

Article

Data-Driven Comprehensive Security Region Assessment for Hydro–Wind–Solar Hybrid Systems with HVDC Integration

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Abstract

The massive integration of “hydro–wind–solar hybrid” generation transmitted via AC/DC hybrid grids with High-Voltage Direct Current introduces unprecedented challenges to power system transient stability. Traditional Dynamic Security Assessment heavily relies on time-domain simulation and high-density Monte Carlo sampling, which suffer from massive computational burdens and are strictly prohibitive for intra-day operational dispatch. To address this long-standing bottleneck, this paper proposes a novel data-driven comprehensive security region assessment framework based on an Active Learning query strategy and a Support Vector Machine surrogate model. By seamlessly coupling Python with the DlgSILENT PowerFactory simulator, the proposed AL algorithm actively queries and evaluates only the critical operating points near the stability margin, effectively avoiding redundant simulations in obviously safe or unsafe zones. Extensive simulations under a severe N-1-1 contingency demonstrate that the proposed framework can accurately map the non-linear boundaries of both transient rotor angle and short-term voltage stability constraints. Furthermore, the framework’s scalability is rigorously validated in complex 3D high-dimensional operational spaces. By integrating an ϵ -greedy exploration strategy with a Label Flip Rate (LFR) early stopping criterion, the proposed algorithm successfully overcomes the curse of dimensionality. Quantitatively, the proposed method achieves nearly identical boundary resolution using merely 65 physical simulations, as opposed to the 40,000 evaluations required by conventional high-density grid scanning. The total computational time is drastically reduced from 28.6 h to approximately 2.8 min, yielding a remarkable acceleration of over 600 times, making it highly suitable for near-online dynamic security monitoring.



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Keywords: dynamic security assessment; active learning; support vector machine; hydro–wind–solar hybrid system; transient stability

1. Introduction

In recent years, the massive integration of renewable energy sources has profoundly transformed the operational paradigms of modern power systems [1,2]. To mitigate the volatility and intermittency of wind and solar power, the “hydro–wind–solar hybrid” generation scheme has emerged as a promising and sustainable solution [3]. Specifically, bundling massive hydropower with nearby renewable energy and transmitting the bulk

power over long distances via High-Voltage Direct Current (HVDC) through an AC/DC hybrid grid significantly enhances renewable accommodation efficiency [4–6].

However, the intricate dynamic interactions among synchronous hydro-generators, power electronic converters of renewables, and complex HVDC controls pose unprecedented challenges to grid stability. Dynamic Security Assessment (DSA) is crucial for ensuring the reliable operation of interconnected power systems against severe contingencies. In high-proportion renewable AC/DC grids, transient stability issues—particularly rotor angle divergence and transient voltage dips—have become prominent operational bottlenecks that can trigger cascading failures [7,8]. Beyond traditional dynamic stability, the increasing complexity of modern power systems necessitates a broader evaluation of system resilience under severe disturbances. Advanced HVDC systems and their flexible controls have proven highly effective in improving grid resilience and strengthening the security of power system stability [9]. Furthermore, as renewable-dominated grids increasingly rely on communication infrastructure, robust resilience enhancement strategies against uncertain cyber–physical coordinated attacks have become a critical research frontier [10]. Therefore, an accurate and ultra-fast dynamic security assessment is not only essential for preventing physical transient instability but also serves as the foundational core for holistic cyber–physical grid resilience.

Traditionally, DSA relies on deterministic Time-Domain Simulation (TDS) for stability evaluation [11]. To evaluate the system’s security region under various operating conditions and uncertainties, statistical techniques such as Monte Carlo Simulation (MCS) and Latin Hypercube Sampling (LHS) are widely employed to generate comprehensive operational datasets. While LHS improves upon naive MCS by ensuring more stratified and evenly distributed sampling across the multidimensional feature space, both methods remain fundamentally “blind” sampling techniques [12]. Although TDS is strictly reliable and mathematically rigorous, solving the non-linear differential-algebraic equations is highly time-consuming. Consequently, executing exhaustive MCS or LHS is computationally prohibitive for large-scale hybrid systems. These traditional methods waste immense computational resources on operating points that are “obviously secure” or “obviously insecure,” while failing to densely capture the critical points near the highly non-linear transient stability boundary [13].

To address the severe computational burden of traditional DSA, data-driven surrogate models based on machine learning and artificial intelligence have been widely investigated in the recent literature [14–16]. Techniques such as artificial neural networks, decision trees, Gaussian processes, and Support Vector Machines (SVM) can accurately map the non-linear relationship between pre-fault operating conditions and post-fault security status, achieving millisecond-level online assessment [17,18]. Recently, advanced paradigms such as physics-informed machine learning have also demonstrated immense potential in capturing complex physical dynamics, enabling highly robust applications like climate-aware digital twins for intelligent energy systems [19]. Nonetheless, a critical bottleneck remains in the offline data preparation phase: training a robust and generalized ML classifier still inherently relies on those inefficient blind sampling methods to build the initial database. Recognizing this data-generation dilemma, several recent studies have begun exploring active data generation strategies to reduce computational waste [20–23].

To comprehensively overcome the limitations regarding data generation efficiency, this paper proposes a novel data-driven comprehensive security region assessment framework based on Active Learning (AL) and an SVM surrogate model. Instead of blindly scanning the entire grid space, the AL algorithm actively queries and simulates only the “most uncertain” boundary points during the iterative training process. By seamlessly coupling the

AL algorithm with the DIgSILENT PowerFactory 2021 SP2 simulator, the proposed method constructs highly accurate, continuous stability boundaries with minimal simulation calls.

The main contributions of this paper are summarized as follows:

1. A comprehensive security region modeling framework is established for a practical hydro–wind–solar bundled AC/DC hybrid system, considering both static constraints and transient stability constraints.
2. An AL-assisted SVM surrogate model is proposed, which dynamically searches for critical boundary points, effectively addressing the computational bottleneck of traditional MCS data generation. Unlike conventional AL methods that rely on heuristic stopping rules or fixed simulation budgets, the proposed AL surrogate model incorporates an autonomous Label Flip Rate convergence criterion and an ϵ -greedy exploration strategy to systematically avoid underfitting and local topological traps in multi-dimensional spaces.
3. Extensive simulations demonstrate that the proposed method accelerates boundary delineation by hundreds of times compared to conventional MCS, drastically minimizing the Boundary Distance Error while maintaining a near-zero False Secure Rate.
4. The scalability and robustness of the framework are explicitly verified in complex high-dimensional operational spaces. By decoupling multi-source renewable dynamics and incorporating HVDC dispatch constraints, the algorithm successfully circumvents the curse of dimensionality, providing highly precise, continuous spatial decision manifolds for holistic system operation.

2. System Description and Modeling

In this section, the detailed mathematical modeling and topological configuration of the hydro–wind–solar hybrid generation system with HVDC integration are presented. The simulations are conducted using DIgSILENT PowerFactory 2021 SP2 software.

2.1. Topology of the AC/DC Hybrid Grid

The studied system represents a practical high-proportion renewable AC/DC hybrid transmission grid, structurally inspired by a hydro–wind–solar grid-connected project in southwestern China. As illustrated in Figure 1, the generation side mainly consists of several large-scale synchronous hydropower units, bundled with nearby utility-scale wind farms and photovoltaic power plants.

