"A Technical Briefing on Machine Learning for Transient Stability Assessment in Power System"

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Outline

I. Introduction

Transient Stability Analysis (TSA) is the process of determining a power system's ability to maintain synchronism after a large disturbance, such as a fault or sudden loss of generation/load.

Renewable Energy Impact

Lower inertia ,
Higher uncertainty

Traditional Methods

TDS & TEF
Accurate but computationally intensive

TDS: Time-Domain Simulation
TEF: Transient Energy Function

Modern Grid Requirements

Faster assessment,
adaptive online TSA

Machine Learning (ML) Benefits

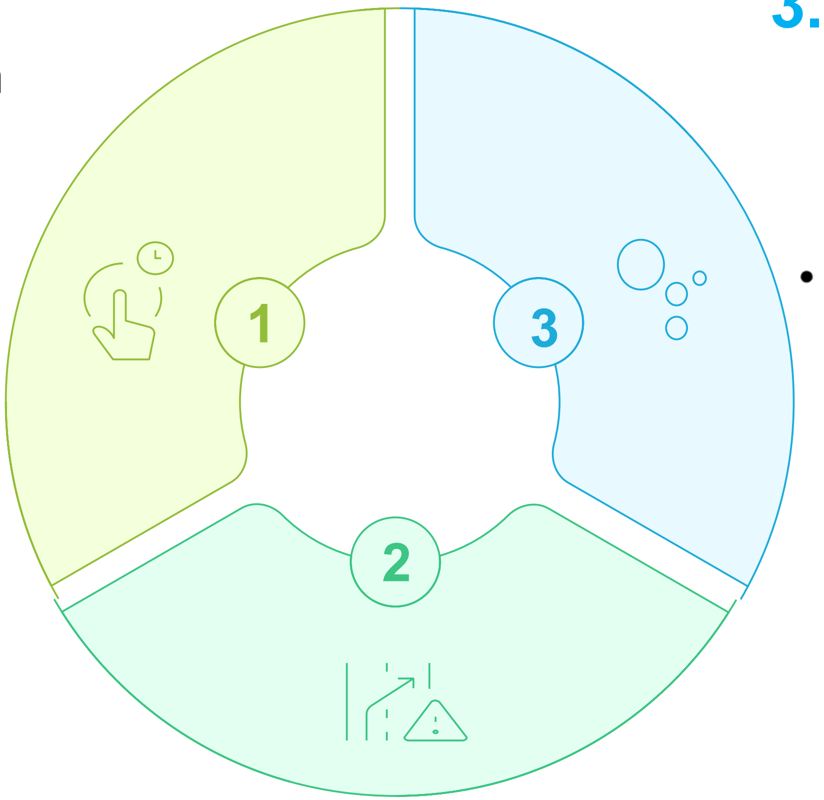
Data-driven,
real-time, risk-aware TSA

II. ML for TSA : Benefits & Role

1. Learn Stability Patterns

ML algorithms analyze & learn system dynamics and fault events.

- Data from Dynamic simulations



3. Real-Time Decision-Making

ML supports immediate actions to maintain grid stability.

- Data from PMU measurements

2. Predictive Assessment

ML predicts potential instability before it occurs.

II. ML for TSA : Benefits & Role

Which ML problem type to use for TSA?

