A Physical Monte Carlo Framework for Probabilistic Transient Stability Assessment of Power Systems

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Manuscript received May 11, 2026; revised July 13, 2026; accepted August 7, 2026; published September 22, 2026
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***Abstract*—Transient (rotor-angle) stability under severe disturbances is critical for the secure operation of modern power systems. Increasing uncertainty associated with operating conditions necessitates probabilistic approaches beyond conventional deterministic simulations. This paper proposes a probabilistic transient stability assessment framework based on repeated electrodynamic physical experiments interpreted as a physical implementation of the Monte Carlo process. Single-machine and multi-machine systems are investigated under three-phase short circuits and varying power transfer levels. The maximum rotor angle deviation is treated as a random variable, and its statistical characteristics are evaluated. The results show that the dispersion of rotor-angle responses increases from approximately 2–4% under moderate operating conditions to significantly higher values near the stability boundary, with an additional 25–30% increase observed in multi-machine systems due to inter-machine coupling effects. This leads to widening confidence intervals and a transition from deterministic to probabilistic stability margins. The proposed framework provides experimentally derived probabilistic characteristics for validation of Electromagnetic Transient (EMT) and Root Mean Square (RMS) simulation tools and supports uncertainty-aware transient stability assessment and risk-informed power system operation.**

***Index Terms*—transient stability, probabilistic assessment, electrodynamic physical modeling, Monte Carlo method, rotor angle deviation, uncertainty quantification, power systems, multi-machine systems**

I. Introduction

Transient (rotor-angle) stability is essential for the secure and reliable operation of electric power systems, including generating stations, transmission networks, and interconnected grids. Loss of synchronism of synchronous generators under severe disturbances may result in cascading failures and large-scale blackouts. The fundamental principles and engineering interpretation of transient stability have been extensively developed in classical studies [1–3] and remain the basis for modern stability assessment methodologies.

Conventional transient stability analysis is primarily performed using deterministic time-domain simulations of detailed mathematical models. However, the increasing penetration of renewable energy sources, inverter-based generation, and low-inertia operation has introduced significant uncertainty into system dynamics [4]. As a result, stability margins are no longer fixed values but depend strongly on operating conditions, system topology, and disturbance characteristics.

To address these challenges, probabilistic and uncertainty-aware approaches have been actively developed. Early studies introduced statistical and Bayesian formulations [5, 6] of transient stability assessment, while later works focused on probabilistic characterization of critical clearing time and stability indicators using probability density functions [7, 8]. More recently, data-driven techniques, surrogate modeling, and advanced uncertainty quantification methods have been proposed to accelerate probabilistic security assessment [9–15].

Recent probabilistic and deep-learning-based transient stability approaches provide efficient uncertainty quantification and accelerated security assessment [16–20]. However, many of these methods rely on surrogate models and numerical datasets.

Despite significant progress in probabilistic transient stability assessment, most recent approaches are primarily based on numerical simulations, surrogate models, or machine-learning techniques. Experimental probabilistic characterization of transient stability indicators using repeated electrodynamic physical experiments remains underexplored. In particular, limited attention has been paid to experimentally derived probability distributions and uncertainty quantification of rotor-angle dynamics under severe disturbances.

doi: 10.18178/ijeetc.15.5.357-366

Such approaches may not fully capture nonlinear electromagnetic and electromechanical interactions inherent in real power systems, particularly under severe disturbances and near stability limits. This highlights the need for experimentally validated probabilistic data and physically grounded uncertainty characterization.

Unlike recent uncertainty-aware, machine-learning-based, and probabilistic transient stability approaches reported in [11–20], which primarily rely on numerical Monte Carlo simulations, surrogate models, or purely computational uncertainty quantification, the proposed framework introduces a physical Monte Carlo methodology based on repeated electrodynamic experiments. Instead of generating statistical realizations numerically, probabilistic characteristics are obtained directly from repeated physical experiments performed under nominally identical operating conditions. This approach naturally incorporates nonlinear electromagnetic interactions, controller imperfections, parameter tolerances, and measurement uncertainties that are difficult to reproduce accurately using purely numerical models. Consequently, the proposed methodology provides experimentally grounded probabilistic information that complements conventional numerical methods for transient stability assessment.

In the proposed framework, repeated experiments performed under nominally identical conditions are interpreted as a physical implementation of the Monte Carlo process, enabling direct estimation of probabilistic stability characteristics from measured data.

The objective of this work is to develop a probabilistic framework for transient stability assessment based on electrodynamic physical modeling and to quantify the reproducibility and uncertainty of stability indicators obtained from repeated experiments.