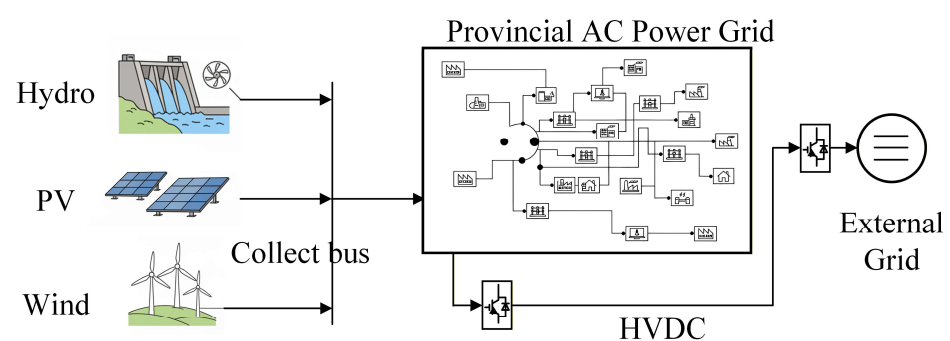


Figure 1. Diagram of the studied hydro–wind–solar bundled AC/DC hybrid transmission system.

The generated power is primarily supplied to the local 500 kV AC grid to satisfy the local active power demand. Subsequently, the surplus bundled power is transmitted over a long distance through the High-Voltage Direct Current transmission corridor. The complex dynamic coupling among the mechanical inertia of hydropower units, the fast-switching power electronics of renewables, and the commutations of the HVDC converters

dominates the transient stability of the system. The integration capacity ratio between hydro and renewables fundamentally reshapes the system's dynamic responses. An increased penetration of renewables inherently reduces the overall mechanical inertia and dynamic reactive power reserve. During a severe N-1-1 contingency, this degradation exacerbates transient voltage dips at the converter buses, significantly increasing the vulnerability of the LCC-HVDC to commutation failures. The resulting massive active power blockade forces the synchronous hydro generators into severe acceleration, thereby strongly coupling short-term voltage stability with transient rotor angle stability.

2.2. Core Equipment Control Models

To accurately capture the transient dynamics during severe grid faults, detailed control models are implemented for the core equipment.

(1) Synchronous Hydropower Units:

To achieve a high-fidelity simulation of the hydro-generator's transient characteristics, this study employs a sixth-order synchronous machine model incorporating d-q axis damper windings, complemented by a suite of detailed, as-built control systems. Specifically, the Automatic Voltage Regulator is represented by a bespoke multi-variable controller that processes terminal voltage, active/reactive power, and speed signals and integrates critical limiters such as UEL and OEL. For enhanced system damping, a unique BPA SI-type Power System Stabilizer is implemented, which innovatively features dual inputs of active power and rotor speed deviation. Furthermore, the prime mover dynamics are meticulously represented by a detailed electro-hydraulic governing system, comprising a PID control module cascaded with an actuator to capture the non-linear servo-mechanical response precisely.

The electromechanical dynamics of the i -th synchronous generator are governed by the classic swing equations [24], representing the relationship between the rotor angle and the active power imbalance:

$$\begin{aligned} M_i \frac{d\Delta\omega_i}{dt} &= P_{m,i} - P_{e,i} - D_i \Delta\omega_i \\ \frac{d\delta_i}{dt} &= \omega_0 \Delta\omega_i \end{aligned} \quad (1)$$

where M_i and D_i are the inertia constant and damping coefficient, respectively; $P_{m,i}$ and $P_{e,i}$ denote the mechanical power input from the hydro-turbine and the electrical power output; δ_i is the rotor angle, and $\Delta\omega_i$ is the rotor speed deviation.

(2) Renewable Energy Inverters:

Both wind power and photovoltaic generation units are connected to the grid via voltage-source converters. A vector control scheme based on dq-axis decoupling is employed in their control systems, which consists of an outer-loop controller for active and reactive power regulation and an inner-loop controller for fast current reference tracking. To comply with grid code requirements, the inverters activate their low-voltage ride-through control logic during system faults, prioritizing the provision of dynamic reactive power support to the grid to help maintain voltage stability at the point of common coupling.

To comply with grid code requirements, the inverters activate their low-voltage ride-through (LVRT) control logic during system faults. This mode transition strictly follows a piecewise non-linear reactive current injection constraint [25], formulated as:

$$I_q = \begin{cases} 0, & V_t \geq 0.9 \\ k \cdot (0.9 - V_t) \cdot I_N, & 0.2 \leq V_t < 0.9 \end{cases} \quad (2)$$

where V_t is the terminal voltage, I_q is the reactive current reference, and k is the dynamic support coefficient. This discrete shift from active power prioritization to reactive power support inherently introduces hard non-linearities into the system dynamics.

(3) HVDC Transmission System:

The HVDC link operates as the crucial power evacuation channel. To ensure global power balance, the active power reference of the HVDC rectifier, P_{dc}^{ref} , is dynamically coordinated with the total hydropower generation P_h and the constant local load P_{local} . Considering the physical capacity limits of the DC corridor, the control law is formulated as:

$$P_{dc}^{ref} = \min(P_h - P_{local}, P_{dc}^{max}) \quad (3)$$

where P_{dc}^{max} is the rated maximum capacity of the HVDC link.

As depicted in Figure 2, the detailed electrical topology of the hybrid LCC-VSC HVDC transmission system implemented in DIgSILENT PowerFactory 2021 SP2 is presented. The system-level power dispatch strategy generates the total HVDC active power reference P_{dc}^{ref} , which coordinates the operation of the distinct converter stations. On the rectifier side, the station utilizes a bipolar Line-Commutated Converter topology. Its control objective focuses on tracking the dispatched active power and maintaining a constant DC current flow. An inner current regulator, synchronized via a Phase-Locked Loop, generates precise firing angle commands for the thyristor valves to ensure stable bulk power injection into the DC link. Conversely, the inverter side employs an advanced Voltage Source Converter topology. To support the global DC voltage and provide dynamic reactive power compensation to the receiving AC grid, the VSC utilizes cascaded outer DC/AC voltage loops and inner current control loops. These loops translate the grid requirements into Pulse Width Modulation signals for the insulated-gate bipolar transistors, thereby achieving independent regulation of the AC voltage and reactive power at the Point of Common Coupling while strictly maintaining DC voltage stability.

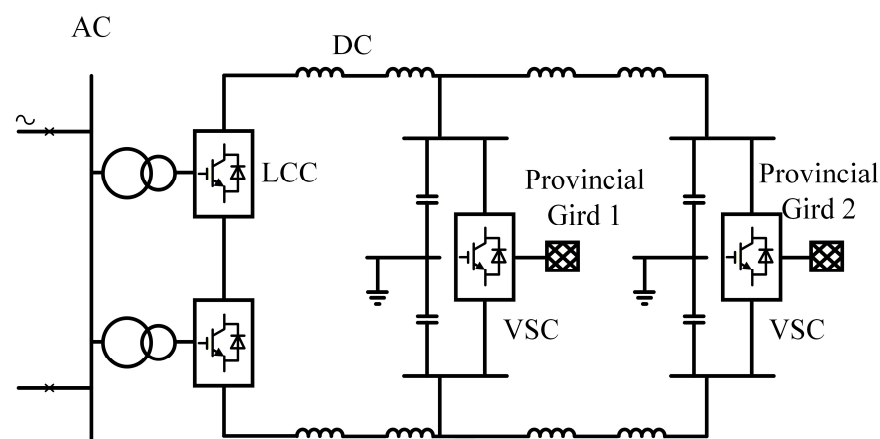


Figure 2. Detailed electrical topology of the hybrid LCC-VSC HVDC transmission system.

