Article

Power System Event Ranking Using a New Linear Parameter-Varying Modeling with a Wide Area Measurement System-Based Approach

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Abstract: Detecting critical power system events for Dynamic Security Assessment (DSA) is required for reliability improvement. The approach proposed in this paper investigates the effects of events on dynamic behavior during nonlinear system response while common approaches use steady-state conditions after events. This paper presents some new and enhanced indices for event ranking based on time-domain simulation and polytopic linear parameter-varying (LPV) modeling of a power system. In the proposed approach, a polytopic LPV representation is generated via linearization about some points of the nonlinear dynamic behavior of power system using wide-area measurement system (WAMS) concepts and then event ranking is done based on the frequency response of the system models on the vertices. Therefore, the nonlinear behaviors of the system in the time of fault occurrence are considered for events ranking. The proposed algorithm is applied to a power system using nonlinear simulation. The comparison of the results especially in different fault conditions shows the advantages of the proposed approach and indices.

Keywords: wide-area measurement system; event ranking; power system stability; nonlinear systems; linear parameter-varying modeling

1. Introduction

Event and contingency analysis has been used for reliability and security assessment and improvement of power systems in recent years [1–7]. Usual approaches for importance tracking and ranking are based on the steady-state effects of the events on the power grid such as loading, voltage violations, etc. Recently, the inter-area oscillations have become an important concern for operators. Although standard Power System Stabilizers (PSSs) have been traditional tools used to improve the damping of system modes, they may not be quite effective for damping of all oscillations, especially after various event occurrences [8]. Hence, the oscillatory modes might have undesirable damping or cause instability under some conditions. The uncertainties in the response to disturbances have some noticeable effects on Dynamic Security Assessment (DSA) which requires Time-Domain Simulation (TDS) [9]. Too much time is required to analyze so many events in a complicated power system using TDS. Hence, sorting and detection of critical events are the essential issues in DSA and for design or tuning the control schemes. Consequently, event ranking can be used to create a priority list for more actions to reduce the probable undesirable performance [10].

Not many studies about screening and ranking for DSA have been reported [11]. In many references such as [12–15] the modes of the small signal conditions at post-event and steady-state conditions are analyzed for event assessment. For example, the eigenvalues of critical modes for post-outage conditions are estimated using just the nominal condition of eigenvalues and post-outage system state matrices in [11]. Also, steady-state displacement of modes of power system with

contingency is used for ranking in [12], while the dynamical behaviors of the system are not considered. However, as a novel method in the present paper, not only the steady-state situation but also the dynamical behaviors of the system are investigated for event ranking by polytopic LPV modeling of the system based on transient responses of the system.

On the other hand, the traditional approach to evaluate the system reliability with $(N-1)$ contingencies is no longer sufficient [16] and recently, $(N-k)$ contingency studies have acquired a very important role in the operation and expansion planning of power systems [17]. Although the conventional single contingency $(N-1)$ criterion is useful to reduce risks in power systems, the insufficiency of this criterion has been known by analysis of recent blackout events. This fact shows that it is necessary to use better criteria to ensure robust power system operation. Some reliability standards such as North American Electric Reliability Corporation (NERC) Standard PRC-023 have been improved to require utilities to consider not only single outages, but also $(N-k)$ events which could start some cascading events [18], and there are some issues like terrorism or potential attacks that make utilities study several events [19]. The problem is that an event may cause a condition in the nonlinear dynamic power system to start cascading outages. In response to these issues this paper presents a new approach to investigate the effects of events on power system performance during nonlinear dynamic responses while common approaches use steady-state conditions after events.

Recently, consideration of the nonlinear dynamical systems by some combination of linear sub-systems has received significant attention. The efficiency of linear systems for developing control concepts in a simple fashion may be the main reason for this interest. This matter has caused a growing tendency to shape hybrid, LPV, and polytopic linear models [20–24]. The main perturbation in a nonlinear system, coming from the nonlinearity effects due to operating point variations, can be studied by constructing the polytopic linear model based on LPV modeling [25]. The method represents system dynamical equations as a linear state-space model with time-varying parameter-dependent matrices. The dynamics are linear but non-stationary [26]. In fact, the nonlinearity of the system is described by the parameter variation of LPV model. As a novelty of this paper, the LPV-modeling method is used to cover the nonlinearity of power system in event ranking whereas it is not utilized in other ranking methods.

