Transfer Learning-Enabled Real-Time Resilience Assessment for Power Systems

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***Abstract*—The abrupt occurrence of extreme natural disasters necessitates real-time resilience assessment for power systems. Although deep neural networks can significantly accelerate this assessment, the mechanisms governing their deployment and updating during disaster evolution remain insufficiently studied. In this study, a transfer learning-enabled real-time resilience assessment approach for power systems is proposed. The real-time resilience indices under disaster scenarios are constructed using the Impact Increment Enumeration Method (IISE). A Transformer network-based Optimal Power Flow (OPF) surrogate model is developed to facilitate fast estimation of load shedding. An online transfer learning strategy is adopted, enabling the Transformer neural network to sustain high prediction accuracy throughout disaster evolution via rapid retraining and incremental adaptation. The proposed approach is validated on the RTS-79 and IEEE-118 systems, demonstrating high prediction accuracy and computational efficiency.**

***Keywords*— power system resilience, real-time assessment, Transformer neural network, transfer learning.**

I. INTRODUCTION

In recent years, global climate change has resulted in the increasingly frequent occurrence of extreme natural disasters, posing severe threats to the secure and reliable operation of power systems [1]. Therefore, performing resilience assessment is essential. It enables quantitative evaluation of the system's resistance to disturbances and recovery ability, and helps identify potential weak components. The assessment results further provide technical support for resilience enhancement and system planning.

Currently, most existing resilience assessment studies are conducted offline. Some are performed in the planning stage to design preventive strategies and reinforcement schemes [2], while others are carried out during disaster events to evaluate the effectiveness of resilience enhancement measures [3]. However, the impacts of natural disasters on power systems exhibit significant spatiotemporal evolution and uncertainty [4]. As a result, pre-disaster assessments alone cannot support real-time adaptive decision-making during the disaster. Therefore, it is necessary to develop real-time, early-warning–oriented resilience assessment methods that cover the entire disaster process. In this context, this paper focuses on early-warning-oriented resilience assessment in the post-damage stage, aiming to provide timely online warnings of resilience degradation as operating conditions and network states evolve during extreme events, thereby supporting adaptive in-disaster decision-making.

Currently, the improvement of resilience assessment efficiency mainly focuses on two aspects. The first is to enhance the representation of system uncertainties by selecting appropriate system states [5]. The second is to accelerate the computation of Optimal Power Flow (OPF) [6]. Methods for uncertainty modeling can be categorized into analytical approaches and simulation-based approaches. Simulation-based methods rely on probabilistic sampling, whereas the complexity of high-order fault scenarios is challenging for neural network training. To accelerate OPF computation, problem decomposition and convex relaxation techniques are commonly adopted. With the rapid development of artificial intelligence, data-driven surrogate models have gradually become an effective alternative for accelerating OPF computation. In addition, deep learning models such as Convolutional Neural Networks (CNNs) and Deep Neural Networks (DNNs) have been applied to further improve computational efficiency [7-8]. However, during disaster evolution, AI-based methods often suffer from performance degradation due to changes in system structure and operating conditions, thus limiting their applicability in real-time resilience assessment. During extreme natural disasters, the sudden influx of new data patterns deviates markedly from the pre-disaster training distribution. Meanwhile, the scarcity of historical extreme-disaster data makes it difficult for neural networks to generalize to previously unseen operating conditions.

Despite the above efforts, existing studies have not yet addressed how to maintain the effectiveness of AI-based OPF models under dynamically evolving disaster scenarios in real time. To address these problems, this paper proposes a transfer learning-enabled real-time resilience assessment method for power systems. First, the Impact Increment State Enumeration (IISE) method is introduced to simulate the evolution of system failures by enumerating only lower-order fault states. Then, a Transformer network-based OPF computation approach for resilience assessment is developed. As disasters evolve continuously, maintaining the effectiveness of neural networks during disaster events becomes an essential challenge. This challenge is associated with the degradation of model generalization capability when encountering previously unseen samples. One possible solution is to continuously update the model. However, rapidly changing disaster conditions render real-time large-scale retraining impractical, limiting the feasibility of continuous model updating. Transfer learning[9], as a model updating strategy based on parameter transfer and feature reuse, can leverage the feature representations learned by a pretrained model and achieve fast adaptation using a small amount of new data collected during or after the disaster. Therefore, transfer learning is suitable for updating neural networks during disaster events. Through rapid retraining and online correction, the model can continuously and promptly adapt to changes in system topology and operating conditions. Meanwhile, the state generation method based on IISE keeps the new samples consistent with the original data distribution, which helps avoid model performance degradation during the second update.