The novelty of the proposed framework lies in interpreting repeated electrodynamic experiments as a physical implementation of the Monte Carlo process. Unlike conventional probabilistic approaches that generate stochastic realizations exclusively through computational sampling, the proposed methodology derives probability distributions directly from repeated physical measurements of power system dynamics. This provides experimentally verified probabilistic characteristics of transient stability indicators and establishes a direct connection between laboratory experiments and uncertainty-aware stability assessment.

The proposed methodology is not intended to replace conventional numerical Monte Carlo analysis but to complement it by providing experimentally derived benchmark data for validation and calibration of EMT and RMS simulation tools. Such benchmark datasets enable comparison not only of deterministic trajectories but also of statistical properties, including probability distributions, confidence intervals, and dispersion characteristics of transient stability indicators.

The main contributions of this paper are summarized as follows:

- A probabilistic transient stability assessment framework based on repeated electrodynamic physical experiments is proposed;
- Repeated experiments are interpreted as a physical implementation of the Monte Carlo process;
- Experimentally derived probability distributions of rotor-angle deviations are obtained for both single-machine and multi-machine systems;
- The probabilistic widening of transient stability margins near the stability boundary is quantitatively demonstrated;
- The obtained results can serve as benchmark data for validation and calibration of EMT and RMS simulation tools.

The remainder of this paper is organized as follows. Section II presents the proposed physical Monte Carlo framework together with the experimental setup and investigated power-system configurations. Section III describes the statistical methodology adopted for uncertainty quantification. Section IV discusses the obtained probabilistic characteristics, compares the proposed framework with existing uncertainty-aware transient stability approaches, and highlights its engineering significance. Finally, Section V summarizes the main findings and outlines directions for future research.

II. Physical Monte-Carlo Modeling and Test Systems

The study was carried out using an electrodynamic physical model that reproduces electromagnetic and electromechanical processes and preserves physical similarity to real power systems. The experimental platform, measurement architecture, and monitoring subsystems were developed based on previously proposed electromechanical monitoring solutions and hardware–software integration techniques [21].

Fig. 1 illustrates the conceptual framework of the proposed probabilistic transient stability assessment approach, in which repeated physical experiments are interpreted as a physical implementation of the Monte Carlo method. The framework integrates experimental data acquisition, extraction of transient stability indicators, and statistical processing to obtain probabilistic characteristics of system response.

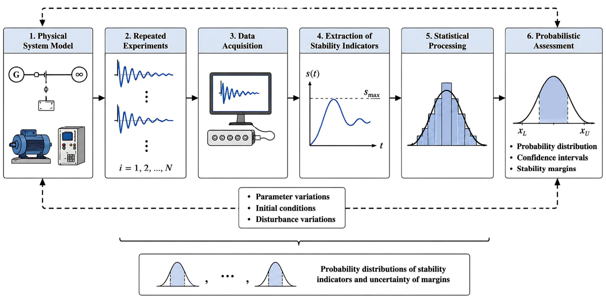

Fig. 1. Conceptual framework of the proposed probabilistic transient stability assessment based on repeated electrodynamic experiments interpreted as a physical Monte Carlo process.

In contrast to a single deterministic experiment, the present study is based on multiple experiments performed under nominally identical initial conditions. Each repetition represents an independent realization of the system response influenced by small random variations of initial states, regulator dynamics, parameter tolerances, and measurement noise.

Within this framework, the maximum rotor angle deviation is selected as the primary transient stability indicator and is treated as a random variable. The repeated experimental realizations form empirical probability distributions of this indicator, enabling estimation of its statistical properties and uncertainty.

The proposed physical Monte Carlo procedure consists of the following steps:

- initialization of the system at a specified operating point;
- application of a disturbance (e.g., three-phase short circuit);
- recording of transient responses and extraction of stability indicators;
- repetition of experiments under nominally identical conditions;
- statistical processing of the obtained data to estimate probabilistic characteristics.

This approach enables direct experimental quantification of the dispersion and uncertainty of transient stability margins. In contrast to purely numerical Monte Carlo simulations, the physical setup inherently accounts for nonlinear electromagnetic interactions and real system dynamics, providing more realistic probabilistic characteristics of stability indicators.

TABLE I: COMPARISON OF CONVENTIONAL NUMERICAL MONTE CARLO AND THE PROPOSED PHYSICAL MONTE CARLO FRAMEWORK

Feature	Numerical Monte Carlo	Proposed Physical Monte Carlo
Principle	Repeated numerical simulations	Repeated electrodynamic experiments
Source of randomness	Random sampling of model parameters	Natural physical variability of repeated experiments
Representation of nonlinear effects	Limited by mathematical model	Directly reproduced by the physical system
Hardware imperfections	Usually neglected	Naturally included
Measurement uncertainty	Artificially modeled	Directly measured
Experimental benchmark data	Not available	Directly obtained
Computational cost	Low for individual simulations but high for large sample sizes	Higher experimental effort but realistic probabilistic information
Typical application	Probabilistic prediction	Experimental validation and calibration of EMT/RMS models

To clarify the methodological differences between the proposed physical Monte Carlo framework and conventional numerical Monte Carlo approaches, a comparative summary is presented in Table I. The comparison highlights the principles of uncertainty generation, representation of nonlinear system behavior, experimental capabilities, and typical application areas of both methodologies. Rather than competing alternatives, the two approaches should be regarded as complementary tools for probabilistic transient stability assessment.