In recent years, wide-area measurement systems (WAMS) have become well-known in analysis and operations, especially for event, fault and control studies such as described in [27–29]. In this paper, the proposed LPV modeling uses a new approach based on WAMS and remote signals for studying the system nonlinearity as a complex property. Event and contingency ranking are done by computing some proposed and enhanced indices to show the effects caused by each event on the system dynamic behavior. A nonlinear simulation of a 9-bus power system is done for illustrating the method, and the power flow of a transmission line is considered as a monitoring variable (remote signal) through WAMS in the presented approach for ranking. The results show the effectiveness of the proposed method and indices. Briefly, there are some novelties, highlights and advantages of this paper for the purpose of power system event ranking such as:

- Considering not only steady-state response but also the dynamical behavior of the system after event occurrence.
- Using polytopic LPV modeling for covering the nonlinearity of the system in transient responses.
- Proposing some new and enhanced indices and comparing them using nonlinear simulations.

In this paper, after the Introduction, basic concepts are stated in Section 2. In Section 3 the proposed indices for ranking are described and Section 4 presents the simulation results before the conclusions.

2. LPV Model for Power System Event Condition

Before representing the proposed approach for modeling, some concepts of the problem should be reviewed and a set of models for transient operating points of power system would be introduced in order to cover the nonlinearity effects and uncertainties.

The dynamic behavior of a power system is affected by its complex components (generators, exciters, transformers, etc.), which are coupled with the network model. However, the nonlinearity of the system is obvious, specifically in transient behavior, whenever a fault or a disturbance occurs. The mathematical model of the power system can be represented by two sets of equations: one set of differential equations and one set of algebraic equations as:

$$\begin{aligned} \dot{x} &= f(x, \xi, u) \\ 0 &= g(x, \xi, u) \end{aligned} \tag{1}$$

where $x \in \Re^n$ (with n as the number of the states) is the vector of state variables, $\xi \in \Re^q$ is the vector of (non-state) network variables such as load flow variables (q is the number of these variables) and $u \in \Re^p$ (with p as the number of the inputs) is the vector of control inputs such as reference signal of Automatic Voltage Regulator (AVR) called V_{ref}.

It is assumed that the function $f(x, \xi, u)$ and $g(x, \xi, u)$ to be continuously differentiable a sufficient number of times. The solution of (1) for specific control input $\bar{u}(t)$ is presented by a vector of $\bar{x}$ and $\bar{\bar{\xi}}$, and define $\theta(t)$ in below as power system transient trajectory:

$$\theta(t) := \begin{bmatrix} \bar{x}(t) \\ \bar{\bar{\xi}}(t) \\ \bar{u}(t) \end{bmatrix} \tag{2}$$

If the consideration is:

$$\begin{aligned} x &= \bar{x} + \delta x \\ \xi &= \bar{\bar{\xi}} + \delta y \\ u &= \bar{u} + \delta u \end{aligned} \tag{3}$$

then the function $f(x, \xi, u)$ can be approximated by a linear Taylor expansion with respect to its components. In fact, the power system dynamics in the immediate proximity of the transient trajectory $(\bar{x}, \bar{\bar{\xi}}, \bar{u})$ are approximated by the first terms of the Taylor series, so the following LPV model $P(\theta)$ can be introduced for the power system about the transient trajectory:

$$\delta \dot{x} = A(\theta(t))\delta x + B(\theta(t))\delta u \tag{4}$$

where

$$A(\theta(t)) := \left[\frac{\partial f}{\partial x} - \frac{\partial f}{\partial \bar{\xi}} \left(\frac{\partial g}{\partial \bar{\xi}} \right)^{-1} \frac{\partial g}{\partial x} \right]_{\substack{x = \bar{x} \\ \xi = \bar{\bar{\xi}} \\ u = \bar{u}}} \tag{5}$$

$$B(\theta(t)) := \left[\frac{\partial f}{\partial u} \right]_{\substack{x = \bar{x} \\ \xi = \bar{\bar{\xi}} \\ u = \bar{u}}} \tag{6}$$

The output variable about its transient trajectory is defined as $\delta y \in \Re^m$ (m is the number of output variables), which is a selected WAMS signal to support general overview of the system nonlinearity and dynamic effects. In general, it has the following form:

$$\delta y = C(\theta(t))\delta x + D(\theta(t))\delta u \tag{7}$$

where in the power system, without loss of generality, it can be assumed that $D(\cdot) = 0$. However, this assumption is not implausible in power systems. The matrix $C(\cdot)$ can be computed when the desired output variables are defined.