Furthermore, the vulnerability of the LCC-HVDC to commutation failure is strictly governed by the extinction angle γ [26], which is dynamically constrained by the AC bus voltage:

$$\gamma = \arccos\left(\cos \beta - \frac{\sqrt{2}X_c I_d}{V_L}\right) \geq \gamma_{min} \quad (4)$$

where V_L is the commutating AC voltage, I_d is the DC current, X_c is the commutating reactance, and β is the advance firing angle. A sudden transient voltage dip that violates the critical threshold γ_{min} will immediately trigger commutation failure and consecutive active power blockades.

3. Transient Security Criteria Formulation

To construct the dynamic security region, it is essential to define strict stability boundaries. Since this study primarily investigates the system's resilience against severe disturbances, it is assumed that all pre-fault operating points satisfy the static power flow constraints. The security assessment focuses exclusively on the transient dynamic responses in the post-fault period.

3.1. Transient Security Constraints

During a severe grid fault, the system must maintain both rotor angle synchronism and short-term voltage recovery. An operating point (P_H , P_{RES}) is labeled as "Secure" ($Y = 1$) if and only if both of the following constraints are simultaneously satisfied after fault clearance; otherwise, it is labeled as "Unsafe" ($Y = 0$).

The relative rotor angle of any synchronous generator with respect to the reference frame must not exceed the pre-defined transient limit to prevent excessive electromechanical oscillations. The criterion is expressed as:

$$\max |\delta_i(t) - \delta_{ref}(t)| \leq \delta_{max}, \forall i \in \mathcal{G} \quad (5)$$

In this study, the maximum allowable transient rotor angle deviation δ_{max} is strictly set to 120° [27]. A violation of this constraint indicates that the system has entered a critically stressed state, even if it might eventually re-synchronize.

Large-scale integration of power electronics weakens the AC grid's voltage support capability. To prevent converter blocking, load shedding, and potential voltage collapse, the transient voltage magnitude at all active buses must recover and stay above a critical dip limit after fault clearance. The criterion is formulated as:

$$V_{max} \geq |V_j(t)| \geq V_{min}, \forall j \in \mathcal{B} \quad (6)$$

where V_{min} and V_{max} are set to 0.8 p.u. and 1.2 p.u., respectively, in accordance with common grid code requirements.

3.2. Time-Domain Response Analysis Under Typical Faults

The transient security boundary is intrinsically shaped by the system's time-domain behaviors. To intuitively demonstrate the proposed security criteria, time-domain simulations are conducted under a typical N-1 contingency, a three-phase short-circuit fault on the 500 kV main transmission line.

As depicted in Figure 3, for an operating point lying within the safe region, the rotor angles of the hydro units oscillate but remain bounded below the 120° limit. Conversely, under a critically stressed (unsafe) condition, the generators' rotor angles overshoot the threshold during their first swing, thus violating the transient security constraint (red curve).

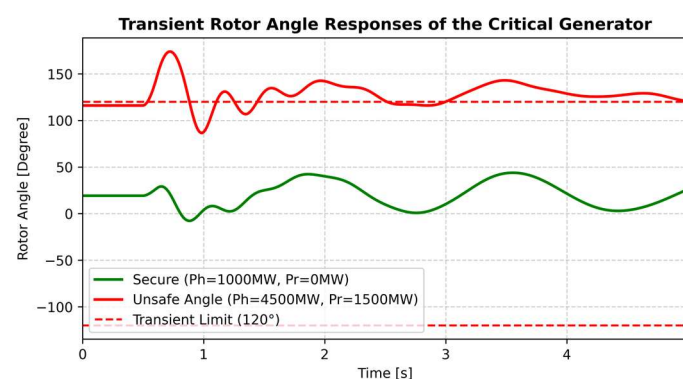


Figure 3. Rotor angle trajectories of the hydro generators.

Similarly, Figure 4 presents the transient voltage responses at a critical AC bus. It can be observed that for unsafe operating points lacking sufficient dynamic reactive power support, the bus voltage fails to recover adequately and dips below the 0.8 p.u. threshold for a period after fault clearance, triggering the short-term voltage security violation.

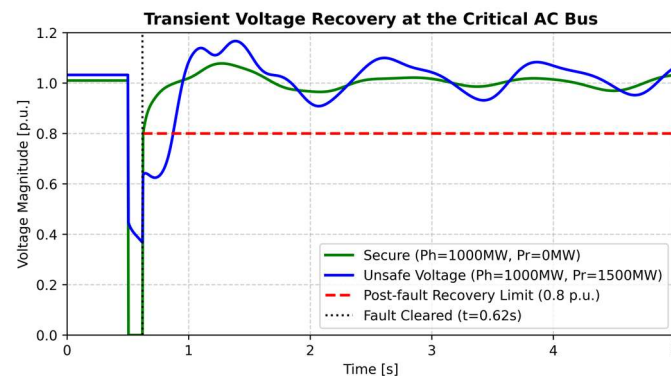


Figure 4. Transient voltage responses at a critical bus.

4. Proposed Data-Driven Assessment Methodology

To address the severe computational burden associated with traditional time-domain simulations for assessing dynamic security boundaries, this paper proposes an efficient data-driven framework. The framework synergistically combines Latin Hypercube Sampling, an Active Learning query strategy, and a Support Vector Machine surrogate model.

4.1. Mapping Physical Dynamics to Data-Driven Space

Fundamentally, the transient stability assessment of the hydro–wind–solar hybrid system integrated with HVDC involves solving a high-dimensional set of nonlinear differential-algebraic equations. The system dynamics can be generalized as:

$$\begin{cases} \dot{Y} = h(Y, Z, W) \\ 0 = k(Y, Z, W) \end{cases} \quad (7)$$

where Y represents the state vector that encompasses the dynamic variables critical to determining the system's transient stability. Specifically, Y primarily incorporates the electromechanical states of the synchronous generators (i.e., rotor angle δ and rotor speed ω), the transient and sub-transient internal electromotive forces governing the flux decay (e.g., E_q' , E_d'), and the dynamic state variables of the excitation and electro-hydraulic governing systems. Furthermore, it includes the fast-switching controller states of the renewable inverters and HVDC converters, such as the Phase-Locked Loop angles and DC link voltages. Z denotes the algebraic variables (e.g., bus voltages and phase angles), and W stands for the control inputs.

Furthermore, the actual security boundary in the (P_H, P_{RES}) operational space is highly non-linear and severely distorted. This topological distortion primarily originates from the aforementioned discrete physical hard constraints triggered during severe faults. Specifically, the abrupt activation of the piecewise LVRT logic (Equation (2)) alters the network's admittance dynamics, while the stringent commutation failure threshold (Equation (4)) induces instantaneous massive power blockades. These abrupt state transitions strictly disrupt the continuity of the differential-algebraic equations, forcing the operational boundary to exhibit distinct non-linear mutations, which completely invalidates the linear approximation assumptions.

Because of these hard non-linear constraints, traditional blind uniform sampling methods waste vast computational resources on “obviously safe” or “obviously unsafe”

regions and completely fail to accurately capture the twisted critical boundary points. This physical complexity necessitates an Active Learning paradigm. The AL strategy is introduced not merely to accelerate data generation, but specifically to mathematically target and capture these non-linear physical mutations along the critical stability margin.