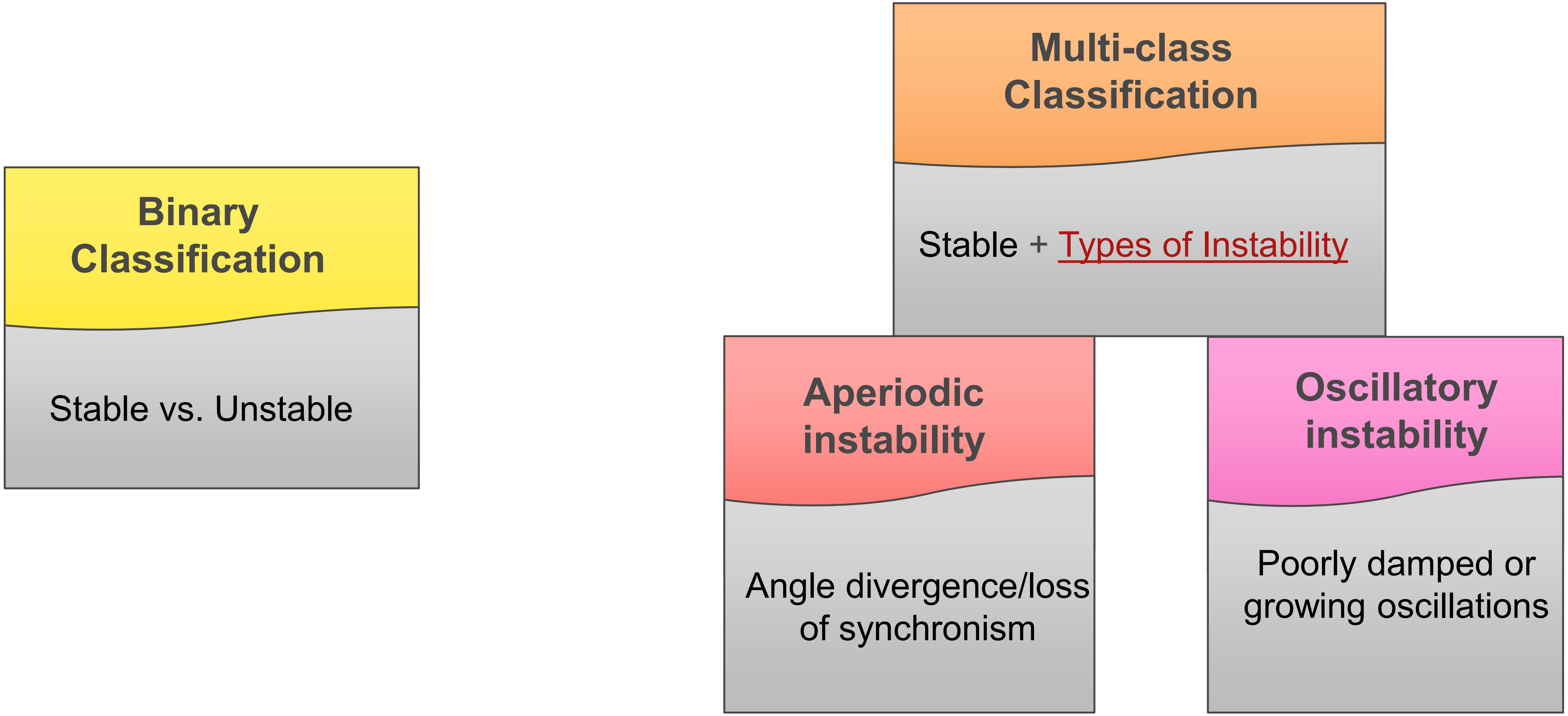
Classification Problem

Predict whether the system is stable/unstable .

Regression Problem

Estimates proximity to instability.

III. Classification Approach



III. Classification Approach

Severe contingencies may cause

rotor **angle instability (Aperiodic)** & short-term **voltage instability (Oscillatory)**

independently or together

Which control strategy should be selected based on the identified instability mode?

Dominant Instability Mode (DIM)

Rotor Angle Instability

Resolved by **generator tripping** to maintain system stability.