The main contributions of this work are as follows:

1) A transfer learning-enabled real-time resilience assessment method for power systems is proposed, enabling fast and accurate resilience evaluation under disaster scenarios.

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2) A dual-acceleration strategy combining artificial intelligence and the IISE is developed, which greatly enhances the assessment efficiency.

3) A transfer learning-based neural network updating strategy is introduced to ensure that the model can continuously provide accurate predictions during disaster evolution.

II. Resilience Indices Formulation and Optimal Load Shedding Computation

A. Resilience assessment indices

In prior studies, the state enumeration method based on impact increments has been shown effectively assess the resilience level of power systems [10]. The dimensionality reduction property of the IISE allows sampling to be performed only within lower-order failure scenarios, simplifying both Transformer network training sample construction and feature extraction. To characterize the evolution of the disaster, the disaster process is discretized into multiple consecutive time intervals according to the power system dispatch cycle. Accordingly, the impact increment of state s at time t is defined as follows:

$$\Delta L_{\mathrm{shed},l,s}(t)=\sum_{k=0}^{n_s}(-1)^{n_s-k}\sum_{r\in\Omega_s^k}L_{\mathrm{shed},l,s}(t) \tag{1}$$

n_s is the number of failure states corresponding to topology state s. Ω_s^k represents the k-order subset of state s. $L_{\mathrm{shed},l,s}(t)$ denotes the load shedding amount at time t under topology state s and source–load level l, which is obtained by OPF.

The modified failure probability is given by:

$$\Delta P_s(t)=\sum_{s\in\Omega}\left(\prod_{d\in s}P_d^{\mathrm{line}}(t)\right) \tag{2}$$

$P_d^{\mathrm{line}}(t)$ denotes the failure probability of transmission line d at time t, which is assessed by the meteorological early-warning module based on real-time disaster information.

To comprehensively evaluate the resilience performance of the system under disaster scenarios, this study introduces three types of resilience indices: the system-level expected load shedding index, the weak transmission line identification index. These indices are capable of capturing system state variations in real time, thereby providing early indication and warning of potential risks during disaster evolution.

(1) *Expected Load Shedding Index R_{sys}*

The resilience level of the system under disasters is characterized by the expected load shedding, which is used to evaluate potential risks during the evolution of an ice disaster.

$$R_{\mathrm{sys}}(t)=\sum_{k=1}^{N}\sum_{s\in\Omega_{\mathrm{T}}^k}\Delta P_s(t)\Delta L_{\mathrm{shed},l,s}(t) \tag{3}$$

N denotes the maximum order of failure state enumeration; Ω_{T}^k represents the set of enumerated topological states.

(2) *Weak Transmission Lines Identification Index R_{m}*

This index is used to identify weak elements in the system at future time steps, and it represents the reduction in the expected load shedding of the system.

$$R_m(t)=R_{\mathrm{sys}}(t)-R_{\mathrm{sys},m}(t) \tag{4}$$

$R_{\mathrm{sys},m}(t)$ denotes the expected load shedding index of the m-th transmission line when its failure probability is zero.

B. Transformer network-based optimal load shedding computation

To characterize the impact of disasters on the system under different operating conditions, an OPF model is employed. At each time step, OPF calculations are performed with the objective of minimizing load shedding, taking into account the system topology, available generation, and source–load levels. The resulting OPF solution quantifies the system's supply capability under disaster-induced operating states and forms the basis for constructing the resilience indices.

