Predict-and-Adjust Scenario Generation Method for Power System Operation Risk Assessment

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***Abstract*—Accurately capturing the uncertainty impacts introduced by high-penetration renewable energy sources remains a key challenge in current power system operation risk assessment. Existing assessment methods predominantly focus only on the inherent randomness of renewable energy during scenario generation, while neglecting the system's dispatch response capability, which compromises the authenticity of the scenarios. To address this, this paper proposes an integrated predict-and-adjust framework for scenario generation, based on a hybrid data-driven and physics-constrained model. The framework directly outputs feasible operating states of the system under multiple uncertainties, achieving a paradigm shift in scenario generation. After constructing the time-series prediction agent and the grid feature agent, a physics-inspired attention mechanism is employed to guide the fusion of implicit information, which is then passed to the power flow adjustment decision network. The developed model avoids error accumulation inherent in static stepwise prediction and achieves better final objectives through collaborative optimization. Physical constraint regularization is embedded to guide the model toward power flow feasibility. Case study results verify that the proposed framework offers higher prediction accuracy and physical feasibility with high computational efficiency compared to traditional methods, thereby supporting rapid scenario generation for risk assessment.**

Keywords—scenario generation; predict-and-adjust framework; operation risk assessment; data-driven; physical mechanism constraints

I. INTRODUCTION

As the global energy system accelerates its transition towards decarbonization, the high penetration of renewable energy into the grid has become a prevailing trend. However, the inherent strong stochasticity and volatility of renewables pose significant challenges to power system risk assessment. Scenario analysis has been extensively studied as an effective method for characterizing the uncertainty in system operational states and can serve as an upstream process to provide a data foundation for risk assessment. Nevertheless, existing scenario generation models often focus solely on the inherent randomness of renewable sources, producing only chronological renewable power output scenarios. While these models capture variability at the generation level[1]-[2], they frequently fail to incorporate the resulting power flow changes and the system's adaptive responses. This limitation compromises the authenticity of the scenarios and the accuracy of subsequent risk assessments.

Compared to the conventional decoupled processing of prediction and optimization, an integrated framework ensures more complete propagation of uncertainties. [3] proposed a synergistic prediction-optimization framework, which achieves a robust optimization scheme with statistical guarantees and leads to enhanced decision efficacy. In the domain of power forecasting, traditional approaches such as multiple linear regression, autoregressive integrated moving average (ARIMA) models[4], and Markov chains[5] have been widely adopted, yet they exhibit limitations in capturing nonlinear relationships. In contrast, deep learning techniques offer inherent advantages in mining complex data correlations. Among them, Long Short-Term Memory (LSTM) networks have shown notable effectiveness in power forecasting due to their capability to model long-term temporal dependencies[6]. While the Newton-Raphson method remains the prevailing tool for power flow analysis in current engineering practice, its efficiency may be compromised in large-scale power grids[7]. Furthermore, traditional decoupled approaches require repetitive power flow or optimization calculations for each scenario within the massive time-series datasets produced by scenario generation. This imposes an immense computational burden, making it difficult to satisfy the requirements for rapid risk assessment. Although deep learning offers significant efficiency benefits through rapid inference, it often suffers from insufficient accuracy and credibility due to difficulties in strictly adhering to physical equation constraints[8].

To bridge this gap, this paper proposes an integrated predict-and-adjust framework for scenario generation, which rapidly produces a set of probabilistic operating scenarios to support risk assessment. The framework constructs a multi-agent architecture that leverages LSTM networks for temporal forecasting and Graph Neural Network (GNN) for extracting grid structural features. The resulting high-dimensional implicit information is then fused under the guidance of a cross-attention mechanism, which propagates uncertainty to the decision network. A multi-stage training strategy is developed to enhance model accuracy and convergence by coordinating the multi-agent optimization. The results demonstrate that the integrated framework achieves smaller prediction errors while maintaining high computational efficiency compared to conventional approaches.