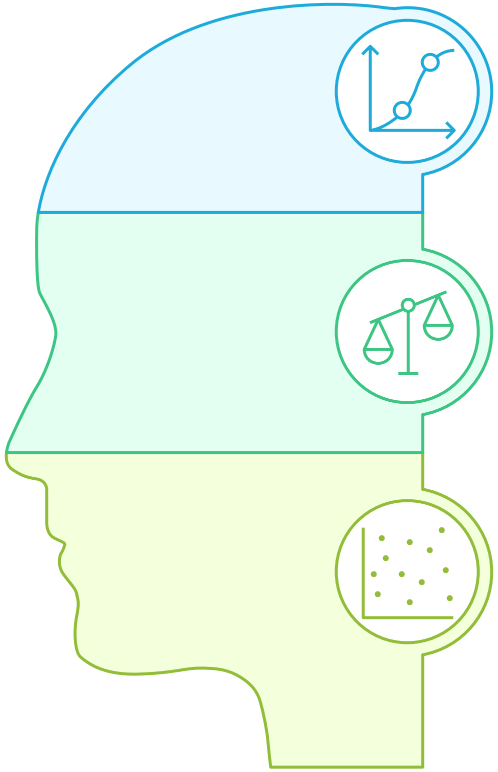
Short-term Voltage Instability

Resolved by **load shedding** to prevent voltage collapse.

Traditional DIM detection: Thevenin equivalent, unstable equilibrium point tracking, etc

→ Complex & less adaptable

IV. Regression Approach



Continuous Stability Indicators

Predicts stability using continuous measures

Quantitative Measure

Provides a numerical assessment of stability proximity

Limitation of Classification

Overcomes the discrete nature of classification methods

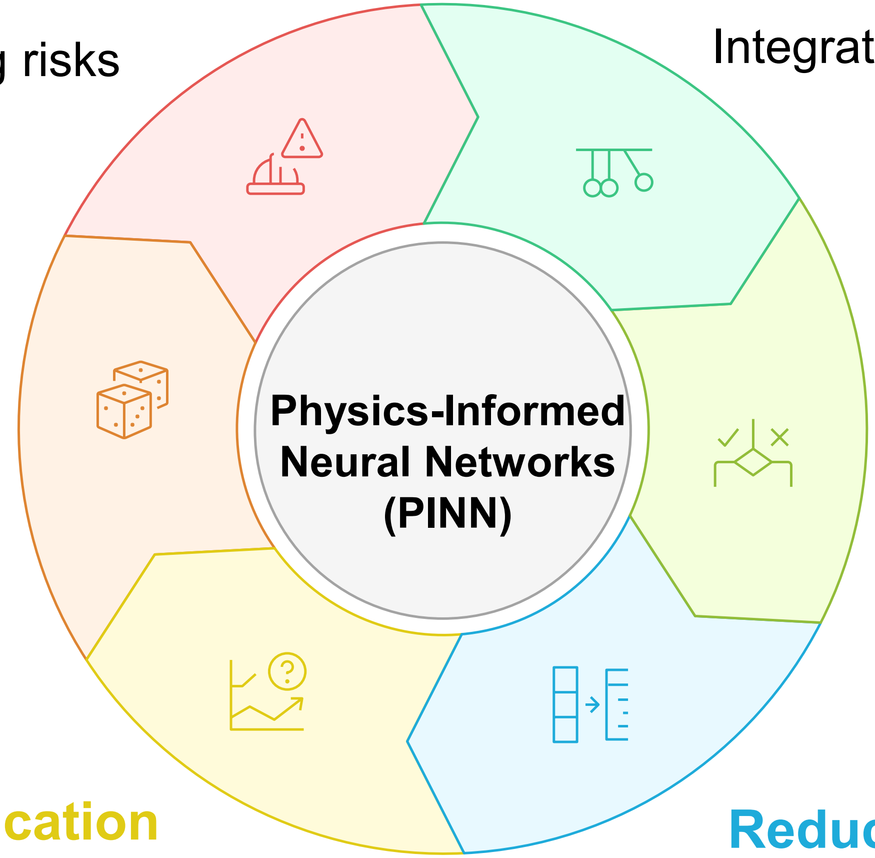
IV. Regression Approach

Enable Risk-Aware Operation

Facilitate operations considering risks

Embed Physical Laws

Integrate physics into the learning process



Provide Probabilistic Predictions

Offer predictions with probabilities

Ensure Physics Consistency

Guarantee predictions align with physics

Add Uncertainty Quantification

Incorporate uncertainty measures

Reduce Data Dependence

Minimize reliance on large datasets

V. Input Data Type

- Model accuracy & generalization depend heavily on the type & quality of features
- Different ML/DL methods work best with specific data types