To characterize the impact of disasters on the power system under different operating conditions, an optimal power flow (OPF) model is employed for analysis. The OPF is formulated as an optimal load shedding problem to maintain operational feasibility when system performance is degraded by disasters, while considering the current network topology, available generation capacity, and source–load operating levels. The resulting OPF solution quantitatively characterizes the system's supply capability under disaster conditions and provides a basis for the subsequent construction of resilience indices.

$$\begin{cases}\min L_{\mathrm{shed},l,s}=\sum_{i=1}^{n_{\mathrm{bus}}}L_{\mathrm{shed},l,s,i}\\ s.t.\begin{cases}g(x,u)=0\\ h(x,u)\le 0\end{cases}\end{cases} \tag{5}$$

In the equation, $L_{\mathrm{shed},l,s}$ denotes the total optimal load shedding across all buses; n_{bus} is the number of buses; and $L_{\mathrm{shed},l,s,i}$ represents the optimal load shedding at bus i. $g(x,u)$ represents the set of equality constraints, including the AC power flow equations and the active/reactive power balance conditions at all buses. $h(x,u)$ denotes the set of inequality constraints, such as generator operating limits, voltage magnitude bounds, transmission line thermal limits, and the allowable range of load shedding.

To accelerate the computation of the above ACOPF, artificial intelligence algorithms are employed. The network susceptance $\boldsymbol{B}$ before and after topology changes and the nodal injected power $\boldsymbol{P}_{\mathrm{inj}}$ are selected as input features of the neural network.

The input feature matrix is expressed as:

$$\begin{cases}\boldsymbol{X}_{\mathrm{S\&L}}^{P}=\begin{bmatrix}P_{\mathrm{inj},1}^{\max} & P_{\mathrm{inj},2}^{\max} & \cdots & P_{\mathrm{inj},n}^{\max}\end{bmatrix}_{1\times n}\\ \boldsymbol{X}_{\mathrm{S\&L}}^{Q}=\begin{bmatrix}Q_{\mathrm{inj},1}^{\max} & Q_{\mathrm{inj},2}^{\max} & \cdots & Q_{\mathrm{inj},n}^{\max}\end{bmatrix}_{1\times n}\\ \boldsymbol{X}_{\mathrm{S\&L}}^{P,Q}=[\boldsymbol{X}_{\mathrm{S\&L}}^{P}\quad \boldsymbol{X}_{\mathrm{S\&L}}^{Q}]\end{cases} \tag{6}$$

$P_{\mathrm{inj},i}^{\max}$ and $Q_{\mathrm{inj},i}^{\max}$ denote the maximum active and reactive power outputs of the generator connected to bus i.

The input and output feature matrices are represented as:

$$\begin{cases}\boldsymbol{X}_{\mathrm{in}}=\begin{bmatrix}\boldsymbol{X}_{\mathrm{S\&L}}^{P,Q} & \boldsymbol{X}_{\mathrm{Topo}}^{\boldsymbol{B}}\end{bmatrix}_{N\times 3n}\\ \boldsymbol{Y}_{\mathrm{out}}=[L_{shed,l,s}]_{N\times 1}\end{cases} \tag{7}$$

The input feature $\boldsymbol{X}_{\mathrm{in}}$ consists of the topology feature matrix $\boldsymbol{X}_{\mathrm{Topo}}^{\boldsymbol{B}}$, which characterizes the topology variations during the disaster, and the source-load feature matrix $\boldsymbol{X}_{\mathrm{S\&L}}^{P,Q}$, which reflects the source and load conditions. The output feature matrix $\boldsymbol{Y}_{\mathrm{out}}$ corresponds to the total load shedding amount $L_{\mathrm{shed},l,s}$ of the system at each time step.

III. Neural Network Training Strategy Adapted for Resilience Assessment

A. Timeliness analysis of real-time resilience assessment

For a given natural disaster event, a corresponding set of $\{S_t,S_{t+1},\ldots,S_{t+h}\}$ scenario groups needs to be evaluated. During disaster evolution, this assessment scenario set changes dynamically as both the operating environment and system conditions evolve. Within a future horizon Tstarting from time t, the system may undergo various topological

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reconfigurations and source–load variations. Although the neural network is trained using a diverse set of potential operating scenarios, the continuous progression of the disaster can still generate previously unseen, out-of-distribution system states. Such distribution shifts may gradually degrade the model's prediction accuracy, ultimately affecting the reliability of real-time resilience assessment.

