. J. Applied energy, 191: 582-592.
[6] Rocco C M, Moreno J A. (2002) Fast Monte Carlo reliability evaluation using support vector machine. J. Reliability Engineering & System Safety, 76: 237-243.
[7] Urgun D, Singh C, Vittal V. (2019) Importance sampling using multilabel radial basis classification for composite power system reliability evaluation. J. IEEE Systems Journal, 14: 2791-2800.
[8] Chi L, Su H, Zio E, et al. (2021) Data-driven reliability evaluation method of Integrated Energy Systems based on probabilistic deep learning and Gaussian mixture Model-Hidden Markov Model. J. Renewable Energy, 174: 952-970.
[9] Kou Y, Bie Z, Li G, et al. (2021) Reliability evaluation of multi-agent integrated energy systems with fully distributed communication. J. Energy, 224: 120123.