In fact, the power system transient trajectory $\theta(t)$ may be interpreted as a time-varying scheduling signal vector for the mappings $A(\cdot)$ and $B(\cdot)$. The compact set $P_\theta \subset \Re^{n+p+q} : \theta \in P_\theta, \forall t > 0$ is considered as a polytopic defined by the convex hull:

$$P_\theta := Co\{\theta_{v1}, \theta_{v2}, \ldots, \theta_{vN}\} \tag{8}$$

where, N is the number of vertices. It follows that the system can be represented by a linear combination of LTI models at the vertices; this is called a polytopic LPV system:

$$P(\theta) \in Co\{P(\theta_{v1}), P(\theta_{v2}), \ldots, P(\theta_{vN})\} = \sum_{i=1}^{N} \alpha_i P(\theta_{vi}) \tag{9}$$

where $\sum_{i=1}^{N} \alpha_i = 1$ and $\alpha_i \geq 0$ are the convex coordinates. The ith vertex of this convex polytope is defined by $P_i := (A_i, B_i, C_i)$ for $i = 1, 2, \ldots, N$, where each of this matrices is constant.

The convex polytope can be used as the model of power system exposed to an event. Each model is computed at an operating point which is considered at a sampling instant in system transient trajectory during the response of the system after the event. The models are obtained through linearization of the power system during Time-Domain Simulation (TDS) of each event.

3. The Proposed Indices for Event Ranking

The system response after each event can be used for representing the event and it can be considered as a measure for event ranking compared to normal or pre-fault conditions. For this purpose, some ways are available: TDS, Frequency Response (FR) and modal analysis. Some indices related to each way would be described in this section. Although their computational methods and theoretical basis are conventional, their final structure are novel because one index has new factors and the others are involved with the polytopic LPV modeling concepts. As a result, the proposed indices will contain a novel event ranking process capability.

3.1. Non-Linear TDS Based Ranking Index

It is obvious that if an event causes instability, it is an important event with high risk but the risk is not clear in stable conditions. By nonlinear simulation of power system events and considering the resulted oscillations, it is feasible to compute an index to present the event effects and rank them based on the probable instability conditions.

Some references such as [30–35] utilized an index called Integral of Time multiplied Absolute Error (ITAE) as a performance index for some optimal tuning and noise effect minimizing problems especially for control design. Although ITAE is known in other literatures, it is adapted for event ranking purpose in this paper by normalizing and called as Non-linear TDS based ITAE (NTDSITAE) index for the ith event:

$$NTDSITAE_i = \int_{t_0}^{t_1} t \left| \frac{y_i(t) - y_{iss}}{y_{iss}} \right| dt, \tag{10}$$

where, t is time in s, t_0 is starting time, t_1 is end time of simulation (i.e., the time that oscillations are damped and the value of the index is not changed), $y_i(t)$ is the monitored variable as the system output (such as active power of a transmission line), and y_{iss} is the steady-state value of the output variable. The last term (y_{iss}) is proposed in this paper for normalizing and increasing the contrast of ranking index.

Time multiplying helps to weight and signify the oscillation with slower damping. This proposed modified index is suggested for ranking the events with undesirable dynamic effects. As a novelty, this enhanced index can describe the traditional conception of events ranking in which the oscillations show the event importance.