II. AN INTEGRATED PREDICT-AND-ADJUST FRAMEWORK WITH MULTI-AGENT COLLABORATION FOR SCENARIO GENERATION

A. *Construction of the Forecasting and Grid Structural Feature Extraction Agents*

LSTM is particularly adept at resolving long-term dependencies in time series due to its unique gating mechanism and cell state. It serves as an ideal forecasting model for renewable energy and load power fluctuations, which exhibit temporal dependencies and long-term

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regularities. The core mechanism lies in how the information outputs from the forget gate and input gate collectively determine the update to the cell state

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{1}$$

where C_{t-1} and $\tilde{C}_t$ tare the cell states before and after the update, respectively. The forget gate f_t determines which historical patterns to discard based on the current fluctuations in renewable energy and load power. The input gate i_t identifies the salient features of the current power fluctuations. The complementary relationship between renewable energy and load, as well as the spatiotemporal correlations among multiple nodes, are automatically learned through the weight matrices W_f and W_i of the forget gate and input gate.

GNN possess an inherent advantage in learning power flow distributions due to their explicit modeling of network topology and mathematical isomorphism with Kirchhoff's laws. This paper constructs a power-grid-specific Graph Convolutional Network (GCN) to learn the system's topological characteristics and electrical state parameters, starting with the construction of node feature vectors.

$$\mathrm{v}_i = [type_i, V_{m,i}, V_{a,i}, P_{in,i}, Q_{in,i}] \tag{2}$$

where $type_i$ denotes the bus type; $V_{m,i}$ and $V_{a,i}$ represent the voltage magnitude and phase angle, respectively; $P_{in,i}$ and $Q_{in,i}$ represent the active and reactive power injection, respectively.

Based on the topological connectivity, an adjacency matrix $\mathrm{A} \in \{0,1\}^{n \times n}$ is constructed. The feature vector of each edge is defined as:

$$e_{ij} = [r_{ij}, x_{ij}, b_{ij}] \tag{3}$$

where r_{ij}, x_{ij} and b_{ij} represent the resistance, reactance, and susceptance of transmission line, respectively. The core process involves propagating electrical neighborhood information through a neighborhood aggregation mechanism:

$$h^{(l+1)} = \sigma\left(\mathrm{D}^{-\frac{1}{2}} \mathrm{A} \mathrm{D}^{-\frac{1}{2}} h^{(l)} \mathrm{W}^{(l)}\right) \tag{4}$$

where σ denotes the activation function; $h^{(l)}$ is the feature representation of node *i* at the *l*-th layer, and $\mathrm{W}^{(l)}$ denotes the learnable weight matrix at the *l*-th layer.

Through the above graph structure, the learning of electrical coupling relationships naturally embeds physical constraints in a preliminary manner.

B. *Implicit Information Fusion and Physical Constraint Embedding*

The LSTM network constructed in the previous section outputs high-dimensional implicit information H_p, which exceeds the original time-step dimensions and serves as an implicit representation of future power fluctuation trends. Simultaneously, the GNN captures and outputs implicit information H_f containing grid structural features. These representations are then projected into query Q, key K, and value V vectors through linear transformations

$$\mathrm{Q} = \mathrm{H}_f \mathrm{W}_q, \quad \mathrm{K} = \mathrm{H}_p \mathrm{W}_k, \quad \mathrm{V} = \mathrm{H}_p \mathrm{W}_v \tag{5}$$

where W_q, W_k and W_v are learnable projection matrices.

After projecting the multi-modal features into a unified semantic space, the attention weight matrix A_w is computed via the dot product, which reflects the degree of attention that the power grid state pays to different temporal patterns

$$\mathrm{A}_w = \mathrm{softmax}\left(\frac{\mathrm{QK}^{\mathrm{T}}}{\sqrt{d_k}}\right) \tag{6}$$

where each element a_{ij} of the matrix A_w quantifies the responsiveness of the *i*-th grid feature to the *j*-th temporal power pattern.

Subsequently, a weighted summation of the value vector V is performed using A_w to obtain the context vector C, which integrates comprehensive information on both the grid structure and temporal dynamics. To capture features from different subspaces, this study employs a multi-head attention mechanism for computation, followed by concatenation via a linear projection layer.

$$\mathrm{H}_{fused} = [\mathrm{C}_1; \mathrm{C}_2; \ldots; \mathrm{C}_h] \mathrm{W}^o \tag{7}$$

The fused feature vector H_{fused} is subsequently fed into a decision network. Leveraging a cross-attention fusion mechanism, the model adaptively extracts relevant information from temporal predictions based on the real-time structural state of the power grid, thereby generating a more accurate power flow prediction that conforms to physical constraints.