Data Source	Description	Applications
Steady-State Features	Pre-disturbance operating points, (Bus voltages and line flows)	Margin prediction, online TSA
Dynamic Trajectories	Time-series data during fault events (e.g., rotor angles, voltages)	LSTM, Transformer-based TSA
Physics-Driven Variables	System-level parameters (Inertia, Damping, and Swing equations)	PINNs, hybrid physics-aware models
Derived or Engineered Features	Computed indicators (e.g., ROCOF, energy margins, line loadings)	Enhancing feature space for ML models

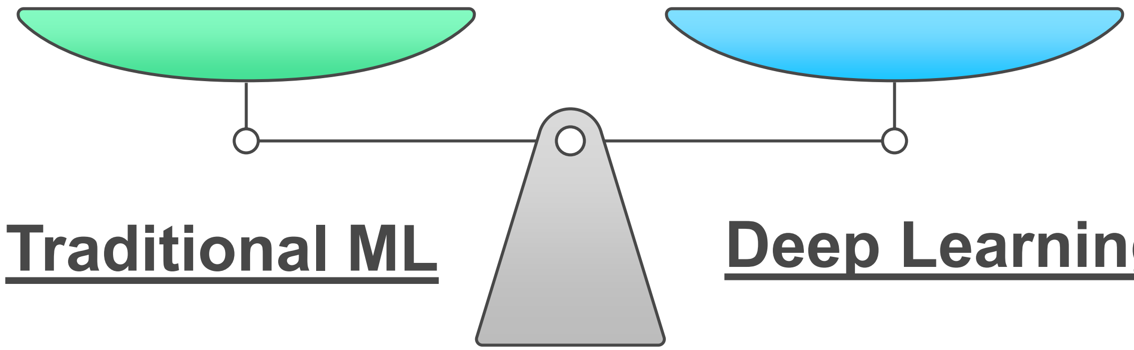
VI. Emerging Trends

Fast processing speed

Discrete label output

Rich feature extraction

Temporal dependency modeling



Traditional ML

Deep Learning (DL)

SVM → Find optimal decision boundary between stability classes

Decision Trees → Split data into decision rules based on key features

MLP → Learn nonlinear mappings between inputs and stability outcomes

CNN → Extract spatial features

RNN/LSTM → Model temporal dependencies

VI. Emerging Trends

Advanced DL Techniques

Spatiotemporal Deep Learning

Captures network topology and temporal evolution in systems

(Graph Neural Networks (GNNs), Spatiotemporal GCNs)

Hybrid Physics-Informed Learning

Combines physics and neural net works for accurate predictions

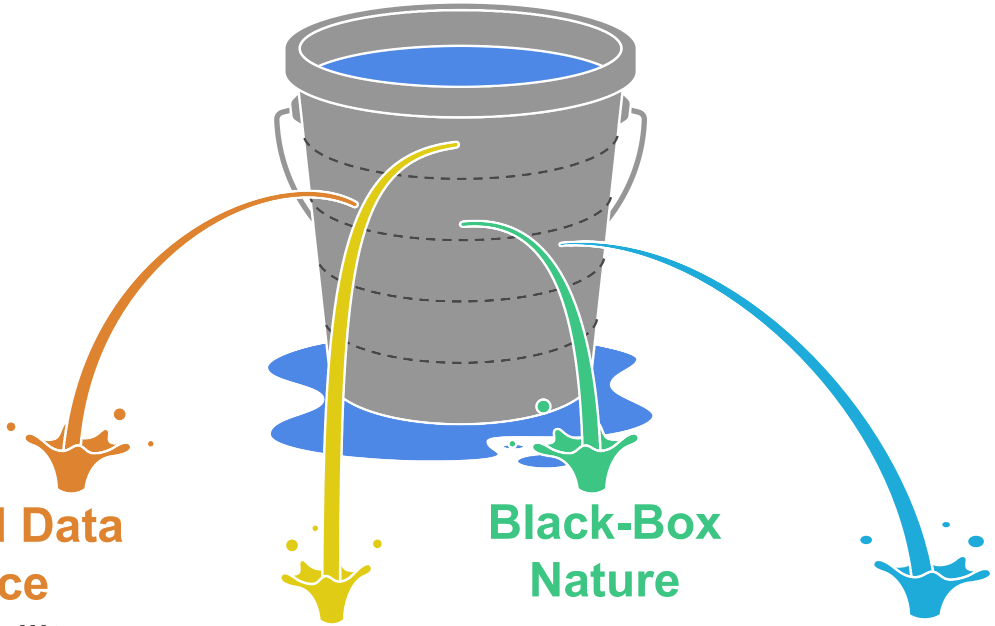
(PINNs, Neural Lyapunov Models)

