Real-time monitoring and assessment of rotor angle stability

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Tryck:

Summary

Integration of large scale renewable power electronics based production in current AC bulk power system can result in a decrease of the system inertia, short-circuit capacity and synchronizing torque which will cause more rapid changes in the rotor angles of the generators and thereby a higher risk for rotor angle instability. Real-time monitoring and prediction of rotor angle stability is therefore an important tool for a transmission system operator to measure the system capability for ensuring a secure operation when major disturbances occur thereby to avoid power outages.

In this project, Maximum Lyapunov Exponent (MLE) has been applied for online Transient Stability Assessment (TSA). This method only relies on real-time time series data which is the rotor angle difference of two selected generators. A method has been developed to identify those two generators. Using this time series data, the MLE-based TSA is then applied to assess the rotor angle stability/instability within a short time after a large disturbance. Once rotor angle instability is assessed, a corrective control action is applied to stabilize the power system within a short time interval.

Keywords: Transient Stability Assessment (TSA), Maximum Lyapunov Exponent (MLE), corrective control action

Sammanfattning

Integrering av storskalig förnybar och kraftelektronikbaserad elproduktion i dagens växelströms dominerade kraftsystem kan resultera till en minskning av systemets energirörelse, kortslutningseffekt och synkroniserande moment vilket kommer att orsaka snabbare förändringar i generatorernas rotorvinklar och därmed en högre risk för rotorvinkelinstabilitet. Realtidsövervakning och prediktion av rotorvinkelstabilitet är ett viktigt verktyg för en systemoperatör för att mäta systemets förmåga så att säkerställa driftsäkerheten vid stora störningar och därmed undvika elavbrott.

I detta projekt har "Maximum Lyapunov Exponent (MLE)" tillämpats för online "Transient Stability Assessment (TSA)". Denna metod förlitar sig endast på tidsseriedata i realtid som är rotorvinkelskillnaden av två utvalda generatorer. En metod har utvecklats för att identifiera dessa två generatorer. Med hjälp av denna tidsseriedata appliceras sedan MLE-baserade TSA för att bedöma rotorvinkelns stabilitet/instabilitet inom en kort tid efter en stor störning. När rotorvinkelinstabiliteten väl har bedömts, vidtas korrigerande kontrollåtgärder (avhjälpande åtgärder) för att stabilisera kraftsystemet inom ett kort tidsintervall.

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Chapter 1

Introduction

1.1 Background

Managing transient stability emerges as a critical obstacle in power system dynamics. Transient Stability Assessment (TSA) has become increasingly challenging as rapid disturbances, intensified by the growing integration of renewable resources into existing power networks, must be monitored and managed within ever-shorter time frames to ensure timely, effective intervention. In recent decades, TSA has emerged as a pivotal domain in power systems research. Various methodologies have been formulated to address its complexities, each of which exhibits its distinct strengths and shortcomings. The Time Domain Simulation (TDS) approach, though providing an in-depth analysis of power system dynamics, suffers from high computational demands, making it less suitable for real-time TSA applications. Consequently, more expedient techniques such as the Transient Energy Function (TEF) [1] and the SIngle Machine Equivalent (SIME) [2] came into prominence. PMU data has also been widely utilized among scientists and researchers to perform TSA. For example, in [3] the concept of self-adaptive decision trees was utilized to perform a dynamic security assessment to detect the important parameters of the system online. In [4], the PMU data has been used to perform comparative analysis based on trajectory patterns that were stored in the database; this prediction has been used for the TSA. In [5], estimations based on artificial neural networks were introduced. According to the authors, this technique offers faster computation times and improved accuracy but may struggle with uncertainties, changing network topologies, or rare system events. Recently, the Maximum Lyapunov Exponent (MLE) has attracted considerable attention as a method for online TSA, primarily due to its inherent strengths [6]. This approach adopts a model-free framework that relies on carefully chosen time series of system variables, thereby eliminating the need for a detailed mathematical model describing the dynamics of system [7] - [8]. For instance, [9] - [10] demonstrated a model-free MLE approach for TSA, employing PMU data to facilitate online parameter learning. Building on this idea, [11] extended the model-free MLE method to encompass wide-area measurements—primarily sourced from PMUs- and proposed a TSA criterion based on MLE and generator rotor speed. Further advancement in online rotor angle stability assessment was presented in [12], where PMU-based insights were integrated with an MLE estimation process grounded in recursive least squares and optimized parameter settings. Moreover, the robustness and accuracy of MLE-driven, real-time stability assessment strategies have been reinforced by comparisons with other online TSA techniques, as seen in [13]. The application of nearest neighbor methods within the MLE framework represents an exploration in power systems, as presented in [14]. The next wave of idea in TSA involves integrating advanced machine learning (ML) models, as demonstrated in [15], which offers a comparative assessment of an ML-based framework and the MLE method using the same dataset.