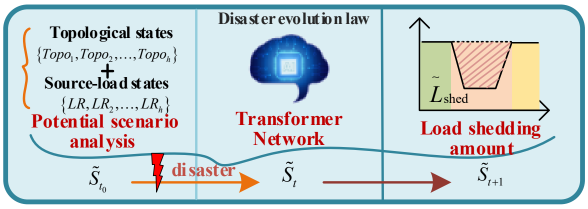

Fig. 1. The framework of the proposed resilience assessment method

B. Fast network updating strategy based on Transfer-Learning

As the disaster evolves, the system may undergo significant changes, such as substantial variations in renewable energy penetration or topological modifications that exceed the applicable scope of the IISE. Under these circumstances, the neural network trained in the pre-disaster stage may no longer retain its initial high-performance characteristics. Therefore, it is necessary to update or retrain the network in order to maintain accurate load shedding prediction during disaster evolution, thereby ensuring the reliability of the resilience indices R_{sys} *and* R_m. However, for large-scale power system and neural networks with numerous parameters, the training process is time-consuming and cannot meet the urgent need for rapid resilience assessment during disasters.

From the perspective of transfer learning, the pre-disaster dataset can be regarded as the source domain $D_S=\left\{(x_i^S, y_i^S)\right\}$, while the disaster-period dataset forms the target domain $D_T=\left\{(x_i^T, y_i^T)\right\}$. Due to transient disturbances during disaster, the feature space, marginal distribution, and conditional distribution of the target domain generally differ from those of the source domain, $X_S \neq X_T$, $P(X_S) \neq P(X_T)$ and $P(Y_S|X_S) \neq P(Y_T|X_T)$. To bridge these differences, a fine-tuning–based deep transfer learning strategy is adopted. In this approach, the model pretrained on the source domain serves as the initialization for the target domain. Since the shallow layers of deep neural networks extract general and transferable features, these layers are kept frozen, while only the remaining layers are updated using target-domain samples. This fine-tuning mechanism avoids full retraining, reduces computational burden, effectively increases the usable sample size of the target domain, and enhances model robustness.

Transfer learning allows knowledge learned from a source task to be reused in a target task. By transferring model parameters, the retraining cost under rapidly changing system states can be substantially reduced. The Kullback-Leibler (KL) divergence is employed to quantify distribution shifts between samples and is used as the criterion for triggering transfer learning. A lower KL divergence indicates a higher similarity between sample distributions, whereas a larger value represents greater distributional differences among samples. In this paper, a threshold value KL_{limit} is empirically set to 0.1 as the criterion. During the prediction of load shedding for the next time period, the average KL divergence of the samples to be evaluated is compared with KL_{limit} to determine whether transfer learning should be executed. The probability density is estimated using the binning method to obtain the original-domain probability P_{origin} and the target-domain probability P_{new}. The criterion for determining whether transfer learning should be executed is defined as follows:

$$\begin{cases} D_{KL}^i(P_{\text{new}}^i \,||\, P_{\text{origin}}^i) = \sum_i \left(P_{\text{origin}}^i + c\right)\log\left(\dfrac{P_{\text{origin}}^i + c}{P_{\text{new}}^i + c}\right) \\ \overline{D_{KL}} = \dfrac{1}{d}\sum_{i=1}^{d} D_{KL}^i \end{cases} \tag{8}$$

To avoid numerical instability caused by undefined logarithmic operations or division by zero during the computation of KL divergence, a small constant $c=10^{-9}$ is introduced. When transfer learning is triggered, only the feed-forward layers and the output layer of the Transformer network are retrained, while the positional encoding layer and the encoder layers are kept frozen to ensure rapid adaptation without disturbing the overall model structure. The criterion for determining whether transfer learning should be executed is defined as follows: transfer learning is performed when the average KL divergence exceeds the threshold KL_{limit}; otherwise, the update is skipped and the model continues inference with the existing parameters.

C. Overall Process of the Proposed Resilience Assessment Method

The overall framework of the proposed transfer learning–enabled real-time resilience assessment method is illustrated in Fig. 2.