3.2. Modal Based Event Ranking Index

Nonlinearity can change or shift the modes of the power system during its dynamic behavior. This issue is especially significant in event conditions. Therefore, the modes locations as a criterion for stability assessment may be used for ranking the events. Polytopic LPV modeling helps us to apply this approach with more accuracy and generality. Considering modes of a simple second order system as complex numbers:

$$\lambda_{1,2} = \sigma \pm j\omega \tag{11}$$

The Damping Ratio (*DR*) of each mode as a popular index for dynamic security assessment [36] is:

$$DR = \zeta = \frac{-\sigma}{\sqrt{\sigma^2 + \omega^2}} \tag{12}$$

The number of system modes with undesirable damping ratio in the behavior trajectory after each event may be selected as an index for ranking. Therefore, by polytopic LPV modeling of the system, Modal based Probabilistic ranking index (*MP*) for the *i*th event is defined as:

$$MP_i = \frac{n_{u\_i}}{n_{m\_i}} \times 100 \tag{13}$$

where n_{u_i} is the number of modes of all vertices for the *i*th event with a damping ratio less than desired damping ratio and n_{m_i} is the number of all modes of all vertices for the *i*th event. As a new index, it helps to recognize an approximate probability of undesirable oscillation damping or system instability after each event.

3.3. FR Based Event Ranking Index

This index as a novel tool for event ranking is based on comparing the transfer functions of the polytopic LPV models of the events with the nominal transfer function (before each event). The ranking results present the strength of each event to change the system dynamic behavior. Frequency Response Error for *k*th vertex of polytopic LPV model in *i*th event condition is defined by:

$$FRE_{ki} := \|F_{ki}(j\omega) - F_0(j\omega)\|_2, \ \omega \in [\omega_{\min}, \omega_{\max}], \tag{14}$$

where $\omega_{\min}$ and $\omega_{\max}$ are respectively the minimum and maximum frequency in rad/s, $\| \cdot \|_2$ is 2-Norm operator, F_0 is the system transfer function in normal condition, and F_{ki} is the transfer function of *k*th vertex of the polytopic LPV model in *i*th event condition. Using 2-norm definition, it can be summarized to (in dB):

$$FRE_{ki} = 20 \log \left(\sqrt{\sum_{m=1}^{n_\omega} |F_{ki}(j\omega_m) - F_0(j\omega_m)|^2} \right), \tag{15}$$

where n_ω is the number of frequency samples. Using infinite norm of *FRE* for all vertices of the polytopic LPV model at each event condition, Frequency Response Error After Event (*FREAE*) as an overall index for *i*th event can be proposed by:

$$FREAE_i = \|FRE_{ki}\|_\infty = \sup_k FRE_{ki}, \ k = 1, 2, \ldots, N. \tag{16}$$

In other words, *FREAE* is a new index for representing the maximum effect of *i*th event on the system frequency response. It is useful for power systems because low-frequency oscillations are typically in the range of 0.2–2.5 Hz [32]. Increasing n_ω results in more accuracy of the index.

4. Simulation Results and Evaluation

4.1. Power System Representation

In this section, a 9-bus power system model [37] is used for analysis by applying the data used in [38]. It represents a small transmission system which consists of nine buses, three generators, three loads, six lines and three transformers; its single line diagram is shown in Figure 1.
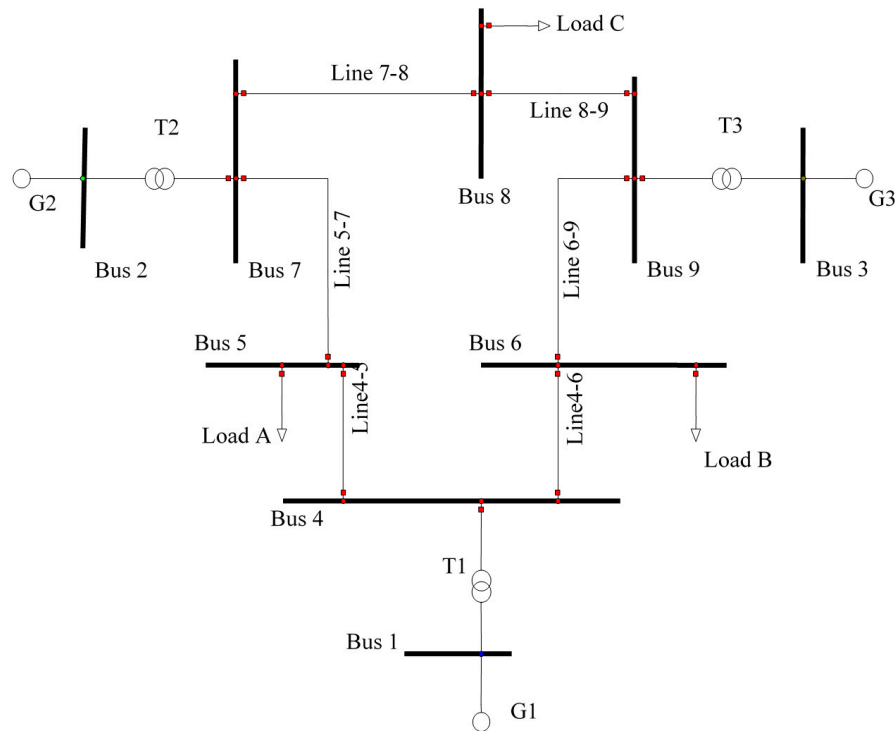