As shown in Table I, conventional numerical Monte Carlo analysis provides computational efficiency and scalability for large power systems, whereas the proposed physical Monte Carlo framework offers experimentally derived probabilistic characteristics that naturally include nonlinear electromagnetic interactions, controller dynamics, hardware imperfections, and measurement uncertainties. Consequently, the proposed methodology complements numerical simulations by providing experimental benchmark data for validation and calibration of EMT and RMS models.

A. Single-Machine System and Mathematical Formulation

In the first stage, a single synchronous generator connected to an infinite bus through a transmission line was investigated (Fig. 2). This classical single-machine–infinite-bus (SMIB) configuration makes it possible to study the fundamental statistical properties of rotor angle stability in a well-controlled environment.

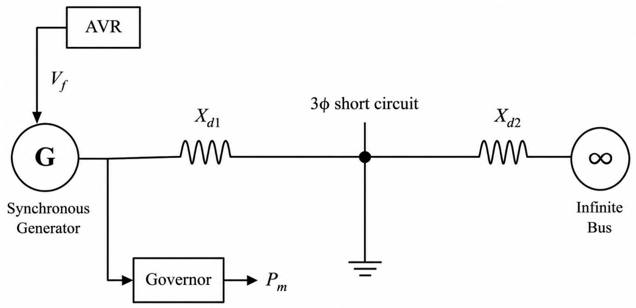

Fig. 2. Single-machine–infinite-bus electrodynamic model used for probabilistic transient stability analysis and statistical characterization of maximum rotor angle deviations.

From a mathematical viewpoint, the transient stability of the system is described by the swing equation:

$$\frac{d^2\delta}{dt^2} = \frac{\omega_s}{2H}\left(P_m - P_e(\delta)\right) \quad (1)$$

where δ is the rotor angle relative to the infinite bus, ω_s is the synchronous angular velocity, H is the inertia constant, P_m is the mechanical input power, and $P_e(\delta)$ is the electrical output power, which is a nonlinear function of the rotor angle.

Within the proposed probabilistic framework, the maximum rotor angle deviation

$$\delta_{\max} = \max_t \delta(t) \quad (2)$$

is selected as the primary transient stability indicator and is treated as a random variable:

$$\delta_{\max} \sim f(\delta) \quad (3)$$

where $f(\delta)$ denotes the empirical probability distribution obtained from repeated experimental realizations.

The initial operating conditions were defined by the generator terminal voltage, active and reactive power, and the pre-fault rotor angle. Three-phase short circuits at the sending end of the line were applied as the primary disturbance, and different fault clearing times were considered. The parameters of the investigated operating conditions are summarized in Table II.

TABLE II: INITIAL OPERATING POINTS, TRANSMITTED POWER LEVELS, AND FAULT CLEARING TIMES FOR THE SINGLE-MACHINE–INFINITE-BUS CONFIGURATION

No.	Parameter			
	Angle δ_0	Power P_0, W	Time, sec	
			$t_{s/c}$	t_c
I	58^0	1330	0.20	0.426
II	66^0	1605	0.20	0.325
III	72^0	1990	0.20	0.249
IV	72^0	1990	0.21	0.249

For each operating point, a series of 60–70 repeated experiments were carried out. The number of repetitions was selected based on preliminary statistical convergence analysis. It was observed that after approximately 60 independent realizations, the estimated mean values, standard deviations, and confidence intervals became practically stable, while additional experiments resulted only in minor variations of the statistical estimates. Therefore, 60–70 repetitions were considered sufficient to ensure reliable estimation of the probabilistic characteristics of transient stability indicators while maintaining a reasonable experimental effort. The maximum rotor angle deviation with respect to the infinite bus, δ_{max}, was recorded for every realization and treated as a random variable characterizing the transient stability margin.

B. Measurement System and Multi-machine Configuration

The electromechanical variables were recorded using an automated measurement and data acquisition system (Fig. 3). Rotor angles, electromagnetic power, terminal voltages, and system frequencies were measured synchronously and converted into digital form. This ensured consistent sampling conditions for all experimental realizations and enabled accurate statistical processing of time-domain responses, including extraction of peak values and their corresponding time instants.