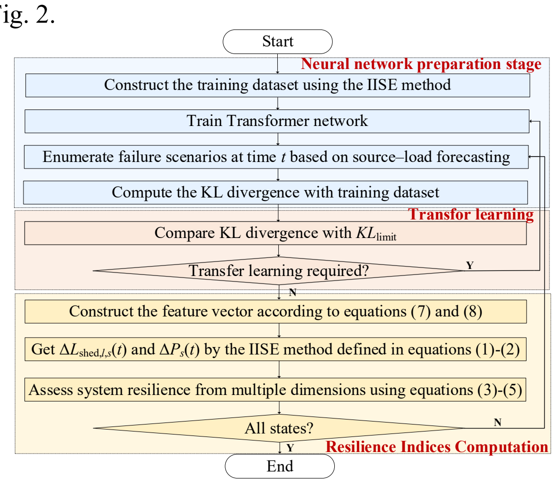

Fig. 2. The overall process of the proposed resilience assessment method

The steps are as follows:

Step 1: Construct the training dataset using the IISE method and perform data standardization.

Step 2: Train the Transformer network according to the proposed scheme.

Step 3: Enumerate failure scenarios at time t based on source–load forecasting.

Step 4: Compute the KL divergence with the training dataset according to equation (8).

Step 5: Compare KL divergence with KL_{limit}.

Step 6: Check whether transfer learning is required. If so, go to Step 2 to update the neural network; otherwise, proceed to the Step 7.

Step 7: Conduct resilience assessment, and construct the feature vector according to equations (6) and (7).

Step 8:Get $\Delta L_{\text{shed},l,s}(t)$ and $\Delta P_s(t)$ by the IISE method defined in equations (1)-(2).

Step 9:Assess system resilience from multiple dimensions using equations (3)-(4).

Step 10: Check whether all states have been processed. If so, end; otherwise, go to Step 3 and continue.

IV. Case Study

The proposed method is validated on RTS-79 [11] and IEEE-118 [12] test systems. The neural network model is implemented in Python using the PyTorch framework. The simulations are conducted on a workstation equipped with dual Intel ® Xeon ® Platinum 8180 processors, 128 GB of RAM, and an NVIDIA GeForce RTX 4060Ti GPU.

The Transformer network encoder structure adopted in this study consists of an input embedding layer, fixed positional encoding, multi-head self-attention mechanism, and a two-layer feed-forward network. The Adam optimization algorithm is used to train the model with a learning rate of 0.001 and a mini-batch size of 64. The root mean square error is selected as the loss function to guide training. Model parameters are iteratively optimized through forward propagation, backpropagation, and parameter updates. Detailed configuration of the Transformer network encoder components is provided in Table I. The detailed system parameters are provided in Table II.

TABLE I. TRANSFORMER NETWORK PARAMETERS

Name	Type	Output Dim	Heads Dim	Activation Function
Input	Input	64	-	-
Embed	Linear Projection	28	-	ReLU
PE	Positional Encoding	128	-	-
MHAttn	Multi-Head Attention	128	4	-
FFN	Feed Forward	128	-	ReLU
Output	Feed Forward	3	-	-

TABLE II. TEST CASES

Case	Nodes	Generators	Lines	Load capacity (MW)	Generator capacity (MW)
RTS-79	24	33	38	2850	3405
IEEE-118	118	54	186	4242	6515

The Jones model is adopted to describe the ice accretion growth on transmission lines. In the RTS-79 system, the duration of the ice-snow disaster is set to 48 hours, whereas in the IEEE-118 system, the disaster duration is set to 96 hours. The modified failure probability is calculated according to (2). In addition, the source-load variation data and the ice–snow evolution information is obtained from real operating records and meteorological observations, ensuring the reliability and practical relevance of the case study.

A. *Efficiency Analysis of Transfer Learning*

To verify the effectiveness of the proposed transfer learning strategy, two test scenarios are designed as follows.

Test Case 1: In the RTS-79 and IEEE-118 systems, the maximum output limits of renewable generation units are assumed to be reduced to 50% of the original scenario due to the disaster.

Test Case 2: The maximum output limits of renewable generation units are assumed to be reduced to 25% of the original scenario.