In the realm of power systems, TSA has traditionally been integral to evaluating system stability. However, the Corrective Control Scheme (CCS) has emerged as an equally critical counterpart, focusing on dynamic, real-time responses to guide power systems through transient disturbances with minimal disruption. A preventive approach to CCS is outlined in [16], which employs the SIME technique for TSA. This method re-calibrates power iteratively until stability is achieved. Building upon this, [17] introduces an emergency control strategy that integrates with the preventive control in [16].

Among external stability-enhancing devices, Braking Resistors (BRs) have been widely studied in the literature for their role in transient stability improvement [18, 19]. These resistors momentarily connect to synchronous generators after disturbance, dissipating excess energy and slowing down the generator. Once stability is restored, they are disconnected to prevent unnecessary power dissipation.

Fast valving (FV) is another widely adopted control action, involving the rapid closure of steam inlet valves in turbines to limit speed increases and maintain power system stability after disturbances [20]. Also known as early valve actuation (EVA), it aims for the fastest initiation of intercepting valve closure and subsequent reopening to quickly reduce turbine power [21]. This helps prevent rotor angle instability and loss of synchronism. Various implementations, including momentary and sustained actions on control and intercept valves, have been tested to enhance system reliability [22]. Another control action involves the use of shunt capacitors to enhance transient stability.

This project also includes a Corrective Control Scheme (CCS) that utilizes Maximum Lyapunov Exponent (MLE) techniques for real-time Transient Stability Assessment (TSA) in power systems. Using MLE evaluations, the scheme implements different control actions to mitigate instability after a large disturbance. A comparative analysis of various MLE-based TSA methods and control actions is conducted to evaluate their effectiveness.

1.2 Objectives

Considering the previous motivation and problem formulation, there are two main objectives (Os) in this project:

- O1: Develop/utilize MLE-based TSA using online data, ensuring fast TSA.
  - One task for O1 is to identify two important generators whose rotor angle data is used for MLE-based TSA.
- O2: For unstable cases identified using MLE-based TSA, design and implement control strategies to stabilize the power system within a short time interval, enhancing overall power system stability and resilience.

Chapter 2

Transient Stability Assessment

2.1 Concept of Maximal Lyapunov Exponent

The dynamics of a system may be represented by a set of differential equations as:

$$\frac{dx}{dt} = f(x) \tag{2.1}$$

where, x, an n_x–dimensional state vector, resides in the Euclidean space $\mathbb{R}^{n_x}$. The solution to (2.1) can be expressed as:

$$x(t) = x(t_0) + \int_{t_0}^{t} f(x)\, dt \tag{2.2}$$

where $x(t_o)$ indicates the system's initial state at time $t = t_o$. The MLE provides insight into the dynamics of a trajectory in proximity to $x(t)$, illustrated in Figure 2.1. With $\Delta\, x(t_o)$ sufficiently small, the trajectory's sensitivity based on its initial condition is:

$$\Delta x(t) = \Delta x(t_0)\, e^{\lambda t} \tag{2.3}$$

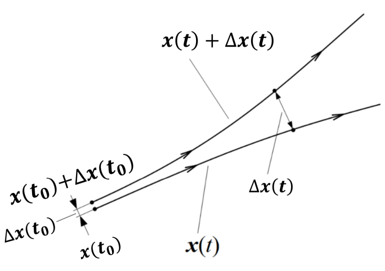

Figure 2.1: Maximal Lyapunov Exponent Framework

The exponential term $e^{\lambda t}$ describes the difference between the original and neighboring solutions in time. From (2.3), deduce:

$$MLE = \lambda = \lim_{t \to \infty} \frac{1}{t} ln \left(\frac{||\Delta x(t)||}{||\Delta x(t_0)||} \right) \tag{2.4}$$

where λ is an average based on the initial and final difference vector norms, offering insights into trajectory dynamics. System stability is inferred from the MLE's sign: negative and positive values correspond to stable and unstable systems, respectively [7].

2.2 Model-Based Approach

To calculate MLE in this approach, a deformation matrix $M(t)$ (see Figure 2.2) is used as a transformation matrix from the initial separation of trajectory to next separation as time increases [23].