Compared with generating explicit static power prediction points, the implicit representation, whose dimensionality far exceeds the number of time steps, preserves richer information pertaining to trend fluctuations and prediction errors. The fusion of such implicit information enables the model to mitigate the adverse effects of errors and minimize the final loss through joint optimization within an end-to-end training paradigm. According to the chain rule, the gradient of the total loss *L* with respect to the parameters ω of the prediction agent is expressed as:

$$\frac{\partial L}{\partial \omega} = \frac{\partial L}{\partial \mathrm{P}} \cdot \frac{\partial \mathrm{P}}{\partial \mathrm{H}_{fused}} \cdot \frac{\partial \mathrm{H}_{fused}}{\partial \mathrm{H}_p} \cdot \frac{\partial \mathrm{H}_p}{\partial \omega} \tag{8}$$

During model optimization via backpropagation, the negative impact of local errors in temporal forecasting is mitigated. Furthermore, explicit probabilistic distribution outputs for predictions lead to computational challenges in optimization and difficulties in incorporating physical constraints.

To address the limitation of conventional data-driven methods in adequately satisfying physical constraints, a decision agent is constructed using a multi-layer fully connected network. Inspired by the framework of Physics-Informed Neural Networks (PINN), a physical regularization

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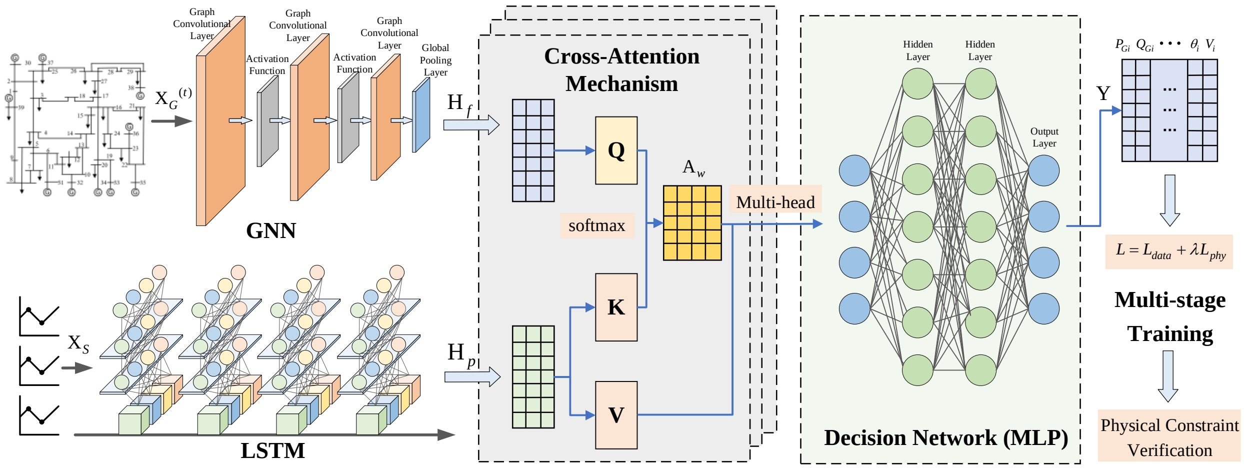

Fig. 1. The Integrated Predict-and-adjust Framework with Multi-Agent Collaboration for Scenario Generation

term L_{phy} is introduced into the loss function based on the node power balance equations

$$L = L_{data} + \lambda L_{phy} \tag{9}$$

$$L_{phy} = \frac{1}{N}\sum_{i=1}^{N}\left[(P_i(\theta,V) - \tilde{P}_i)^2 + (Q_i(\theta,V) - Q_i)^2 \right] \tag{10}$$

$$L_{ineq} = \alpha_V L_V + \alpha_S L_S + \alpha_G L_G \tag{11}$$

where λ serves as the weighting coefficient for the physical regularization term; $P_i(\theta,V)$ represents the nodal injection power calculated from the predicted voltage magnitude V and phase angle θ, while $\tilde{P}$ denotes the injection derived from the predicted active power of generators and loads; L_V, L_S, and L_G denote quadratic penalties for violations of voltage, line flow, and generator power limits, respectively.