The measurement system plays a key role in the proposed physical Monte Carlo framework by ensuring experimental repeatability and consistent data acquisition across multiple realizations.

For each experimental realization, the power system was first stabilized at the specified operating point by adjusting the generator excitation, mechanical input power, and network loading conditions. After steady-state operation had been achieved, a three-phase short circuit was initiated at the predefined location and cleared after the prescribed fault-clearing time. During each experiment, the rotor angles, active power, terminal voltages, and system frequency were synchronously recorded by the automated data acquisition system. The maximum rotor-angle deviation was then extracted from the recorded transient response and stored for subsequent statistical processing. The same experimental procedure was repeated under nominally identical operating conditions to obtain an ensemble of statistically independent realizations.

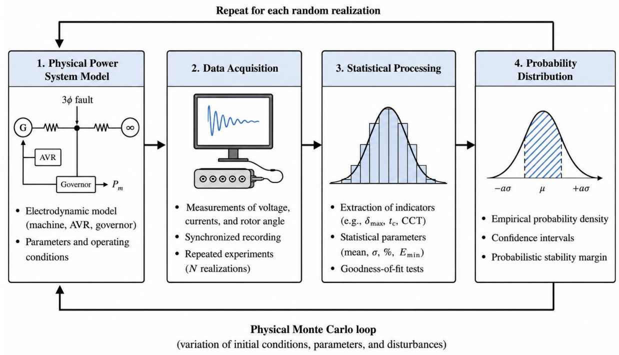

Fig. 3. Physical Monte Carlo framework for measurement, data acquisition, statistical processing, and probabilistic characterization of rotor angle responses.

At the second stage, a three-machine power system with distributed loads was investigated (Fig. 4). The system consists of synchronous generators interconnected by transmission lines and supplying passive loads through step-up transformers. This configuration enables the analysis of inter-machine oscillations and the influence of multimodal electromechanical dynamics on the dispersion of transient stability indicators.

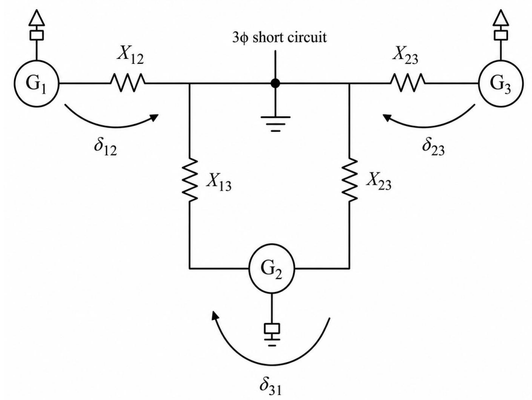

Fig. 4. Multi-machine electrodynamic test system used for probabilistic analysis of inter-machine rotor angle stability and uncertainty of transient stability margins.

The main parameters of generators, network elements, loads, and operating states, including power flows and fault clearing times, are presented in Table III. Similar to the single-machine case, three-phase short circuits and variations in transmitted power were applied, and each operating condition was reproduced through a series of repeated experiments.

For each experimental realization, the relative rotor angles between generators (δ_{21}, δ_{23}, δ_{31}) were extracted from the recorded responses. Their maximum values were treated as random variables and used as probabilistic indicators of transient stability.

TABLE III: GENERATOR VOLTAGES, ACTIVE AND REACTIVE POWER FLOWS, LOAD PARAMETERS, AND FAULT CLEARING TIMES FOR THE MULTI-MACHINE CONFIGURATION

State	Parameters of state																	
	U_1	U_2	U_3	P_1	P_2	P_3	Q_1	Q_2	Q_3	P_{H1}	Q_{H1}	P_{H2}	Q_{H2}	P_{H3}	Q_{H3}	U_{H1}	U_{H2}	U_{H3}	t,s/c
1	200	184	213	1560	1030	2250	1130	180	1230	2250	840	165	45	2160	1430	193	204	203	0.14
2	200	184	213	1810	1135	2460	1200	210	1320	2430	900	245	64	2400	1440	192	203	202	0.25
3	200	184	213	1900	1190	2600	1180	575	1620	2600	1600	300	130	2600	1670	190	210	215	-

The combination of single-machine and multi-machine test systems provides a unified framework for comparative analysis of probabilistic stability characteristics. In particular, it enables the investigation of the increase in dispersion and uncertainty of stability margins as system complexity grows and operating conditions approach the dynamic stability boundary.

III. STATISTICAL PROCESSING AND UNCERTAINTY QUANTIFICATION OF TRANSIENT STABILITY INDICATORS

The adopted statistical methodology follows the general principles of probabilistic transient stability assessment and statistical estimation described in earlier studies [5–8]. Within this framework, the maximum rotor angle deviation is treated as a random variable, and its probabilistic characteristics are evaluated based on repeated experimental realizations under nominally identical operating conditions.