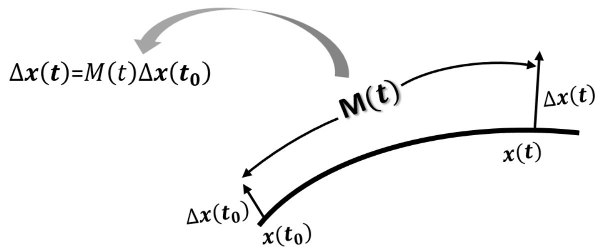

Figure 2.2: Concept of Deformation Matrix [23]

For obtaining $M(t)$ at each time step, the following differential equations are simultaneously solved.

$$\begin{aligned} \dot{x} &= f(x) \\ \dot{M} &= A\,M \end{aligned} \tag{2.5}$$

where, $A = \left[\frac{\partial f}{\partial x}\right]_{x(t_n)}$ is Jacobi matrix updated at each time step t_n. MLE can then be calculated by

$$MLE = \lambda = \frac{1}{N\Delta t} \sum_{n=1}^{N} ln \frac{||\Delta x(t_n)||}{||\Delta x(t_0)||} \tag{2.6}$$

where

$$\Delta x(t_n) = M(t_n) \Delta x(t_0) \tag{2.7}$$

In (2.6) and (2.7), Δt is time step, n is step number, $t_n = n\,\Delta t$ and N is the number of steps. The final time is given by $t_N = N\,\Delta t$. Based on (2.5), this approach requires the full system dynamics, which are then linearized.

2.3 Model-Free Approach

In contrast, the model-free approach does not require knowledge of the system dynamics as in (2.5); it only relies on time series data. In this approach, the MLE is obtained from time series data through phase space reconstruction [24]. This procedure includes delay coordinate embedding, which converts the series into a restructured domain. Unlike in (2.4), MLE is now determined by measuring distances between the principal and neighboring trajectories, focusing on the logarithmic separation rate of adjacent points.

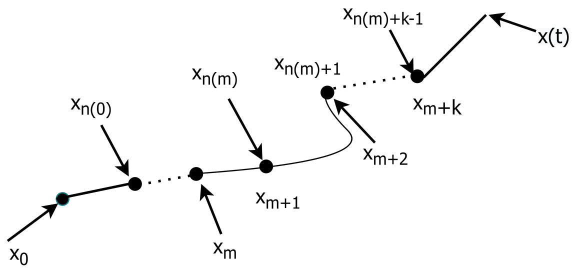

Figure 2.3: Main and Nearby Trajectories in Model-Free Approach

As illustrated in Figure 2.3, both x_0 and $x_{n(0)}$ serve as the starting points for the original and adjacent trajectories, respectively. Here, m functions as an index, marking the starting point for calculating MLE in the time-series data. Moreover, x_{m+k} represents the k^{th} point following x_m on the primary trajectory, while $x_{n(m)+k}$ denotes the k^{th} point following $x_{n(m)}$ on a adjacent trajectory. Let $|x_{n(m)} - x_m|$ represent the Euclidean distance between the initial points for MLE estimation, and $|x_{n(m)+k} - x_{m+k}|$ represent the Euclidean distance between the k^{th} points following the MLE estimation starting point. As stated in (2.8), MLE is subsequently derived as the average logarithmic rate at which the nearest neighbors separate [25]:

$$MLE = \lambda = \frac{1}{t_N} \sum_{k=1}^{N} ln \left(\frac{|x_{n(m)+k} - x_{m+k}|}{|x_{n(m)} - x_m|} \right) \tag{2.8}$$

where t_N=$N\Delta t$, with Δt as the time step, and N as the total number of time steps.

2.4 Application to Power System

This project focuses on two published model-free methods and one proposed method, namely the methods

- M1: which has been proposed in [11].
- M2: which has been introduced in [12].
- M3: which has been presented in [15].

An important issue is selection of online time series data. For the all three methods, the time series data corresponds to the rotor angle difference of two selected generators as follows:

$$\delta_{re}(t) = \delta_k(t) - \delta_l(t) \tag{2.9}$$

Once the time series data is available, the next step is to determine the transient stability assessment time, denoted as t_{assess}. This time represents the moment when the TSA criterion of each method is met, allowing the system's stability/instability to be assessed as follows:

M1: The process of TSA begins by acquiring time series data δ_{re} as specified in (2.9). The MLE is then calculated, as expressed in (2.8) and the transient instability is then assessed based on the following criterion.