Figure 1. Power system under study with 9-bus [37]. Reproduced with permission from publishing company, 2014.

In this study, generator G2 is considered as a synchronous machine using a detailed model with an AVR model IEEE type1 Mag-A-Stat and a PSS model as specified in [38] is added to control the oscillations. Modeling, nonlinear simulation, and linearization are done using the DIgSILENT PowerFactory software (DIgSILENT GmbH, Gomaringen, Germany).

Transmission lines are unprotected from various risks associated with variations in design characteristics and climatic variants that may result in outages [39]. According to the analysis of the most typical sequence of events (especially for blackouts), it was determined that transmission line trips are a group of the most frequent events [40]. Therefore, line outages are considered as the system events in this paper.

On the other hand, NERC has some studies which showed that many important disturbances involved protection systems, as the initiating event [41]. Hence, protection failures are noticed as an important concern in security assessment [42]. Therefore, the line outages due to 3-phase short-circuit (SHC) faults or because of hidden failures such as protection malfunctions are considered in this study. Consequently, an outage of Line 5–7 as Event 1 without any short-circuits is considered.
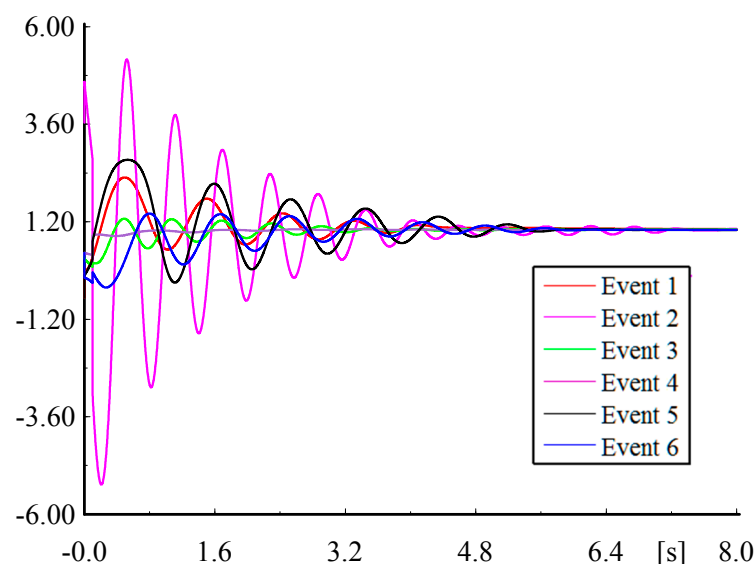
Table 1 presents the list of the events. The steady-state condition of all events is an outage of the affected line.

Table 1. Events list.

Event Number	Description	
	Affected Line	**Fault**
1	Line 5–7	-
2	Line 8–9	3ph-SHC
3	Line 7–8	3ph-SHC
4	Line 6–9	3ph-SHC
5	Line 5–7	3ph-SHC
6	Line 4–5	3ph-SHC

4.2. Nonlinear Simulation of Event Conditions

For investigation of the system events, the normalized nonlinear TDS results are illustrated in Figure 2. The active power of Line 4–6 as the system output is normalized based on its steady-state value for each event. Note that the short-circuit fault (if any) are occurred at $t = 0$ s in 50% of related line length and the switching time is $t = 0.1$ s. Although the system responses are normalized, the amplitudes and oscillation frequencies are different from an event to another. To obtain the polytopic models for the event conditions, linear models at some points of dynamic behavior are necessary.

Figure 2. Normalized active power of Line 4–6 per steady-state value after each event.