For each operating condition, the maximum rotor angle deviation δ_{max} was extracted from the recorded transient responses and considered a realization of a random variable. The statistical analysis was performed using samples obtained from 60–70 repeated experiments.

The following statistical characteristics were determined:

Mathematical expectation (mean value):

$$M = \frac{1}{n}\sum_{i=1}^{n}\delta_{\max,i} \quad (4)$$

Standard deviation:

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(\delta_{\max,i} - M\right)^2} \quad (5)$$

Coefficient of variation:

$$C_v = \frac{\sigma}{M}\times 100\% \quad (6)$$

Skewness:

$$S_k = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\delta_{\max,i} - M}{\sigma}\right)^3 \quad (7)$$

Kurtosis:

$$E_x = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\delta_{\max,i} - M}{\sigma}\right)^4 - 3 \quad (8)$$

To verify the conformity of the empirical distributions to the normal distribution, Pearson's chi-square goodness-of-fit test was applied. The test statistic is given by:

$$\chi^2 = \sum_{j=1}^{k}\frac{\left(n_j - np_j\right)^2}{np_j} \quad (9)$$

where n_j and p_j are the observed and theoretical frequencies in the *j*-th interval, respectively, and n is the total number of observations. The probability $P(\chi^2)$ was used to assess the hypothesis of normality.

In addition to dispersion measures, 95% confidence intervals for the mean value of δ_{max} were estimated assuming normal distribution:

$$M \pm t_{0.975}\frac{\sigma}{\sqrt{n}} \quad (10)$$

where $t_{0.975}$ is the Student's t-coefficient for the selected confidence level.

The repeated electrodynamic experiments were interpreted as a physical Monte Carlo sampling of the system state space. This approach makes it possible not only to estimate average values of transient stability indicators but also to quantify their dispersion and confidence intervals, which characterize the uncertainty of the transient stability margin.

C. Single-machine System

For the single-machine–infinite-bus configuration (Fig. 2), the statistical characteristics of the maximum rotor angle deviation δ_{max} obtained for different fault clearing times and power levels are summarized in Table IV. Each operating state was investigated based on 60–70 repeated experimental realizations.

The results indicate that, under moderately loaded operating conditions, the standard deviation of the maximum rotor angle typically remains within 2–4% of the mean value. As the operating point approaches the transient stability limit, a systematic increase in dispersion is observed, reflecting increased sensitivity of the system response to small perturbations.

The calculated skewness and kurtosis values show only slight deviations from an ideal Gaussian distribution. According to Pearson's chi-square test, however, the hypothesis of a normal distribution cannot be rejected for most operating conditions at the selected confidence level. This confirms the applicability of standard statistical measures for quantitative characterization of transient stability indicators.

TABLE IV: STATISTICAL PARAMETERS OF MAXIMUM ROTOR ANGLE DEVIATIONS (MEAN, STANDARD DEVIATION, SKEWNESS, KURTOSIS, AND PEARSON'S TEST) FOR THE SINGLE-MACHINE CONFIGURATION

Model	State	Number of tests	Mean value M (deg)	Standard deviation σ (%)	Skewness S_k	Kurtosis E_x	χ^2	$P(\chi^2)$
Electrodynamic model	I	68	88.64	3.50	0.33	–0.45	12.06	0.065
	II	68	106.29	3.20	–0.40	–0.21	2.75	0.83
	III	69	130.00	2.62	0.127	–1.15	15.56	0.02
	IV	68	135.55	2.51	0.105	–0.628	7.30	0.30
Reference physical model	1	70	73.05	2.88	0.208	0.37	8.12	0.243
	2	60	80.70	3.04	0.178	–0.113	8.64	0.630
	3	86	85.17	4.18	0.520	–0.049	17.97	0.121
	4	100	109.73	3.04	0.342	–0.312	5.23	0.730

In addition, the correlation between the maximum rotor angle δ_{max} and its corresponding occurrence time t_{max} was evaluated. The obtained correlation coefficients were found to be small, indicating that the peak rotor angle is largely independent of the time of its occurrence and can therefore be considered an independent probabilistic stability indicator.

D. Multi-machine System

For the three-machine configuration shown in Fig. 4, the relative rotor angles δ_{21}, δ_{23}, δ_{31} were analyzed. Their maximum values under three-phase short circuits and varying power transfer levels were treated as random variables. The main statistical characteristics for different operating states and fault clearing times are presented in Table V.

In comparison with the single-machine case, a significantly larger dispersion of results is observed. As the system operates closer to the dynamic stability boundary, the standard deviation of relative rotor angles increases by approximately 25–30%, accompanied by increased skewness and kurtosis. This indicates a transition toward asymmetric and heavy-tailed distributions.