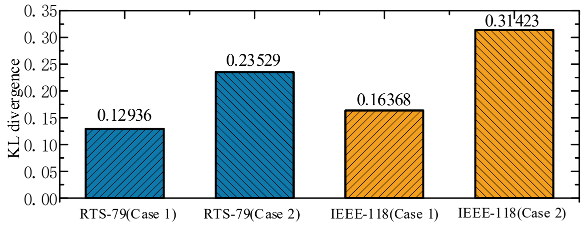

Fig. 3. KL divengence comparison

From the Fig. 3, it can be observed that the average KL divergence in both scenarios exceeds 0.1, indicating that the sample distributions have already deviated significantly from the original dataset and therefore satisfy the condition for triggering transfer learning. Since the data in Case 1 is more similar to the initial sample distribution, its computed KL divergence is relatively smaller, whereas Case 2 exhibits a larger divergence due to its greater deviation from the original distribution.

In the RTS-79 and IEEE-118 systems, the neural network parameters trained under the full-output condition of renewable generation units are adopted. The positional encoding layer and the encoder layers of the Transformer network remain frozen. In Case 1, the training-set loss values of the two neural network approaches are compared during the training process, as shown in Fig. 4 and Fig. 5.

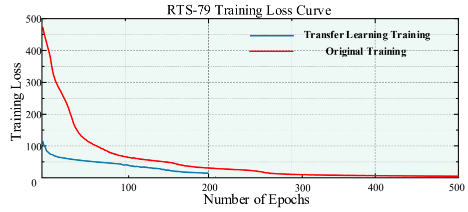

Fig. 4. Comparison of loss convergence between transfer learning and original training of RTS-79 under Case1

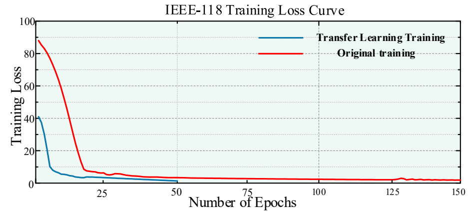

Fig. 5. Comparison of loss convergence between transfer learning and original training of IEEE-118 under Case1

As shown in Fig. 4 and Fig. 5, the proposed transfer learning strategy exhibits a significant advantage in training speed. Unlike original training, which requires hundreds of epochs to enter the low-loss region, transfer learning achieves a rapid loss reduction within only a few epochs and reaches a near-convergent level at an early stage. This demonstrates that the pre-disaster model can be efficiently adapted during disaster evolution with minimal computational effort. In the RTS-79 system, the training loss decreases to 74.2 after 10 epochs of transfer learning, whereas original training requires approximately 87 epochs to reach a comparable loss of 74.39. In the IEEE-118 system, transfer learning achieves a training loss of 5.4 after 10 epochs, while original training requires about 30 epochs to reduce the loss to 5.64. These results consistently show the accelerated convergence enabled by transfer learning across both test systems. Therefore, the proposed method enables rapid neural network updating during disaster evolution, significantly enhancing the real-time performance and practical effectiveness of resilience assessment.

B. *Real-time resilience assessment results*

The Monte Carlo Simulation (MCS) method is used as the baseline for resilience assessment, while the proposed approach is adopted for comparison. During the assessment process, an online evaluation strategy incorporating transfer learning is employed. In the RTS-79 and IEEE-118 systems, the maximum enumeration orders are set to 3 and 2, respectively. The proposed method is then applied to perform resilience assessment, and the resulting expected load shedding index is illustrated in Fig. 6 and Fig. 7.

To accurately reflect the impact of real disaster scenarios on power system operation, this study assumes that several transmission lines experience actual outages during the disaster evolution, and assumes failed lines are repaired according to the order in which the outages occur, and returned to service sequentially after 2.5 hours reparation thereby characterizing the dynamic process of system damage and recovery during the disaster. During the restoration process, sufficient repair resources are assumed to be available.