4.3. Linear Models of Power System for Event Conditions

Using the concept of the wide-area measurement system (WAMS), the power system models are obtained considering the AVR input of G2 as the system input and the active power of Line 4–6 as the system output. The order of each obtained linear model is 28. For simplification in this part, each model is reduced to a 6-state linear model by balanced truncation model reduction technique. Note that the ranking assessment will be executed by using the full-order models. Conventional approaches study the effects of events by modal analysis at steady-state points, so we firstly investigate the system in $t = 7.5$ s at the end of responses. Figures 3 and 4 show the frequency responses and modes locations of the reduced-order models of the power system at $t = 7.5$ s during nonlinear simulation of each event. It is clear that linear models are various but it is not obvious in the nonlinear simulation results because the oscillations are damped at the moment in Figure 2 hence the events have apparently the same effects on the dynamic behavior of the system.
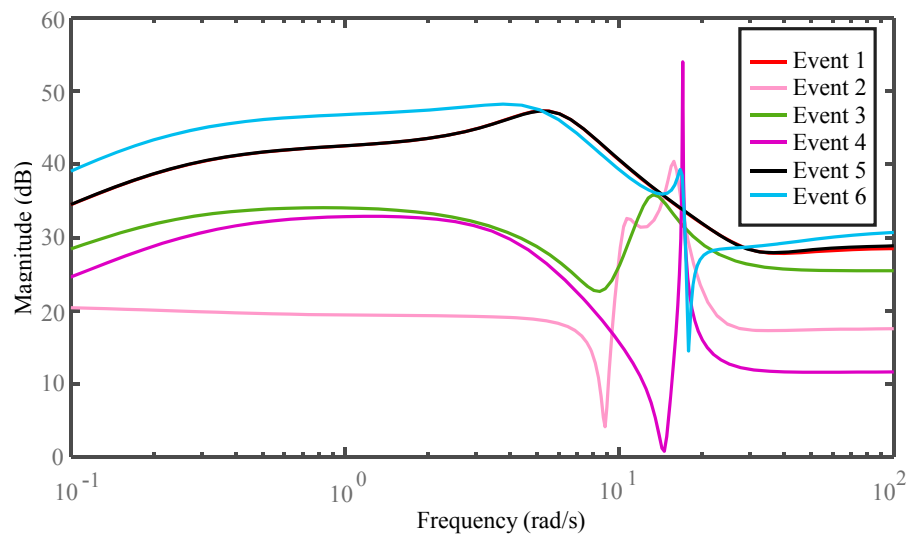
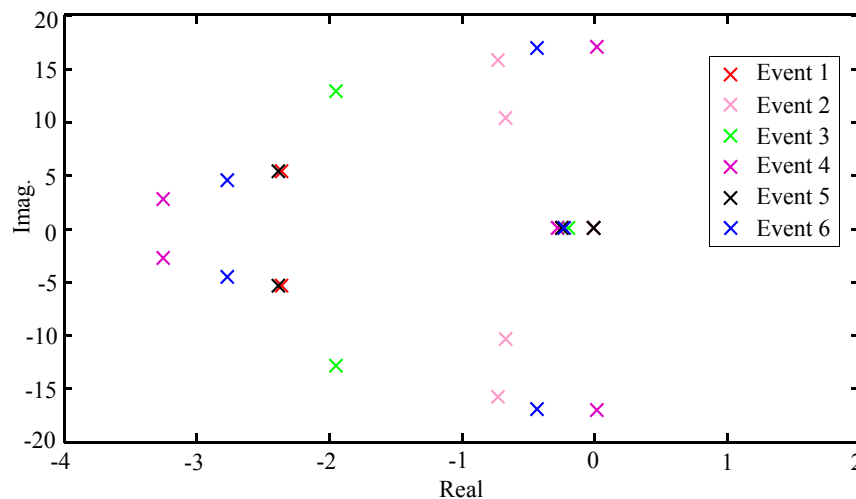**Figure 3.** Bode diagram of models after events (linearization at *t* = 7.5 s).

Figure 4. Modes of reduced order models (linearization at *t* = 7.5 s).

To implement the proposed approach, linearization is done at 30 sample points during TDS and a set of models is obtained as the polytopic LPV model for each event. To show the result of this approach, displacement of system modes during TDS events is shown in Figure 5 using reduced order models. It is clear that the events can change the modes not only at the steady-state situation but also during dynamic behavior.