4.2. Initial Data Generation via Monte Carlo Sampling

The pre-fault operating conditions are fundamentally formulated as a multi-dimensional state vector $x \in \mathbb{R}^d$. While a 2D baseline space $x = [P_h, P_{RES}]$ is initially constructed to benchmark the algorithmic efficiency, the framework is intrinsically scalable to higher-dimensional spaces. The generalized feasible operating domain is strictly constrained by the physical generation and transmission limits, defined as:

$$\mathcal{D} = \left\{ x \in \mathbb{R}^d \mid x_j \in [P_j^{\min}, P_j^{\max}], \forall j \in \{1, 2, \dots, d\} \right\} \quad (8)$$

In this study, the traditional Monte Carlo uniform sampling technique is utilized to generate the initial training dataset and the large unlabeled candidate pool for the subsequent Active Learning algorithm. For the j -th dimension, the i -th sample x_{ij} is randomly and uniformly drawn from the physical constraint boundaries. The mathematical generation process can be expressed as:

$$x_{ij} = P_j^{\min} + U_{ij} \cdot (P_j^{\max} - P_j^{\min}) \quad (9)$$

where U_{ij} is an independent pseudo-random variable following a standard uniform distribution. This sampling strategy provides a completely unbiased baseline initialization for the data-driven surrogate model before the active querying phase begins.

4.3. Active Learning and Support Vector Machine

To prevent the SVM's distance metric from being dominated by the larger magnitude of hydropower output, Z-score standardization is strictly applied to map x_k into x'_k :

$$x'_k = \frac{x_k - \mu}{\sigma} \quad (10)$$

where μ and σ are the mean and standard deviation vectors of the features.

Since time-domain simulation results are deterministic without random noise, the penalty parameter C of the SVM is deliberately set to a very large value [28]. The primal optimization problem is:

$$\begin{aligned} \min_{w,b,\xi} \quad & \frac{1}{2} \|w\|^2 + C \sum_{k=1}^n \xi_k \\ \text{s.t.} \quad & y_k (w^T \phi(x'_k) + b) \geq 1 - \xi_k, \xi_k \geq 0 \end{aligned} \quad (11)$$

To solve this efficiently and capture the highly non-linear boundary, the problem is transformed into its dual Lagrangian form:

$$\begin{aligned} \max_{\alpha} \quad & \sum_{k=1}^n \alpha_k - \frac{1}{2} \sum_{k=1}^n \sum_{j=1}^n \alpha_k \alpha_j y_k y_j K(x'_k, x'_j) \\ \text{s.t.} \quad & \sum_{k=1}^n \alpha_k y_k = 0, 0 \leq \alpha_k \leq C \end{aligned} \quad (12)$$

where α_k are the Lagrangian multipliers. The Radial Basis Function (RBF) is selected as the kernel function K to map the data into a high-dimensional feature space:

$$K(x'_k, x'_j) = \exp(-\gamma \|x'_k - x'_j\|^2) \quad (13)$$

Finally, the decision function of the surrogate model is given by:

$$f(\mathbf{x}') = \text{sgn} \left(\sum_{k \in SV} \alpha_k y_k K(\mathbf{x}'_k, \mathbf{x}') + b \right) \quad (14)$$

From a physical perspective, the mathematical decision boundary $f(\mathbf{x}') = 0$ derived in Equation (14) is not merely a statistical hyperplane; it acts as an implicit data-driven surrogate for the critical stability manifold defined by the physical constraints in Equations (5) and (6). By mapping the operational features into a high-dimensional space via the RBF kernel, the SVM effectively correlates the complex, non-linear physical phase transitions—such as the sudden shift from synchronous operation to rotor angle divergence, or from voltage recovery to collapse—triggered by the underlying DAE system.

To ensure the surrogate model achieves maximum generalization and avoids overfitting on the small-scale boundary dataset, we adopt a two-stage hyperparameter strategy. In the active learning phase, we fix the penalty parameter C to 100 and set the RBF kernel width γ to 'scale'. These robust settings drive a strict exploration of the physical boundary without prematurely biasing the model toward noise. Once the AL boundary converges and the final set of samples is obtained, we perform a rigorous K -fold cross-validation combined with grid search on the selected dataset. The grid search scans over a range of C values $\{1, 10, 50, 100, 200, 500\}$ and γ values $\{\text{'scale'}, \text{'auto'}, 0.01, 0.05, 0.1\}$, with the F1-score as the optimization metric to select the best hyperparameters. Through this cross-validation stage, the ultimate SVM classifier optimally balances the hard-margin physical constraints and the statistical smoothness of the boundary, yielding a highly robust security region.

Instead of randomly running thousands of TDS, the Active Learning (AL) algorithm queries the most "informative" points. To measure uncertainty, Platt scaling [29] is used to convert the raw SVM decision value $d(\mathbf{x}') = \sum \alpha_k y_k K + b$ into a calibrated posterior probability:

$$P(y = +1 | \mathbf{x}') = \frac{1}{1 + \exp(A \cdot d(\mathbf{x}') + B)} \quad (15)$$

where A and B are parameters determined via maximum likelihood estimation during training. The uncertainty of an unlabeled candidate point is defined by how close its secure probability is to 0.5. Thus, the query strategy selects the optimal point $\mathbf{x}$:

$$\mathbf{x}^* = \arg \min_{\mathbf{x} \in \mathcal{U}_{pool}} |P(y = +1 | \mathbf{x}') - 0.5| \quad (16)$$

4.4. Autonomous Early Stopping Criterion

A long-standing challenge in Active Learning applications is determining the optimal stopping point to avoid both under-fitting and unnecessary computational waste. Rather than using a fixed simulation budget, this paper proposes a dynamic early stopping criterion based on the Label Flip Rate (LFR) to monitor the convergence of the stability boundary.

Let U denote a massive, dense unlabeled candidate pool representing the entire operational space. At the k -th iteration, the trained surrogate model predicts the security status $\hat{y}_i^{(k)}$ for all samples $x_i \in U$. The LFR between consecutive iterations is defined as the proportion of samples whose predicted labels have changed:

$$\text{LFR}^{(k)} = \frac{1}{|U|} \sum_{x_i \in U} \mathbb{I}(\hat{y}_i^{(k)} \neq \hat{y}_i^{(k-1)}) \quad (17)$$

where $\mathbb{I}(\cdot)$ is the indicator function. A high LFR indicates a significant shift in the decision boundary, requiring further active querying. Conversely, when $\text{LFR}(k)$ drops below a stringent tolerance threshold (ϵ , set to 0.5% in this study) for consecutive iterations, it mathematically implies that the newly queried critical points no longer alter the overall topological shape of the stability margin. At this juncture, the active learning process autonomously terminates, ensuring maximum computational efficiency without sacrificing boundary resolution.

As illustrated in the flowchart in Figure 5, the entire methodology is realized through an automated co-simulation framework coupling Python (version 3.8.20) and DigSILENT PowerFactory 2021 SP2. Python (version 3.8.20) acts as the intelligent “brain” for sampling, ML training, and AL inference, while DigSILENT acts as the robust “muscle” executing the nonlinear differential-algebraic equations.