Let $t = t_{\text{assess}}$ be the first time at which the MLE passes zero (i.e., changes its sign from negative to positive). The system is then assessed as transiently unstable if,

$$\omega_{re}(t_{\text{assess}}) = \dot{\delta}_{re}(t_{\text{assess}}) > 0 \tag{2.10}$$

Otherwise, transiently stable.

M2: It also follows the M1 methodology in terms of data acquisition δ_{re} as specified in (2.9). To estimate the MLE, two critical parameters, namely the Theiler window and the MLE estimation time step, must be accurately calculated. These parameters are determined separately for six different patterns of $\omega_{re} = \dot{\delta}_{re}$ as discussed in [12]. The MLE is then computed using δ_{re}, applying either the least squares method, as expressed in equation (7) of [12], or the recursive least squares algorithm, as expressed in equation (10) of [12].

The transient instability is then assessed based on the following criterion. Let $t = t_{\text{assess}}$ be the first time at which the MLE reaches a peak value (MLE_{peak}). The system is then assessed as transiently unstable if,

$$MLE_{\text{peak}} > 0 \tag{2.11}$$

Otherwise, transiently stable.

M3: The proposed methodology estimates the MLE by reconstructing the phase space of the time series data δ_{re} as specified in (2.9), employing the delay coordinate embedding method and analyzing ϵ-neighborhoods and scaling regions, as outlined in [8] and [26]. A detailed approach is provided in [14] and [15], with a brief description here. The phase space attractor, represented by vectors $X(t)$ constructed from the time series data, is analyzed to define ϵ-neighborhoods comprising points within a threshold distance ϵ.

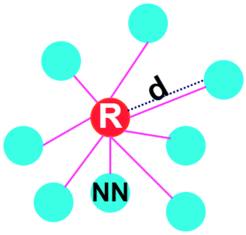

Figure 2.4: Identifying Nearest Neighbor (NN) of Reference Point (R) in Trajectory via Minimum Distance (d)

Using the nearest neighbor principle as illustrated in Figure 2.4, initial and future distances between neighboring points are calculated to evaluate the divergence rate, quantifying the separation of trajectories over time. These rates are then applied in a linear regression to estimate the MLE as the average slope across the scaling region.

$$MLE = \lambda = \frac{1}{M} \sum_{i=1}^{M} a(\epsilon)_{r_i}, \tag{2.12}$$

where M represents the total number of neighborhoods within the scaling region. The MLE is calculated based on the slope $a(\epsilon)$. The MLE serves as a measure of the average exponential rate at which nearby trajectories in the phase space diverge or converge. The time t_{assess} is obtained based on the following criterion [14].

- For $t \geq t_c$, compute $\delta_{re}(t)$, $\omega_{re}(t)$, $S1 = \sin(\delta_{re})\,\omega_{re}$ and $S2 = \dot{\omega}_{re}(t)$.
- Once the sign of one of the two signals $S1$ and $S2$ is firstly changed at time $t = t_1$, check the sign of $\omega_{re}(t)$,
  - if $\omega_{re}(t_1) > 0$, set $t_{assess} = t_1$ to calculate λ for TSA. A positive λ indicates a first swing instability.
  - if $\omega_{re}(t_1) < 0$, continue to compute $x_{re}(t)$, $\omega_{re}(t)$, and the signal whose sign was firstly changed (i.e. $S1$ or $S2$) for $t \geq t_1$. Once the sign of that signal is changed again at time $t = t_2$, set $t_{assess} = t_2$ to calculate λ for TSA. If the MLE (i.e. λ) is negative, the system is considered stable. Conversely, a positive MLE indicates an unstable system.

Corrective Control Scheme (CCS)

Once the system instability is detected based on MLE at t_{assess}, a Corrective Control Scheme (CCS) is activated. This activation time is denoted as t_{act}, and it is defined as $t_{\text{act}} = t_{\text{assess}}$.

The CCS is applied using one of the following two control methods: fast valving or braking resistor. At $t_{\text{act}} = t_{\text{assess}}$,

- for the fast valving, the power of generator k in (2.9) is decreased,
- for the braking resistor, it is connected to a selected bus,
- for the shunt capacitor, it is connected to a selected bus.

The CCS, regardless of the chosen control, is deactivated at the time $t = t_{\text{deact}}$ when $\omega_{\text{re}} = \dot{\delta}_{\text{re}}$ changes its sign for the third time (i.e., crosses zero for the third time).