As an example to show the contribution of the approach of this paper, Event 1 and Event 5 are studied. According to the conventional approach, Figures 3 and 4 show that Event 1 and Event 5 have approximately similar models at *t* = 7.5 s as it was expected because both events have similar steady state conditions (outage of Line 5–7), and there isn't any unstable pole while the proposed approach gives us a different result. According to the proposed approach, as we can see in Figure 5, there are many unstable poles that detected by polytopic LPV modeling during TDS, and the overall system even may be destabilized when these poles are excited.
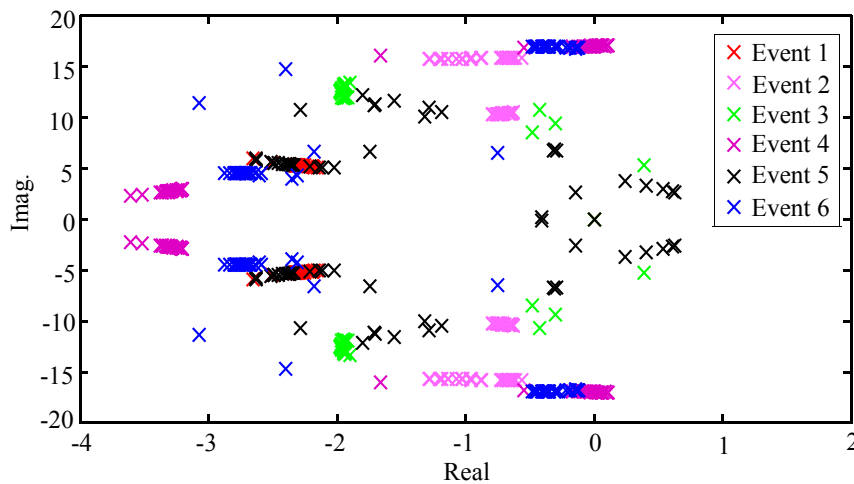
Figure 5. Modes deviations of reduced polytopic LPV models during TDS.

Considering the propagation specifications of modes locations, it may be too complicated to grade the events, therefore, the proposed indices are used in the next section.

4.4. Ranking Results

To use the ranking indices proposed in Section 3, events represented in Table 1 are assessed. The non-linear TDSs of power system, FR and modal analysis of LPV Models are used for calculations. NTDSITAE is calculated by (10) using TDS results shown in Figure 2 considering $t_0 = 0$ s and $t_1 = 8$ s. MP and FREAE which are defined in (13) and (16) respectively, are calculated using full-order polytopic LPV models.

Table 2 summarizes the results for all events and presents the ranking list. The results show that the sorts of the events according to indices are different from each other.

Table 2. Ranking results.

Rank	Event No.	NTDSITAE	Event No.	MP	Event No.	FREAE
1	2	7.89	2	21.43	5	88.11
2	5	5.03	3	21.19	6	74.06
3	6	2.49	5	15.48	1	72.73
4	1	2.27	1	14.29	3	72.49
5	3	0.88	4	14.29	2	72.41
6	4	0.14	6	14.05	4	70.69

4.5. Discussion of Results

The proposed indices have some advantages. According to conventional indices like loading, Event 1 and Event 5 have same final steady-state effects on the network while they have the different values of the proposed indices in Table 2. This illustrates that the proposed approach can distinguish between the different events with the same steady-state conditions. This is expected because the proposed approach covers the system transient behavior, not only by TDS but also by FR. On the other hand, the simulation results show that the events have not enough clear ranking with MP. For example, there is no clear difference between Event 2 and Event 3 or between Event 1 and Event 4 by using MP criterion. This index can be useful for control synthesis based on pole placement approach and the performance evaluation but not much useful for events ranking. In contrast, the first rank according to NTDSITAE and MP is Event 2 but the first rank of FREAE is Event 5. At first glance, ranks of FREAE is not expected because Event 5 leads to better damping in the oscillations shown in Figure 2. System response to Event 2 shown in Figure 2 has the worst damping ratio and approves

the first rank of NTDSITAE and MP. On the other hand, Figure 5 shows that the modes of Event 5 are closer to instability area so this event as the first rank of FREAE may be more important.