By embedding physical prior knowledge into the model, the training process is guided to align with physical laws, thereby reducing violations of physical constraints.

C. Integrated Prediction-Power Flow Adjustment Framework

The multi-agent collaborative framework developed in this study is illustrated in Fig.1, which ultimately achieves the predictive function for dynamic multi-period power flow adjustment in power systems. The temporal forecasting agent takes as input historical time-series data of renewable energy generation and load fluctuations

$$X_S = [p_{\text{wind}}^{(t)}, p_{solar}^{(t)}, p_{\text{load}}^{(t)}]_{t=1}^{T_S} \tag{12}$$

where T_S denotes the historical time horizon, and at each time step t, the input vector x_t incorporates D_t feature dimensions representing fluctuations in renewable energy generation and load power.

On the basis of fixed topology and line parameters in a standard system, node features are updated according to the current real-time system state. These are then superimposed to construct dynamic graph data, which is input into the graph neural network. The power grid graph data is represented as:

On the basis of system topology and line parameters, node features are updated according to the current real-time system state, aggregated, and then structured into dynamic graph data $X_G^{(t)}$ for input to the graph neural network. By defining connection relationships, the model can accommodate different topological structures.

$$X_G^{(t)} = (V^{(t)}, E, X_{\text{nodes}}, X_{\text{edges}}) \tag{13}$$

In the equation, $V^{(t)}$ and E denote the node and edge feature matrices, respectively, where $V^{(t)}$ is dynamically updated according to the real-time grid state. X_{nodes} and X_{edges} represent the node set and edge index matrix, respectively.

To characterize uncertainty and enable probabilistic outputs from the model, dropout layers are incorporated within the agent. During both training and inference stages, a fraction of neurons is randomly deactivated. By repeatedly sampling outputs through Monte Carlo (MC) dropout, a predictive scenario set is constructed and the probability distribution is estimated.

The final model outputs possible power flow operating states across multiple future time steps, including key variables such as generator outputs and node voltage information. The complete data flow is represented as:

$$Y = f_D\left[f_{\text{Attention}}\left(f_{\text{LSTM}}(X_S), f_{\text{GNN}}(X_G) \right) \right] \tag{14}$$

The proposed model leverages specialized agents with complementary strengths for information encoding, constructing an integrated framework through the fusion of temporal dynamics and grid structural features. This architecture achieves a seamless integration of data-driven methods with physical model principles.

III. Model Training Procedure and Strategy

A. Sample Preparation

To provide the model with sufficient training samples for learning convergent power flow adjustment strategies, a computational framework is constructed. For the reference system, a converged optimal power flow solution is taken as the baseline starting point. The corresponding node parameters of the system are modified according to realistic

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load profiles and concurrent renewable power output. To ensure that the power flow converges to the nearest feasible operating point after power disturbances, an integrated power flow adjustment model is developed.

$$\min \sum_{i \in G} \left[(P_{Gi} - P_{Gi}^{0})^2 + (Q_{Gi} - Q_{Gi}^{0})^2 \right] \quad \text{s.t.} \begin{cases} g(x) = 0 \\ h(x) \le 0 \end{cases} \tag{15}$$

where the objective function is to minimize the generator adjustment amount; $g(x)$ represents the equality constraints of the power balance equations, and $h(x)$ denotes the inequality constraints such as node voltage limits and generator output limits.

The primal-dual interior-point method[9] is employed for solution, yielding a large set of realistic time-series power flow solutions.