Chapter 3

Simulation Results

3.1 Nordic Power System (NPS)

For application of MLE-based TSA (O1), 60 different cases are implemented in the Nordic Power System (NPS) as depicted in Figure 3.1. The MLE-based assessment

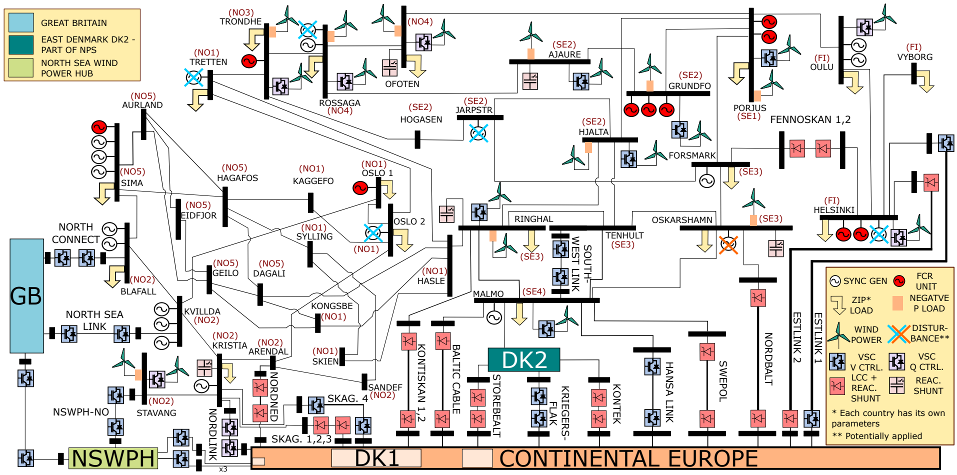

Figure 3.1: Single line diagram of the Nordic Power System (NPS) [27]

is performed at time t_{assess}. Thus, the total time duration for this assessment after the clearing time is $\Delta t_{assess} = (t_{assess} - t_c)$.

For the time series data, two signals, respectively, are used. The signals are either based on the rotor angles of two selected generators (δ_{re}) or the phase angles of two selected terminal buses (θ_{re}). Comprehensive analysis of the proposed MLE (M3) behavior, indicative of stability and instability in the NPS, is depicted in Figure 3.2, featuring MLE assessments based on $\delta_{re}(t)$ following various cases.