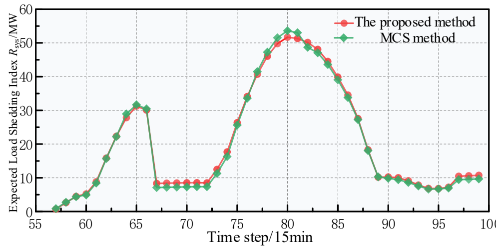

Fig. 6. The result of expected load shedding index of RTS-79

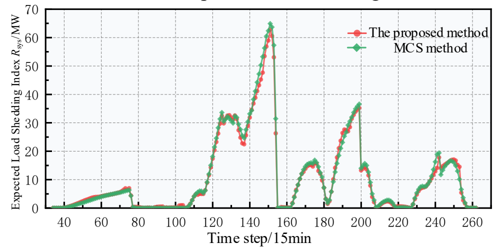

Fig. 7. The result of expected load shedding index of IEEE-118

The results from both the RTS-79 and IEEE-118 systems demonstrate that the proposed transfer learning–enabled real-time resilience assessment method can accurately capture the evolution of system risk and reliably track the expected load shedding throughout the disaster process compared with the results from MCS. During the entire assessment of the RTS-79 system, R_{sys} exhibits a notable decline at time step 67 because the restoration of transmission lines 4 and 7 have been finished, resulting in a rapid reduction in system risk. Between time steps 61 and 71, the resilience curve remains nearly flat, as the ice accretion stage imposes only minor influence on the grid and the previously failed lines remain out of service. Beginning at time step 71, the system enters another high-risk period, with R_{sys} steadily increasing and reaching its peak around time step 80. As the disaster impact gradually diminishes, the system risk decreases accordingly; after time step 99, the grid becomes completely free from disaster-induced effects, and R_{sys} returns to zero. In the IEEE-118 system, the larger network scale and more complex power coupling results in a more pronounced multi-stage evolutionary pattern under the simulated ice-disaster scenario, leading to more intricate variations in system resilience. Throughout the disaster evolution, R_{sys} rises and falls multiple times, which is closely associated with the expansion of the disaster-affected area, fluctuations in source-load conditions, and the outage and restoration of multiple transmission lines.

The proposed weak transmission line identification index predicts potential weak components in future time steps and ranks transmission lines in real time. Five time steps are randomly selected from the assessment process, and the top three identified weak transmission lines are presented.

TABLE III. WEAK TRANSMISSION LINES IDENTIFICATION RESULTS OF THE RTS-79 SYSTEM OF DIFFERENT TIME STEPS

Time step 65		Time step 80		Time step 85		Time step 90		Time step 95	
Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW
4	23.738	5	40.094	5	36.575	5	5.553	5	6.678
8	23.327	10	36.699	10	33.059	18	3.985	-	-
5	6.989	3	7.102	18	0.208	20	3.972	-	-

TABLE IV. WEAK TRANSMISSION LINES IDENTIFICATION RESULTS OF THE IEEE-118 SYSTEM OF DIFFERENT TIME STEPS

Time step 65		Time step 80		Time step 90		Time step 180		Time step 200	
Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW)	Lines	R_m(MW
121	11.961	183	62.608	13	6.251	62	0.574	47	6.001
125	11.961	-	-	2	5.578	68	0.574	46	5.410
151	6.413	-	-	1	0.672	-	-	49	0.699

Based on the calculated weak line identification index R_m, higher-risk transmission lines can be identified at each time step. As shown in the tables, the index captures the dynamic evolution of line vulnerability during the disaster and offers forward-looking risk indications to support timely operational and maintenance decisions.

V. CONCLUSION

This paper presents a transfer learning-enabled real-time resilience assessment for power systems. Unlike conventional approaches that rely on static pre-disaster models, the proposed strategy updates the assessment model online in response to continuous changes in system topology and source-load conditions, thereby enabling accurate and continuous characterization of system resilience. A Transformer-based OPF surrogate model is developed to rapidly estimate load shedding, and an online transfer learning mechanism is incorporated to achieve fast model adaptation with minimal retraining cost, effectively preventing performance degradation caused by distribution shifts during disaster progression. Case studies conducted on the RTS-79 and IEEE-118 systems demonstrate that the proposed strategy significantly reduces computation time while maintaining reliable assessment accuracy. The method provides a feasible and efficient tool for real-time situational awareness, vulnerability identification, and emergency decision-making under extreme disaster conditions.

VI. ACKNOWLEDGMENT

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