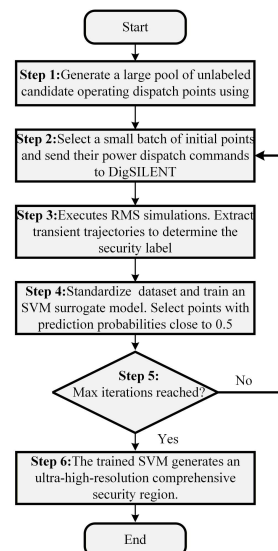


Figure 5. Flowchart of the proposed Data-Driven Assessment Methodology.

5. Case Study and Result Analysis

To verify the effectiveness and accuracy of the proposed data-driven active learning framework, comprehensive simulations are conducted on the hydro–wind–solar hybrid AC/DC grid. The system’s robustness is evaluated under a severe N-1-1 contingency scenario, which involves the simultaneous tripping of a critical 500 kV AC transmission line and the blocking of a bipolar HVDC sub-module. The total simulation time for each dynamic evaluation is set to 5.0 s, and the fault is cleared at $t = 0.62$ s.

5.1. Limitations of the Traditional Monte Carlo Method

Conventionally, drawing a security region relies on dense grid scanning or large-scale Monte Carlo sampling. Figure 6 presents the security assessment results using the traditional MC method with 500 random operating points.

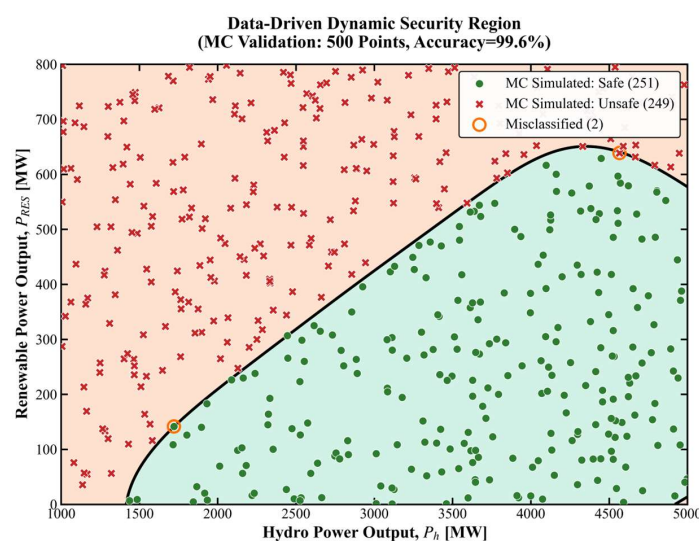


Figure 6. Discrete security region scatter plot generated by the traditional Monte Carlo method ($N = 500$).

As shown in the scatter plot, although the general trend indicates that higher renewable and hydropower penetrations increase the risk of transient instability, the exact stability boundary between the “Secure” (green dots) and “Unsafe” (red crosses) regions remains highly blurry and discrete. To obtain a smooth and precise continuous boundary curve suitable for system operators, the traditional method would require simulating tens of thousands of operating points, which is computationally prohibitive for a complex N-1-1 dynamic scenario.

5.2. Dynamic Evolution of the Active Learning Process

The proposed Active Learning (AL) method drastically changes the boundary exploration paradigm from “blind sampling” to “intelligent querying”.

During the initial phase of the active learning process (Figure 7a, Iteration 1), the SVM surrogate model is trained with a sparse set of 25 samples. Consequently, the initial decision boundary is severely underfitted, presenting a generic, smooth curve that deviates significantly from the true physical stability margin. However, as the AL loops proceed, the query strategy actively searches for the most informative, highly uncertain points—specifically targeting regions where the posterior probability $P(y = +1 | x) \approx 0.5$. These critical candidates are then fed into the DigSILENT simulator for rigorous time-domain evaluations.

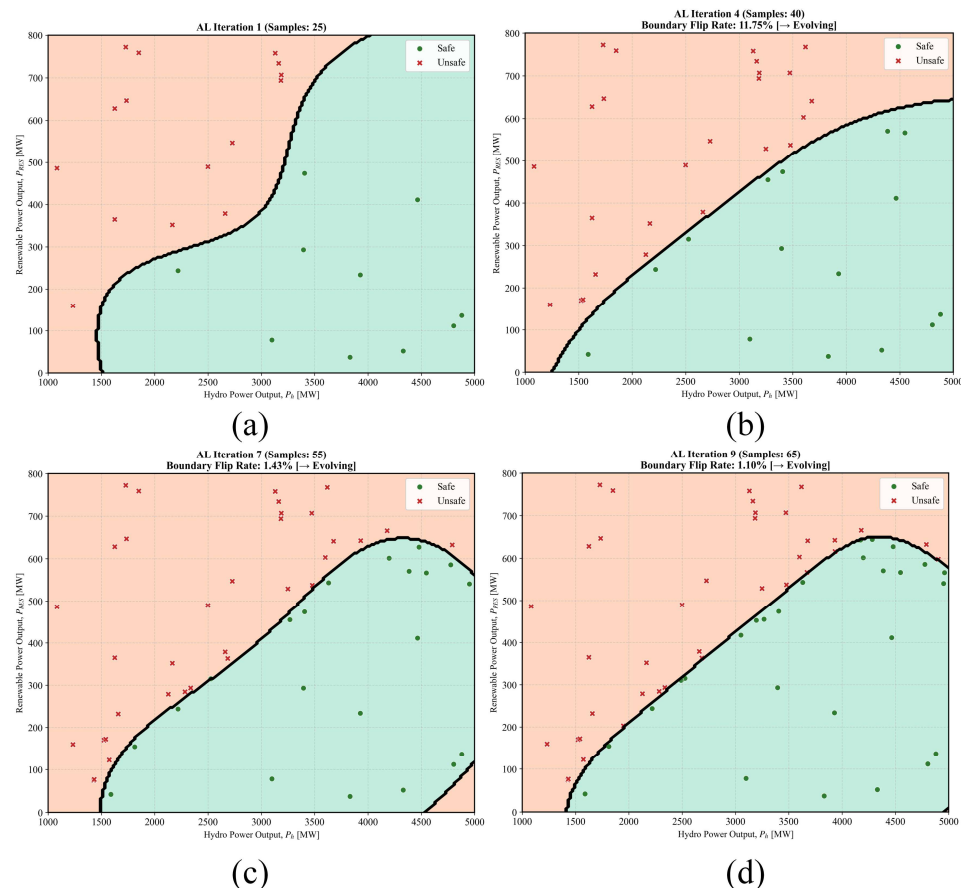


Figure 7. The dynamic evolution of the transient security boundary during the Active Learning process. (a) Iter = 1; (b) Iter = 4; (c) Iter = 7; (d) Iter = 9.

As visually demonstrated in the intermediate state (Figure 7b, Iter = 4), the boundary curve rapidly shifts and begins to tightly wrap around the newly queried critical points. By the final iteration (Figure 7d, Iter = 9), the AL algorithm successfully discovers and traces the complex, non-linear “hump” distortion on the right side of the operational space. The final SVM model accurately captures the highly non-linear topological characteristics of the N-1-1 stability margin, densely sampling only the critical phase transition boundary while

efficiently avoiding redundant computational resources on the obvious interiors of the safe and unsafe zones. This dynamic evolution process is visually demonstrated in Figure 7.