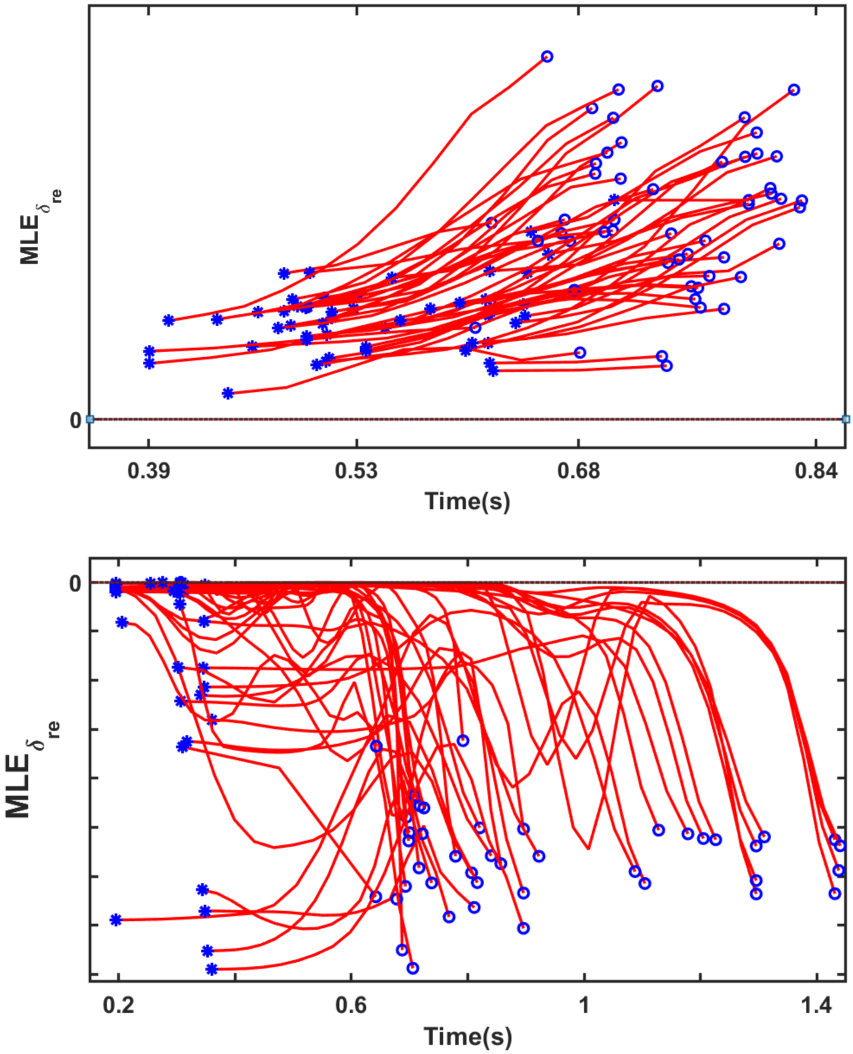

Figure 3.2: The collective visualization of MLE curves highlights MLE's consistent predictive of transient instability in the upper figure, and transient stability in the lower figure, respectively.

In Figure 3.2, the blue stars represent the initial values of MLE assessment at $t_{id} = t_c + \epsilon$, where ϵ is a very short time corresponding to two or three time steps, and the blue circles represent the final values of MLE assessment at t_{assess}. The assessment points with positive values indicate transient instability, and those with negative values indicate transient stability as shown in the figure. This collective visualization of MLE curves underscores the method's consistent accuracy in TSA.

The assessment time Δt_{assess} for stable cases are detailed in Table 3.1. The longest assessment time Δt_{assess} for stable cases with δ_{re} is 1.29 (s), and the average Δt_{assess} for these cases is 0.64 (s). Similarly, the longest assessment time Δt_{assess} for stable cases with θ_{re} is 1.32 (s), and the average Δt_{assess} for these cases is 0.55 (s).

Table 3.1: Summary of TSA Results for Stable Cases

Range of Δt_{assess} (s)	No. of Cases (δ_{re})	No. of Cases (θ_{re})
$\Delta t_{assess} < 0.5$	27	24
$0.5 \leq \Delta t_{\text{assess}} < 1$	21	33
$1 \leq \Delta t_{\text{assess}} < 1.3$	12	3

Table 3.2: Summary of TSA Results for Unstable Cases

Range of Δt_{assess} (s)	No. of Cases (δ_{re})	No. of Cases (θ_{re})
$\Delta t_{assess} < 0.2$	22	26
$0.2 \leq \Delta t_{\text{assess}} < 0.3$	32	31
$0.3 \leq \Delta t_{\text{assess}} < 0.4$	6	3

The assessment time Δt_{assess} for unstable cases are detailed in Table 3.2. The longest assessment time Δt_{assess} for unstable cases with δ_{re} is 0.36 (s), and the average Δt_{assess} for these cases is 0.22 (s). Similarly, the longest assessment time Δt_{assess} for unstable cases with θ_{re} is 0.41 (s), and the average Δt_{assess} for these cases is 0.20 (s).

The accuracy of these results underscores the algorithm's effectiveness for online TSA, marking a significant advancement in detecting transient instabilities by operating independently of preset offline values and relying entirely on real-time data.

3.2 The 2-Area IEEE Test System

For the application of CSS using MLE-based TSA (O2), the 2-area IEEE test system, as shown in Figure 3.3, is used. Six individual unstable cases are considered.

For M1 and M2, the same approach as discussed in chapter 2 is followed to find t_{assess} and $\delta_{\text{re}}(t_{\text{assess}})$. However, for M3, a new method has been developed to find t_{assess} and $\delta_{\text{re}}(t_{\text{assess}})$.

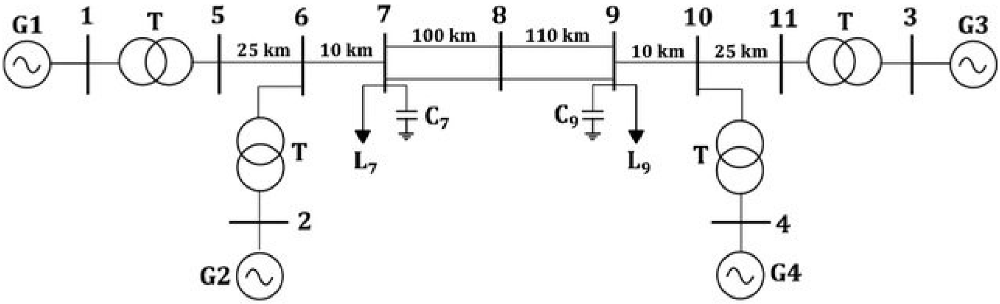

Figure 3.3: The 4-machine, 2-area IEEE test system [28]

A qualitative comparison is presented in Table 3.3, providing an analysis of $\Delta t_{\text{assess}} = t_{\text{assess}} - t_c$ for unstable cases applying the M1, M2, and M3 techniques. According to (2.9), the relative time series data δ_{re} is constructed using $\delta_k - \delta_l$, which involves the selection of two significant generators, k and l for TSA.