This behavior reflects the higher sensitivity of multi-machine electromechanical dynamics to small variations in initial conditions, regulator actions, and system interactions. The presence of multiple coupled oscillatory modes amplifies stochastic perturbations, resulting in a wider spread of possible system responses.

TABLE V: STATISTICAL DISPERSION AND PROBABILISTIC INDICATORS OF INTER-MACHINE ROTOR ANGLE DEVIATIONS UNDER SEVERE DISTURBANCES

State	Fault clearing time, s	Angle	Number of tests	Mean value M (deg)	Standard deviation σ (%)	Skewness Sk	Kurtosis Ex	χ^2	$P(\chi^2)$
1	0.14	δ21	80	54.16	1.85	0.64	0.27	6.34	0.40
		δ23	80	48.71	1.85	0.212	−0.29	4.36	0.57
2	0.27	δ21	70	96.89	4.30	0.14	0.068	3.83	0.70
		δ23	69	89.74	3.68	0.049	−0.615	5.71	0.46
		δ31	66	69.33	3.20	0.078	0.379	–	–
3	0.25	δ21	69	95.66	5.23	0.618	0.505	4.02	0.67
		δ23	69	94.47	4.98	0.730	0.790	7.67	0.27

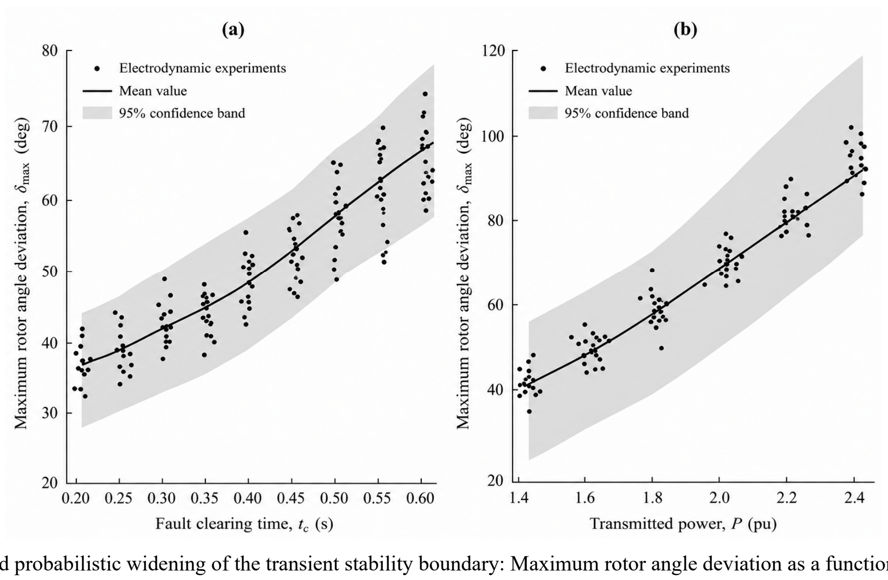

Fig. 5. Dispersion and probabilistic widening of the transient stability boundary: Maximum rotor angle deviation as a function of (a) fault clearing time and (b) transmitted power based on repeated electrodynamic experiments.

The influence of disturbance severity on the uncertainty of stability margins is illustrated in Fig. 5, where the maximum rotor angle deviation is shown as a function of fault clearing time and transmitted power. It can be observed that an increase in both parameters leads not only to higher mean values of δ_{max}, but also to a pronounced widening of confidence intervals. This clearly demonstrates the transition from a deterministic to a probabilistic interpretation of transient stability boundaries.

The obtained results are further analyzed and interpreted in Section IV.

IV. Results and Discussion

The results demonstrate a clear increase in the dispersion of the maximum rotor angle as the operating point approaches the transient stability boundary. Similar probabilistic widening of stability margins has been reported in recent uncertainty-based and data-driven studies [9–13]. This confirms that transient stability indicators should be treated as random variables rather than deterministic limits under stressed operating conditions.

Compared with purely simulation-based probabilistic approaches and recent review-oriented transient stability prediction studies [22], the proposed framework provides experimentally derived statistical characteristics and directly reflects nonlinear electromechanical interactions of real systems.

From a methodological perspective, the series of repeated electrodynamic experiments can be interpreted as a physical implementation of the Monte Carlo procedure. Each experiment represents an independent realization of the system response under small random variations of initial conditions, regulator dynamics, parameter tolerances, and measurement errors. In contrast to purely numerical simulations, the physical setup inherently reproduces real nonlinear electromechanical interactions, providing experimentally derived probability distributions of stability indicators.