B. *Multi-stage Training Strategy*

Practical training results indicate that for the multi-agent collaborative framework proposed in this paper, the complexity of the learning tasks and deep network architecture makes direct end-to-end optimization prone to gradient conflicts, leading to slow convergence or training oscillations. The randomly initialized weights of the LSTM and attention mechanisms may interfere with the physical constraint learning of the power flow computing agent, resulting in suboptimal solutions. To address this, a multi-stage training strategy is introduced：

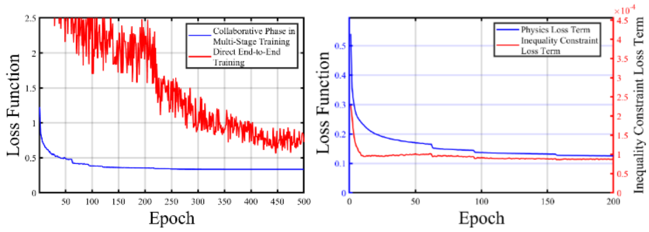
- Stage 1: The model is directly trained for a limited number of epochs to serve as parameter initialization.
- Stage 2: Only the power flow agent, composed of the GNN and the decision network, is trained individually. Supervised learning is employed to ensure that it can capture the grid structure and satisfy physical constraints, thereby generating realistic and accurate power flow solutions.
- Stage 3: The parameters of the power flow agent are fixed, while the prediction agent and the fusion mechanism are trained.
- Stage 4: All module parameters are unlocked for end-to-end collaborative optimization.

Validation results confirm that the proposed training strategy demonstrates enhanced robustness, ensures physical consistency, and is well-suited for the integrated framework presented in this study.

IV. Results Validation

The proposed method is validated on the IEEE 39-bus system with a renewable energy penetration level of 20%, where wind farms and photovoltaic power stations are integrated at buses 20 and 8. The study employs a historical operational dataset provided by State Grid Corporation of China for analysis and computation. This dataset comprises two years (2019-2020) of power output data from renewable energy bases and actual load profiles from a specific region. Based on (15), a total of 70,080 time-series samples are calculated using the interior point method. The collaborative multi-agent model is implemented using the PyTorch deep learning framework and accelerated for training on a GPU CUDA platform. The computational hardware consists of an Intel Core i7-13700KF CPU and an NVIDIA GeForce RTX 4060 GPU.

The complete dataset is partitioned into training, validation, and test sets with a ratio of 70%, 15%, and 15%, respectively. The Adam optimizer is employed with an initial learning rate of 0.001, coupled with a performance-based decay strategy where the learning rate is halved if the validation loss shows no improvement over n_t consecutive epochs. The data loss term L_{data} utilizes Mean Squared Error (MSE), while the physical regularization term weight λ is set to 10^{-3}. During the pretraining phase, the number of training epochs is set to 50. Upon completion of the collaborative training in Stage 4, the integrated prediction-power flow adjustment model is saved. The loss functions of both the direct end-to-end training approach and the proposed collaborative training strategy are illustrated in Fig.2.

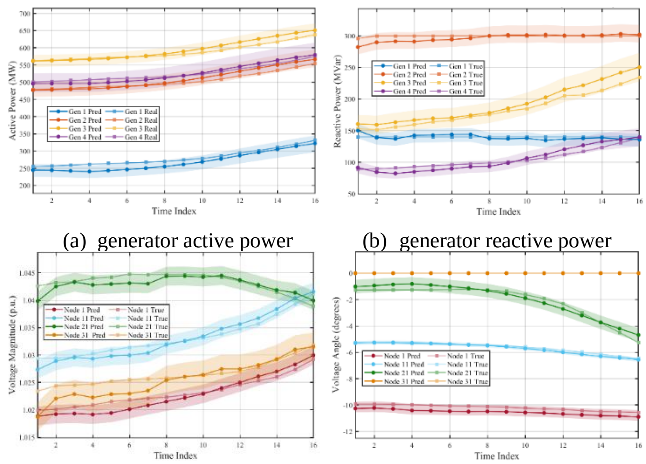


(a) overall loss function (b) loss penalty term

Fig. 2. Loss Functions of Multi-stage Training and End-to-End Training

The loss function results indicate that the proposed multi-stage training strategy achieves superior convergence and training stability compared to direct end-to-end training. Furthermore, the penalty term L_{ineq} rapidly approaches zero in the early stages of training, indicating that the actual constraint values are satisfied.

After training, the model predicts multi-period power flow patterns in the validation dataset. Through repeated sampling, a scenario set of future states under source and load uncertainty is constructed, and their probability distributions are estimated. The adjustment results for partial generator outputs and node voltages are shown in the figure below.