Table 3.3: The TSA results based on M1, M2, and M3 methods.

		M1		M2		M3	
Case	$\mathbf{t_c}$**(s)**	$\delta_k - \delta_l$	Δt_{assess} (s)	$\delta_k - \delta_l$	Δt_{assess} (s)	$\delta_k - \delta_l$	Δt_{assess} (s)
1	1.60	$\delta_1 - \delta_4$	—	$\delta_1 - \delta_4$	1.40	$\delta_2 - \delta_4$	0.54
2	1.46	$\delta_1 - \delta_4$	0.94	$\delta_1 - \delta_4$	1.82	$\delta_1 - \delta_3$	0.89
3	1.25	$\delta_1 - \delta_4$	0.94	$\delta_1 - \delta_4$	1.47	$\delta_2 - \delta_4$	0.60
4	2.24	$\delta_1 - \delta_4$	0.89	$\delta_1 - \delta_4$	1.42	$\delta_2 - \delta_3$	0.47
5	2.08	$\delta_1 - \delta_4$	0.11	$\delta_1 - \delta_4$	1.90	$\delta_2 - \delta_3$	0.51
6	1.30	$\delta_3 - \delta_2$	—	$\delta_3 - \delta_2$	1.63	$\delta_2 - \delta_3$	1.44

In Case 6, it has been observed that the M1 method incorrectly assessed this unstable case as stable. In Case 1, the M1 method fails to provide an assessment time because ω_{re} remains positive, and the MLE does not change sign throughout. Since instability assessment in M1 relies on a sign change in the MLE, no time instance can be identified to assess instability. Consequently, Δt_{assess} cannot be determined for this case. Therefore, cases 1 and 6 for M1 will not be considered in this study.

In Case 2 to Case 5, it has also been observed that although M1 and M2 use the same generator pair, M2 yields a longer Δt_{assess} than M1. This suggests that while

Table 3.4: The results of the three MLE-based activations of CCS.

Category	Case	t_c	$\Delta t_{act} = \Delta t_{assess}$			$\Delta t_{deact} = t_{deact} - t_{act}$		
			M1	M2	M3	M1	M2	M3
Braking Resistor	1	1.60	—	1.40	0.54	—	unstable	2.60
	2	1.46	0.94	1.82	0.89	2.43	unstable	2.37
	3	1.25	0.94	1.47	0.60	unstable	unstable	2.74
	4	2.24	0.89	1.42	0.47	unstable	unstable	2.55
	5	2.08	0.11	1.90	0.51	2.33	unstable	2.62
	6	1.30	—	1.63	1.44	—	unstable	3.10
Fast Valving	1	1.60	—	1.40	0.54	—	unstable	2.63
	2	1.46	0.94	1.82	0.89	2.44	unstable	2.77
	3	1.25	0.94	1.47	0.60	unstable	unstable	2.67
	4	2.24	0.89	1.42	0.47	unstable	unstable	2.47
	5	2.08	0.11	1.90	0.51	2.77	unstable	2.71
	6	1.30	—	1.63	1.44	—	3.13	2.85
Shunt Capacitor	1	1.60	—	1.40	0.54	—	unstable	3.04
	2	1.46	0.94	1.82	0.89	3.18	unstable	2.98
	3	1.25	0.94	1.47	0.60	unstable	unstable	2.98
	4	2.24	0.89	1.42	0.47	unstable	unstable	3.15
	5	2.08	0.11	1.90	0.51	2.69	unstable	3.04
	6	1.30	—	1.63	1.44	—	unstable	unstable

generator selection plays a significant role, the technique and its transient criterion also critically influence Δt_{assess}.

Using MLE-based TSA, the next step is to apply the proposed CCS to stabilize the system. The obtained results are presented in Table 3.4. The cases marked as "unstable" indicate that the system could not be stabilized by the control action, and shortly after the control action some generators lost their synchronism with other generators. For stable cases, the given times Δt_{deact} show the duration of the control actions after they have been applied (activated).

From TABLE 3.4, it is evident that TSA conducted using M3 is significantly more reliable than M1 and M2 in stabilizing the system. When braking resistor control is applied, the activation time Δt_{act} based on M1 is longer and fails to stabilize the system in two cases. Similarly, M2 fails to stabilize any of the cases in this scenario due to even longer Δt_{act}.