A. Single-machine System

For the single-machine–infinite-bus configuration, the statistical analysis indicates good reproducibility of transient stability characteristics under moderately loaded conditions. As shown in Table IV, the coefficient of variation of the maximum rotor angle remains within several percent when the operating point is sufficiently distant from the stability limit. In this region, dispersion is limited, and a deterministic interpretation of stability margins may still be acceptable.

As the fault clearing time increases and the system approaches the critical operating state, a noticeable growth in dispersion is observed. This reflects increased sensitivity of rotor dynamics to small perturbations and leads to a widening of confidence intervals of the maximum rotor angle. Consequently, the stability margin acquires a pronounced probabilistic character and cannot be adequately represented by a single deterministic value.

The calculated skewness and kurtosis indicate only minor deviations from normality, while Pearson's goodness-of-fit test confirms that the Gaussian assumption remains valid for most operating conditions. Therefore, standard statistical measures can be reliably applied for quantitative characterization of transient stability indicators.

Correlation analysis between the maximum rotor angle and the time instant of its occurrence shows weak dependence between these variables. This suggests that the peak rotor angle is primarily determined by the global energy balance and system inertia, whereas its timing is influenced by higher-frequency oscillatory components. Thus, the maximum rotor angle can be considered an independent probabilistic indicator of transient stability.

B. Multi-machine System

For the multi-machine configuration, a significantly greater statistical dispersion of transient responses is observed. As summarized in Table V, under heavily loaded conditions and longer fault durations, the standard deviation of relative rotor angles increases by approximately 25–30% compared with moderate regimes. In addition, the empirical distributions exhibit higher skewness and kurtosis, indicating deviations from symmetric Gaussian behavior.

This effect can be explained by the presence of multiple interacting electromechanical modes in the system. Small stochastic perturbations are amplified through inter-machine coupling, resulting in a wider spread of possible transient trajectories. As a consequence, the transient stability boundary acquires a probabilistic character and cannot be represented by a single deterministic limit.

The influence of disturbance severity on the uncertainty of stability margins is illustrated in Fig. 5. The results show that increasing either fault clearing time or transmitted power leads not only to higher mean values of the maximum rotor angle but also to a pronounced widening of its dispersion. This behavior clearly demonstrates the transition from a deterministic to a probabilistic interpretation of transient stability limits.

This experimentally observed increase in dispersion is consistent with recent uncertainty-aware transient stability studies [9–13], which also report enhanced sensitivity and widening probabilistic stability margins under stressed operating conditions; however, the present results confirm this behavior using repeated physical experiments rather than numerical datasets alone.

A quantitative comparison with recent probabilistic transient stability studies further confirms the validity of the proposed framework. For the single-machine configuration, the experimentally observed standard deviation of the maximum rotor angle remained within approximately 2.5–3.5% under moderate operating conditions, which is comparable to the uncertainty levels reported in recent physics-informed probabilistic approaches [11]. As the operating point approached the stability boundary, dispersion increased significantly, while the multi-machine experiments exhibited an additional 25–30% increase in standard deviation compared with the single-machine configuration. This increase is larger than the variability typically reported for purely numerical probabilistic simulations [9–13], indicating that repeated physical experiments naturally capture hardware imperfections, controller dynamics, and measurement uncertainties that are difficult to reproduce using numerical models alone.

C. Probabilistic Interpretation and Practical Implications

Within the proposed probabilistic framework, the transient stability boundary should be interpreted not as a single deterministic curve, but as a region characterized by confidence intervals of rotor-angle deviations and critical clearing times. Such a representation reflects the stochastic nature of electromechanical transients and is consistent with modern uncertainty-aware stability assessment approaches.

The repeated electrodynamic experiments can be regarded as a physical implementation of the Monte Carlo procedure, where each test corresponds to an independent realization of system dynamics under small random variations of initial conditions, controller behavior, and measurement uncertainties. Unlike purely numerical simulations, the physical setup inherently captures real nonlinearities and electromagnetic interactions, providing experimentally derived probability distributions.

The obtained empirical distributions can serve as benchmark data for calibration and validation of Electromagnetic Transient (EMT) and Root Mean Square (RMS) simulation tools. They also enable objective assessment of conventional Monte Carlo simulations and uncertainty quantification methods used in transient stability analysis.

From an engineering perspective, the proposed probabilistic interpretation provides a more realistic basis for stability assessment and decision-making. The obtained stability margins can be applied to determine conservative protection settings, estimating reliable critical clearing times, and supporting risk-informed operation and control of modern power systems.

Specifically, the experimentally derived probabilistic characteristics may support the selection of conservative protection relay settings, the estimation of reliable critical clearing times with confidence margins, and the validation of EMT and RMS simulation models for uncertainty-aware planning and operation of modern power systems.