A critical challenge in active learning is autonomously determining the optimal stopping point to prevent computational waste. In this study, the proposed Label Flip Rate (LFR) effectively monitors the topological evolution of the dynamic security boundary. As illustrated in the convergence tracking curve (Figure 8), the boundary fluctuates during the initial iterations as the surrogate model actively discovers the complex non-linear margins.

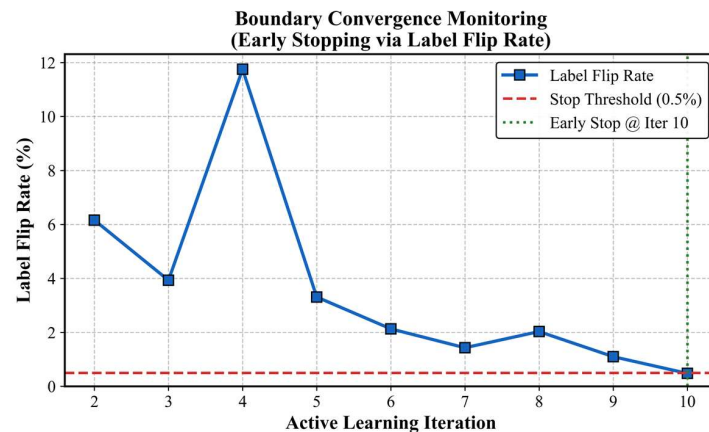


Figure 8. Convergence trajectory of the Label Flip Rate (LFR) throughout the active learning iterations.

However, as the query strategy continuously targets the most informative points, the geometric uncertainty of the boundary sharply decreases. By the 10th active learning iteration, the LFR drops to 0.48%, successfully satisfying the stringent pre-defined early stopping tolerance. At this juncture, the active learning loop terminates autonomously without requiring further blind simulations. The framework successfully constructs a highly precise boundary utilizing a minimal dataset of merely 65 physical simulations, achieving an extraordinary balance between computational efficiency and topological resolution.

After the AL process converges, the trained SVM surrogate model is used to instantly predict a highly dense 200×200 grid. The final high-precision comprehensive security region is depicted in Figure 9.

$$\mathcal{S}_{safe} = \left\{ \mathbf{x} \in \mathcal{D} \mid f_{SVM}(\mathbf{x}') = +1 \right\} \quad (18)$$

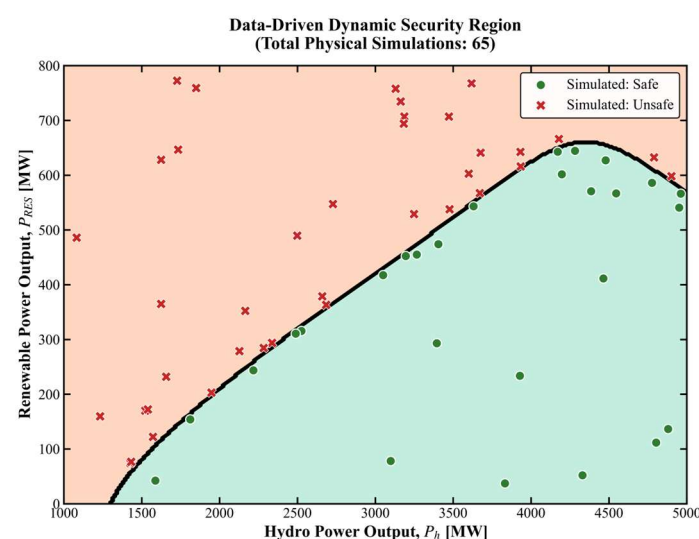


Figure 9. The final high-resolution comprehensive security region predicted by the proposed AL-SVM framework under the severe N-1-1 contingency.

The black solid line in Figure 9 represents the exact transient security boundary, which fundamentally defines the limits within which the transient stability of the system is ensured depending on the share of hydro energy. From a physical perspective, as the operating point moves towards the upper-left region of the coordinate space—indicating a decrease in the share of synchronous hydro energy and an increase in inverter-based renewable penetration—the “Safe” region systematically shrinks. This non-linear shrinkage of the stability boundary is driven by fundamental physical degradation. A reduced hydro share implies a severe deficit in system-level mechanical inertia and dynamic reactive power support. Under the severe N-1-1 fault, this deficiency exacerbates the transient voltage dip at the AC buses, making the LCC-HVDC highly susceptible to continuous commutation failures. If the aggregated renewable power output exceeds this data-driven boundary limit for a given hydro output, the diminished system strength will fail to ride through the transient shock, pushing the hydro units into severe transient over-limit and the system into the unsafe region. Thus, the obtained smooth boundary not only provides an intuitive operational guideline for grid dispatchers but also fully captures the physical vulnerability introduced by the declining share of conventional hydro energy.

5.3. Performance Evaluation: Computational Efficiency and Assessment Accuracy

To comprehensively overcome the long-standing computational bottlenecks of traditional Dynamic Security Assessment, the proposed framework aims to radically accelerate boundary delineation without compromising system safety. While the traditional High-Density Grid Scanning method inherently demands tens of thousands of time-domain simulations (e.g., 40,000 evaluations taking approximately 28.6 h), the proposed AL-SVM algorithm converges utilizing merely a fractional simulation budget. Incorporating the sub-second machine learning latency, the entire assessment is seamlessly completed in approximately 2.8 min, yielding a remarkable computational acceleration of over 600 times.

However, as correctly emphasized in mission-critical power system operations, such drastic reductions in offline computational burden must not sacrifice boundary fidelity. To analytically and empirically validate the proposed framework, an independent, densely sampled out-of-sample dataset comprising 500 operating points was generated via rigorous Time-Domain Simulations. This dense dataset serves as the absolute physical ground truth.

In power system security assessment, misclassifications carry asymmetric physical consequences. A False Alarm merely leads to conservative dispatch and economic curtailment. Conversely, a False Secure prediction is critically dangerous, as operating in this unverified region can trigger catastrophic cascading failures. Therefore, evaluating the dynamic evolution of FSR and overall classification metrics during the Active Learning process is pivotal.

Figure 10 depicts the trajectory of out-of-sample performance metrics as the Active Learning query strategy progressively expands the boundary dataset. Initially, utilizing a sparse training set, the surrogate model severely underfits the complex physical phase transitions, resulting in an unacceptably high False Secure Rate exceeding 25%. However, guided by the proposed uncertainty sampling criterion, the AL algorithm precisely targets and corrects the critical boundary distortions. As demonstrated in Figure 10, the classification quality exhibits a steep improvement curve. By the 10th iteration, both Accuracy and F1-Score firmly plateau at an exceptional 0.996, while the perilous FSR rapidly plunges to a negligible 0.004. This provides strong empirical justification for the early stopping criterion based on the Label Flip Rate discussed in Section 4.4, proving that further queries would only yield diminishing returns.

Furthermore, to quantitatively verify the specific superiority of the active querying strategy, the fully optimized AL-SVM framework is benchmarked against two conventional

offline data generation paradigms: pure Monte Carlo (MC + SVM) and Latin Hypercube Sampling (LHS + SVM). To ensure absolute fairness, all three frameworks are trained under a strictly identical minimal computational budget and validated against the 500-point ground truth. The comprehensive metrics, including Precision, Recall, and Boundary Distance Error, are summarized in Table 1.