In the fast valving scenario, M3 achieves the fastest Δt_{act} and successfully stabilizes the system in all six cases. In contrast, M1, with a longer Δt_{act}, fails in two cases, while M2 stabilizes only one out of six cases due to longer Δt_{act}.

In the shunt capacitor scenario, M1, with a longer Δt_{act}, fails to stabilize two cases, and M2 fails to stabilize any case in this scenario. However, M3 only in Case 6 fails to stabilize the system.

Notably, the M3-based control action is the only approach that successfully stabilizes all cases in both the braking resistor and fast valving scenarios. Its only failure occurs in Case 6 of the shunt capacitor scenario; however, this does not imply that a shunt capacitor is ineffective in improving transient stability. As demonstrated in Cases 1–5, the shunt capacitor has improved transient stability by injecting reactive power.

Chapter 4

Conclusions

The proposed nearest neighbor based Maximum Lyapunov Exponent (MLE) algorithm (M3) as discussed in Section. 2.4 has been adapted for power systems, demonstrating success in transient stability assessment across all 60 stable and unstable, respectively, cases in Nordic Power System (NPS) for both $\delta_{re}(t)$ and $\theta_{re}(t)$. A criterion based on two signals S1 and S2 has been developed to quickly identify potential first swing instabilities. For the stable cases as detailed in Table 3.1, the longest assessment times Δt_{assess} were 1.29 (s) with δ_{re} and 1.32 (s) with θ_{re}, and the average assessment times Δt_{assess} were 0.64 (s) with δ_{re} and 0.55 (s) with θ_{re}, respectively. For the unstable cases as detailed in Table 3.2, the longest assessment times Δt_{assess} were 0.36 (s) with δ_{re} and 0.41 (s) with θ_{re}, and the average assessment times Δt_{assess} were 0.22 (s) with δ_{re} and 0.20 (s) with θ_{re}, respectively. The accuracy of these results underscores the algorithm's effectiveness for online TSA, marking a significant advancement in detecting transient instabilities by operating independently of preset offline values and relying entirely on real-time data. Further research concluded that the phase angles of selected generator terminal buses can effectively replace the rotor angles of selected generators.

Furthermore, this study introduces Corrective Control Scheme (CCS) as discussed in Section. 2.4 employing multiple control actions, including braking resistors, fast valving and shunt capacitor to effectively stabilize unstable systems. The results summarized in Tables 3.3 and 3.4 of Section. 3.2 strongly indicate that the proposed M3 method demonstrates significant potential for corrective control action to stabilize the system.

Chapter 5

Contribution

The main contributions of this project are given in the following.

- Firstly, this work overcomes the existing challenges of previous TSA techniques, such as the model dependency, offline simulation data and consistent pattern identification, while also reducing the time required for transient stability assessment. This is achieved by providing an analytical formulation of the nearest neighbor algorithm that is suitable for power systems. The proposed MLE method M3 —a synthesis of concepts from [26] and [8]—enables the development of a fast MLE algorithm that relies solely on data, making it model-free.

- Moreover, this study demonstrates that the proposed MLE algorithm functions effectively with either the rotor angles of selected generators or the phase angles of selected generator terminal buses. The examined scenario focuses on the large Nordic Power System (NPS), which shows distinct nonlinear reactions following major disturbances.

- The study employs multiple control actions, including braking resistors and fast valving, using the proposed Corrective Control Scheme framework. This diverse control action ensures comprehensive stabilization after disturbance, enhancing the overall robustness of the control scheme.

- A comparative evaluation is conducted to assess the performance of various MLE-based TSA approaches in conjunction with the different control actions. This analysis highlights the relative effectiveness of each MLE-control combination, identifying the most efficient strategies to maintain transient stability after large disturbances.

Chapter 6

List of Publications

I ***A Comparative Analysis Of Techniques For Real-Time Transient Stability Assessment***
Bano, Sayyeda Umbereen and Ghandhari, Mehrdad and Eriksson, Robert
North American Power Symposium (NAPS) (2022)

II ***Maximum Lyapunov Exponent Based Nearest Neighbor Algorithm For Real-Time Transient Stability Assessment***
Umbereen Bano Sayyeda and Mehrdad Ghandhari and Robert Eriksson
Electric Power Systems Research (2024)

III ***Investigating the Performance of MLE and CNN for Transient Stability Assessment in Power Systems***
S.Umbereen, X.Weiss, and A.Rolander, M.Ghandhari and R.Eriksson
IEEE Access (2024)

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