Uncertainty Quantification

Provides probabilistic outputs for risk-informed decisions

(Bayesian Neural Networks, Eensemble-PINNs)

VII. Limitations



Simulated Data Reliance

Real-world instability events are rare

Limited Generalization

Unseen operating conditions impact performance

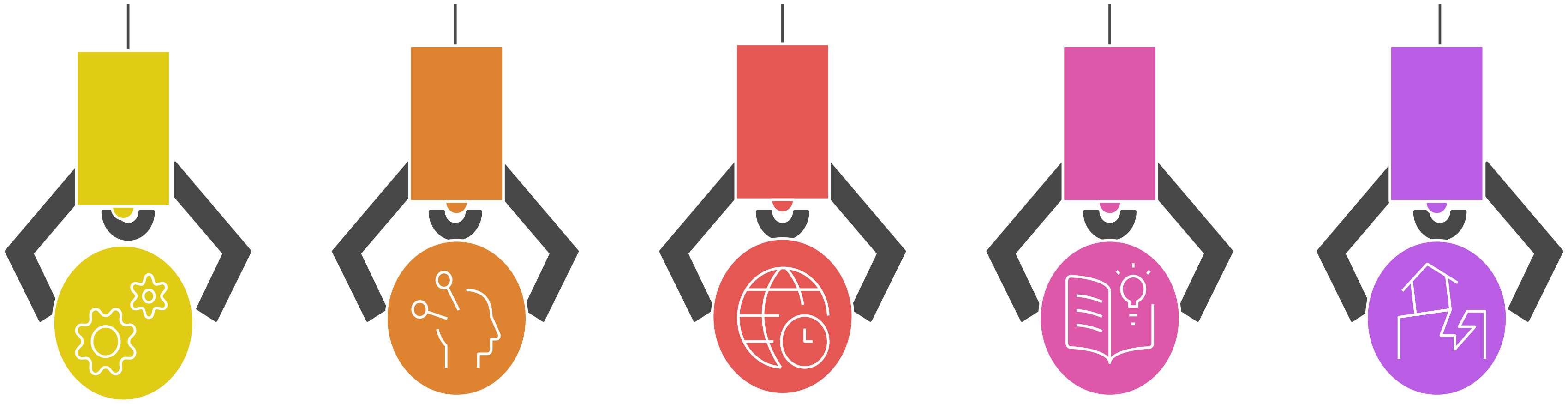
Black-Box Nature

Low interpretability reduces operator trust

Computationally Heavy

Large-scale systems strain resources

VIII. Future Directions



Hybrid ML models

For improved predictive accuracy.

Transfer learning

Faster adaptation to changing conditions

Spatiotemporal frameworks

Better capture dynamic processes.

Explainable architectures

Lightweight, uncertainty-aware architectures for real-time applications

Integrate into EMS

Integrate models into Energy Management Systems for real-world deployment.

IX. Conclusion

- Modern renewable-rich grids demand fast & reliable TSA
- Classification-based TSA → Simple, but no stability margin information
- Regression-based TSA → Quantitative margins but more complex
- Traditional methods → Accurate but slow for modern grids with large size
- ML approaches → Fast but limited by data, generalization, and interpretability
- **Hybrid ML-physics models** → Promising for scalable, real-time TSA

X. Key References

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THANK YOU