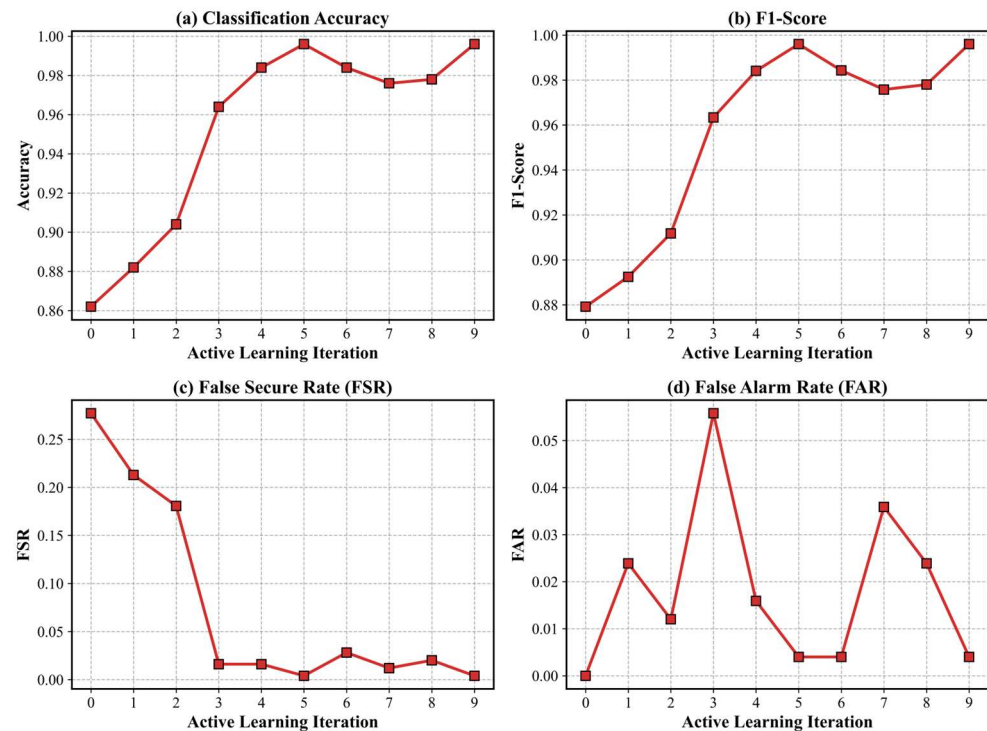


Figure 10. Empirical validation of the active learning stopping criterion: Dynamic evolution of out-of-sample classification metrics (Accuracy, F1-Score, FSR, FAR) across successive AL iterations.

Table 1. Quantitative performance comparison against conventional sampling methods under an identical simulation budget ($N = 65$), evaluated on 500 independent ground-truth testing samples.

Generation Method	Accuracy	FSR	FAR	Precision	Recall	F1-Score	BDE
MC + SVM (Baseline)	93.80%	5.62%	6.77%	0.9435	0.9323	0.9379	0.4751
LHS + SVM (Baseline)	96.00%	6.43%	1.59%	0.9392	0.9841	0.9611	0.5787
Proposed AL-SVM	99.60%	0.40%	0.40%	0.9960	0.9960	0.9960	0.0608

As detailed in Table 1, traditional blind sampling techniques (MC and LHS) inherently fail to capture the highly non-linear “hump” distortion of the stability boundary due to their sparse spatial distribution. This geometric blindness results in dangerously high FSRs of 5.62% and 6.43%, and high Boundary Distance Errors ($BDE > 0.47$). In stark contrast, the proposed AL-SVM method drastically minimizes the BDE to 0.0608. These out-of-sample metrics definitively address the concerns regarding boundary resolution limits, proving that the proposed framework flawlessly translates highly constrained computational resources into maximized dynamic boundary precision.

5.4. Generalizability and Robustness in High-Dimensional Operational Spaces

To strictly address the scalability of the proposed framework and validate its robustness against the “curse of dimensionality” in active learning, the dynamic security assessment is further expanded from the initial 2D operational plane into complex 3D high-dimensional spaces. Two comprehensive scenarios are introduced to reflect the

highly coupled dynamic characteristics and varying operational conditions of modern hybrid grids.

(1) Scenario A: Independent Wind and PV Generation Space (P_h, P_w, P_{pv})

In the initial 2D case, wind and solar power were aggregated as a lumped P_{RES} . However, wind turbines and photovoltaic systems exhibit fundamentally distinct transient behaviors during severe faults, particularly regarding dynamic reactive power support and low-voltage ride-through (LVRT) recovery capabilities. To capture these subtle differences, the operational feature vector is expanded to a 3D space: $x = [P_h, P_w, P_{pv}]$.

As visualized in Figure 11, instead of rendering a localized 2D curve, the proposed AL-SVM framework successfully constructs a highly smooth and continuous 3D decision surface. The robust spatial separation between the “Safe” (green dots) and “Unsafe” (red crosses) operating points fundamentally proves that the proposed framework accurately captures the intricate dynamic coupling between distinct renewable sources without suffering from boundary collapse.

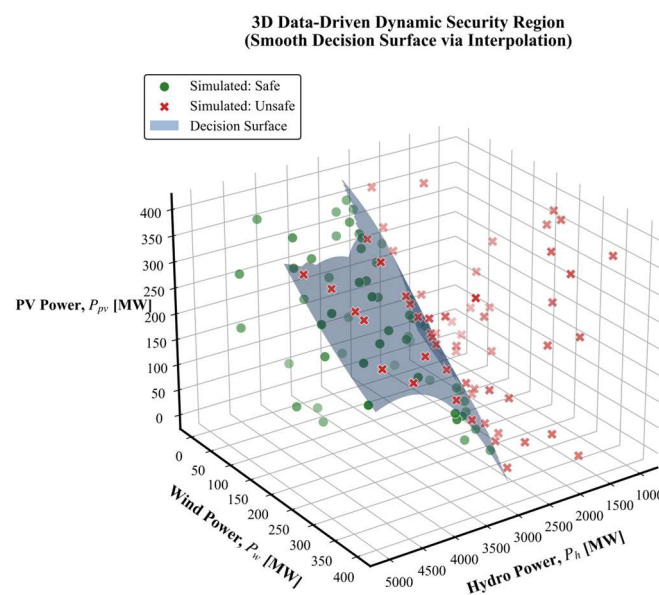


Figure 11. 3D data-driven dynamic security region in the independent wind and photovoltaic generation space (P_h, P_w, P_{pv}).

(2) Scenario B: HVDC Dispatch Constrained Space (P_h, P_{RES}, P_{HVDC})

To evaluate the method’s resilience under different system loading and transmission constraints, the HVDC active power dispatch P_{HVDC} is decoupled and introduced as an independent dimension, yielding $x = [P_h, P_{RES}, P_{HVDC}]$. This scenario imposes strict physical power-balance equations on the AL sampling pool.

As illustrated in Figure 12, the 3D data-driven boundary intuitively reveals a critical operational paradigm: the equivalent transient security volume shrinks significantly as the HVDC transmission level increases. This volumetric reduction is physically attributed to the fact that heavier DC loading exacerbates the vulnerability to commutation failures during AC-side voltage dips. The AL-SVM efficiently discovers this multi-dimensional constraint manifold, providing spatial visual guidance for grid dispatchers to dynamically adapt generation limits based on real-time HVDC schedules.