(a) generator active power (b) generator reactive power

(c) node voltage magnitude (d) node voltage angle

Fig. 3. Partial Prediction Results versus Ground-Truth Values

The presented predictions include the 90% confidence interval and the mean trajectory. Taking active power of generators as an example, the average interval width $W_{90\%}$

is 18.34 MW, and the coverage rate $R_{90\%}$ of the 90% confidence interval for the true trajectory is 92.14%.

Compared with the actual values, the model constructed in this paper can accurately predict the system's response trend under fluctuations in renewable energy and load, and identify the corresponding generator adjustment strategies. Furthermore, it characterizes the uncertainty of outcomes by outputting a probabilistic scenario set.

To validate the effectiveness of the proposed physical constraint embedding, the prediction results of models with different strategies are compared, as shown in the table below. Method 1 refers to the approach incorporating multi-stage training without embedding physical constraint losses. Method 2 employs direct end-to-end training with physical constraints, while Method 3 represents the complete model and training strategy proposed in this work. The physical constraint violation rate R_{phy} is calculated based on the physical loss term L_{phy} and the true power injection values P_i and Q_i, with the result being the average value per time step. To further enhance the rationality of the analysis, the balanced active power deviation P_B is introduced as a metric. The system parameters are modified according to the predicted generator outputs (excluding the slack bus) in the prediction results. The power flow is then solved using the Newton-Raphson method via Matpower 8.0, and the deviation between the slack bus power in the solution and the ground-truth samples is defined as P_B.

$$R_{phy} = \frac{\sum_{i=1}^{N}\left[\left|P_i(\theta,V) - \tilde{P}_i\right| + \left|Q_i(\theta,V) - Q_i\right|\right]}{\sum_{i=1}^{N}(P_i + Q_i)} \times 100\% \quad (16)$$

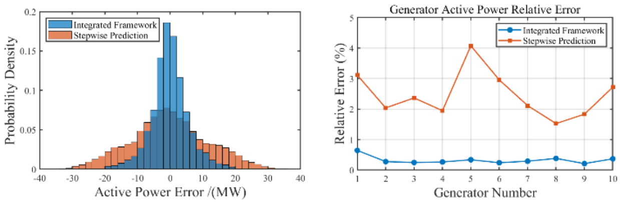
TABLE I. COMPARATIVE ANALYSIS OF MULTI-STRATEGY RESULTS FOR PHYSICAL CONSTRAINT VERIFICATION

Evaluation metrics	Different strategies adopted		
	Method 1	**Method 2**	**Method 3**
R_{phy}	6.48%	2.41%	1.39%
P_B /(MW)	35.11	10.55	7.46

It can be observed that the proposed method achieves superior performance with a notably low physical constraint violation rate of 1.39%, while maintaining acceptable accuracy in power flow validation. The error statistics of the integrated framework are presented in the figure below. For comparison, the error statistics of a conventional approach—where the LSTM explicitly outputs predicted values of renewable energy and load fluctuations, followed by sequential power flow calculations—are also included in the same figure.

The results clearly demonstrate that the proposed multi-agent collaborative framework, based on implicit information fusion, achieves significantly higher accuracy in the final power flow outcomes.

After training completion, the model was saved and reloaded for prediction using historical data. For 100 test samples, 500 predictive scenarios were generated per sample. The model completed inference within 290 seconds, meeting the rapidity requirements for risk assessment applications.



(a) error statistics of generator outputs (b) errors at different nodes

Fig. 4. Comparison of Error Statistics

V. CONCLUSIONS

To bridge the gap in existing scenario generation methods , this paper proposes an integrated predict-and-adjust scenario generation framework for power system operation risk assessment, based on a hybrid data-driven and physics-constrained model. Following the construction of temporal prediction and grid structural feature extraction agents, the fusion of high-dimensional implicit information is guided.

Compared with generating explicit power prediction values, the proposed method enables the entire model to mitigate the negative impact of errors through joint optimization in an end-to-end training process. The model innovatively embeds physical constraints in the form of regularization losses and introduces a multi-stage training strategy tailored for the proposed framework. Case study results validate the significant advantages of the proposed framework and training strategy in terms of accuracy, convergence, and physical consistency.

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