D. Limitations of the Proposed Framework

Although the proposed physical Monte Carlo framework provides experimentally derived probabilistic characteristics that are difficult to obtain using purely numerical approaches, several limitations should be acknowledged. First, the methodology requires access to an electrodynamic laboratory and repeated experimental testing, making it more resource-intensive than conventional numerical Monte Carlo simulations. Second, the present investigation has been validated using single-machine and three-machine laboratory systems, which represent simplified configurations of practical power networks. Finally, the achievable number of repeated experiments is constrained by laboratory time and equipment availability. Therefore, the proposed methodology should be regarded as a complementary experimental validation framework rather than a replacement for large-scale numerical probabilistic analysis.

E. Scalability and Applicability to Large Power Systems

Although the present work focuses on laboratory-scale single-machine and multi-machine systems, the proposed probabilistic framework itself is not limited by system size. The methodology can be extended to larger electrodynamic laboratories, hardware-in-the-loop platforms, digital real-time simulators, and hybrid physical–numerical test environments. In practical applications, repeated experimental measurements may be performed for representative operating conditions, while large-scale probabilistic studies can be carried out numerically using validated simulation models. In this way, experimentally obtained probabilistic characteristics serve as reference data for improving the reliability of transient stability assessment in practical interconnected power systems.

F. Application for Validation and Calibration of EMT and RMS Models

One of the principal engineering applications of the proposed framework is the validation and calibration of EMT and RMS simulation tools widely used in transient stability studies. Conventional model validation is usually based on comparison of deterministic trajectories obtained from simulations and experiments. In contrast, the proposed methodology enables comparison of statistical characteristics, including probability distributions, confidence intervals, standard deviations, and higher-order statistical moments of transient stability indicators. Agreement between experimentally obtained and numerically predicted probabilistic characteristics provides stronger evidence of model adequacy than deterministic trajectory comparison alone. Consequently, the proposed framework may improve the credibility of uncertainty-aware transient stability assessment for modern power systems.

G. Engineering Perspective

From a broader engineering perspective, numerical and physical Monte Carlo methodologies should be regarded as complementary rather than competing approaches. Numerical simulations provide computational efficiency and scalability for probabilistic analysis of large interconnected power systems, whereas repeated electrodynamic experiments supply experimentally verified probabilistic information that enhances confidence in numerical models and supports uncertainty-aware decision-making for secure power system operation.

V. Conclusions

This paper presented a probabilistic framework for transient stability assessment based on repeated electrodynamic physical experiments interpreted as a physical implementation of the Monte Carlo process. The obtained results demonstrate that transient stability indicators exhibit an inherent statistical nature and should be interpreted probabilistically rather than as strictly deterministic quantities under severe disturbances.

For the single-machine system, the dispersion of the maximum rotor angle remained within approximately 2–4% under moderate operating conditions, while significantly larger dispersion was observed near the transient stability boundary. In multi-machine configurations, the standard deviation of relative rotor angles increased by approximately 25–30% due to inter-machine coupling effects and multimodal electromechanical dynamics.

The proposed methodology differs from conventional numerical Monte Carlo approaches by providing experimentally grounded probabilistic characteristics obtained directly from repeated electrodynamic experiments. The obtained probability distributions can be used as benchmark data for validation and calibration of EMT and RMS simulation tools.

From an engineering perspective, the proposed framework supports uncertainty-aware transient stability assessment and provides experimentally validated probabilistic characteristics that can be used to determine conservative protection relay settings, estimate reliable critical clearing times with confidence margins, validate EMT and RMS simulation models, and support risk-informed planning and operation of modern power systems.

Future research will focus on extending the proposed physical Monte Carlo framework to renewable-energy-rich and inverter-dominated power systems, where increasing uncertainty and reduced system inertia introduce additional challenges for transient stability assessment. Another promising direction is the integration of repeated electrodynamic experiments with hardware-in-the-loop platforms and digital real-time simulators to create hybrid physical–numerical probabilistic assessment environments. Furthermore, future work will investigate the application of experimentally derived probabilistic characteristics for calibration of digital twins and for uncertainty-aware protection and control strategies in modern smart grids.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Sona V. Rzayeva developed the research concept and methodology, performed the probabilistic analysis and interpretation of results, and prepared the manuscript. Nijat S. Mammadov participated in experimental investigations, data acquisition, and statistical processing of transient responses. Ilduza A. Guseynova contributed to the analysis of electromechanical processes and validation of experimental results. Mirfatma M. Javadova contributed to the theoretical interpretation of the obtained results and manuscript revision. Gulaga A. Aleskerov participated in the discussion of engineering applications and reviewed the manuscript. Abderrahim Zemmit contributed to the analysis of probabilistic assessment methods and final editing of the paper. All authors reviewed and approved the final version of the manuscript.

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