(3) Computational Scalability and Convergence in High-Dimensional Spaces

A well-known bottleneck in machine learning is that boundary exploration typically requires $O(N^d)$ computational complexity, making high-dimensional grid scanning strictly prohibitive. To maintain the phenomenal acceleration ratio in 3D spaces, the proposed

methodology integrates an ϵ -greedy exploration strategy to avoid local topological traps, coupled with the autonomous early stopping criterion based on the Label Flip Rate.

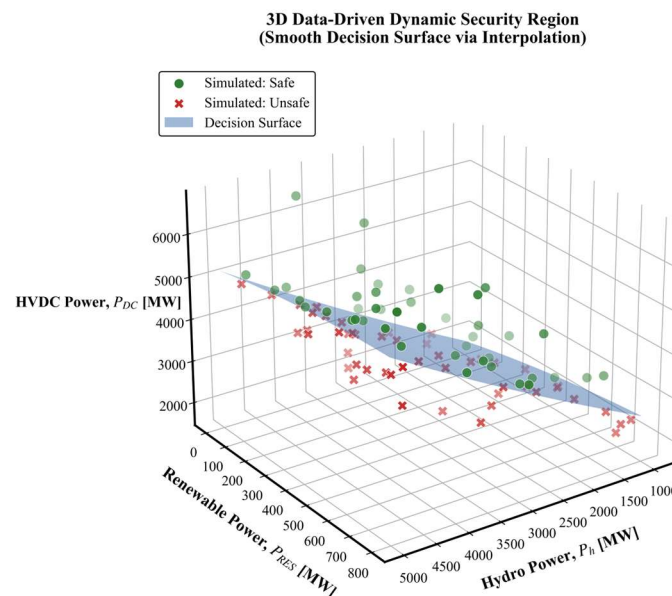


Figure 12. 3D data-driven dynamic security region in the HVDC dispatch constrained space (P_h , P_{RES} , P_{HVDC}).

The quantitative convergence performance of the AL-SVM framework is comprehensively demonstrated in Figure 13. During the initial active querying iterations, the algorithm intentionally targets the most heavily distorted and uncertain regions, as reflected by the short-term fluctuations in the evaluation metrics. However, as the iterations proceed, the model undergoes rapid global stabilization. The Accuracy and F1-Score steadily climb and plateau at exceptional levels (exceeding 97.5%), while the False Secure Rate and False Alarm Rate precipitously drop to near-zero levels.

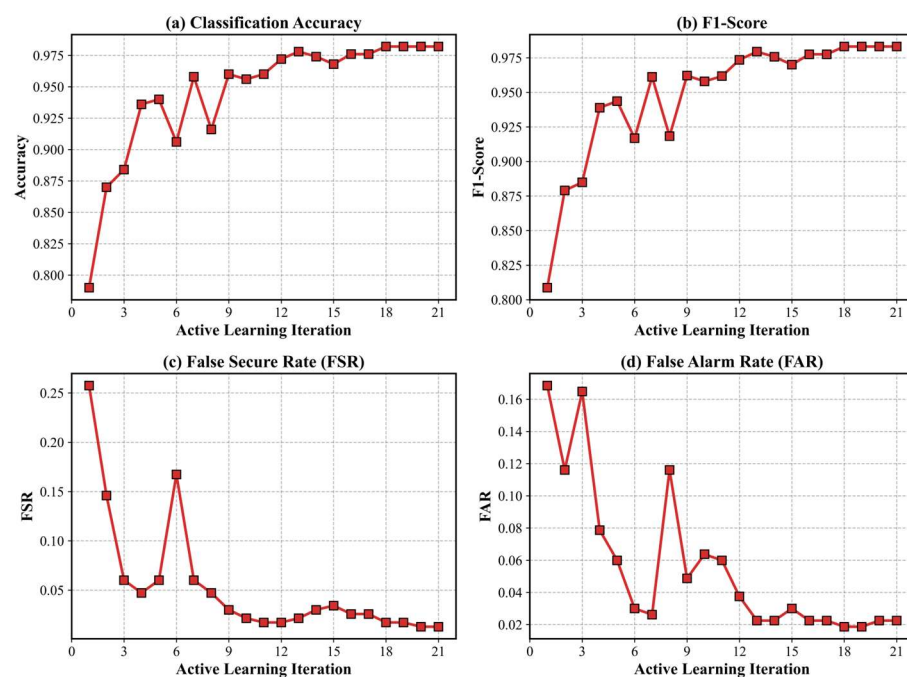


Figure 13. Evolution of the quantitative evaluation metrics during the Active Learning iterations in the high-dimensional operational space.

This robust convergence trajectory serves as compelling evidence that the proposed framework effectively tracks highly non-linear security boundaries in high-dimensional spaces. It guarantees superior assessment precision and ultra-low missing alarm rates utilizing minimal computational budgets, fully verifying its generalizability for practical deployment in complex modern power systems.

6. Conclusions

This paper successfully proposes and implements an ultra-fast, data-driven, comprehensive security region assessment framework for a practical hydro–wind–solar hybrid system with multi-terminal LCC-VSC HVDC integration. By effectively bridging the rigor of physical time-domain simulations with the high-speed inference of machine learning, the long-standing computational bottleneck of traditional dynamic security assessment is systematically resolved. The main conclusions are drawn as follows:

1. **Comprehensive Multi-Constraint Modeling:** The proposed framework successfully integrates both transient rotor angle limits and short-term voltage recovery criteria. Time-domain analysis reveals that under high renewable penetration, the system is highly susceptible to transient voltage dips and electromechanical divergences during severe N-1-1 contingencies. The framework accurately captures these physical limits.
2. **Intelligent Boundary Exploration:** Compared to the “blind sampling” of traditional Monte Carlo or High-Density Grid Scanning methods, the proposed Active Learning strategy guided by Platt-scaled uncertainties exclusively queries the most informative boundary points. This radically changes the data generation paradigm, ensuring that the SVM surrogate model captures the highly non-linear topological characteristics of the stability margin with minimal data redundancy.
3. **Remarkable Computational Efficiency Boost:** Quantitative analysis demonstrates that the proposed AL-SVM methodology drastically curtails the required physical simulations from 40,000 to a mere 65. Consequently, the total computational time is reduced from 28.6 h to approximately 2.8 min, achieving an acceleration ratio exceeding 600 times. This unprecedented efficiency is rigorously validated against an independent 500-point ground-truth dataset, confirming that the drastic reduction in computational overhead entails no sacrifice in boundary fidelity or assessment precision.
4. **Scalability and Robustness in High-Dimensional Spaces:** To overcome the notorious curse of dimensionality, the proposed framework integrates an ϵ -greedy active querying strategy with an autonomous early stopping mechanism based on the Label Flip Rate. Validations in complex 3D operational spaces prove that the method successfully constructs smooth, high-fidelity spatial decision manifolds. It decisively bypasses the $O(N^d)$ exponential computational explosion of conventional grid scanning, maintaining an exceptional F1-Score and near-zero missing alarm rates with highly constrained simulation budgets.

Ultimately, the smooth and high-resolution security boundaries constructed by this framework provide intuitive operational guidelines for grid dispatchers. The sub-second prediction latency and exceptional accuracy make the proposed methodology highly promising for deployment in modern energy management systems for intra-day active power dispatch, proactive preventive control, and early stability warning in renewable-dominated hybrid grids.

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Abbreviations

The following abbreviations are used in this manuscript:

AL	Active Learning
HVDC	High-Voltage Direct Current
MCS	Monte Carlo Simulation
TDS	Time-Domain Simulation

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