However, Figure 2 is the result of simulation at a special operation case as initial condition but it is essential to consider the variable performance and nonlinearity of power system that may change the ranking list in other conditions. Therefore, it is critical to know which index is more useful for DSA and control synthesis. To check the beneficial consequence of the proposed approach and test the robustness of ranking indices, the results can be evaluated by simulation of other scenarios and conditions.

4.6. Ranking Evaluation in Different Conditions

To evaluate if the ranking results are valid in variant and dynamic behavior of power system, some simulations are done with different conditions. Table 3 represents the system operation scenarios (system generation and loads) as the pre-fault conditions of the events. Note that pre-fault condition described for Scenario 4 is the same as the base case of the previous sections according to [38] but the fault location is different from the previous sections. In this section, fault locations are considered in 1% of the line length (a point near the sending end of the line) but the other considerations about fault durations and types of events are not changed.

Table 3. Operation scenarios, loads and generation of power system: P(MW) + j Q(Mvar).

Scenario Number	System Generation			System Loads		
	G1	G2	G3	LoadA	LoadB	LoadC
1	99 + j34	159 + j34	93 + j24	131 + j64	99 + j48	115 + j56
2	110 + j33	139 + j38	70 + j22	125 + j68	90 + j51	100 + j59
3	70 + j19	161 + j11	74 − j6	116 + j47	86 + j29	97 + j34
4	71 + j27	163 + j7	85 − j11	125 + j50	90 + j30	100 + j35
5	155 + j20	163 − j15	0	125 + j36	90 + j26	100 + j29

Figure 6 shows the normalized simulation results for all five scenarios. It is obvious that Event 5 is the most important event because of considerable undesirable damping (Figure 6a,b)) or system instability (Figure 6c–e). These results agree with the tendency of modes in Event 5 shown in Figure 5. The simulation results of different scenarios illustrate that FREAE based on polytopic LPV modeling is more powerful for ranking because other indices could not detect the importance of Event 5 by using the stable behavior of power system.
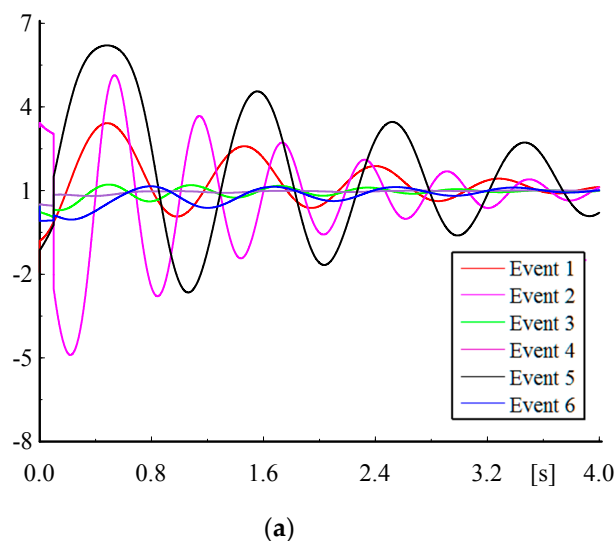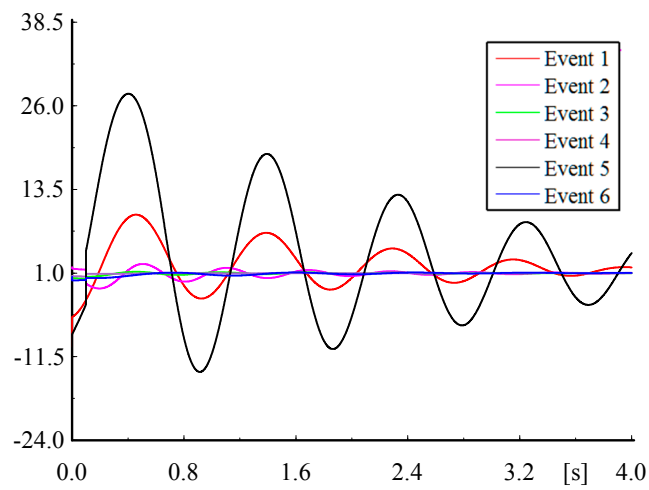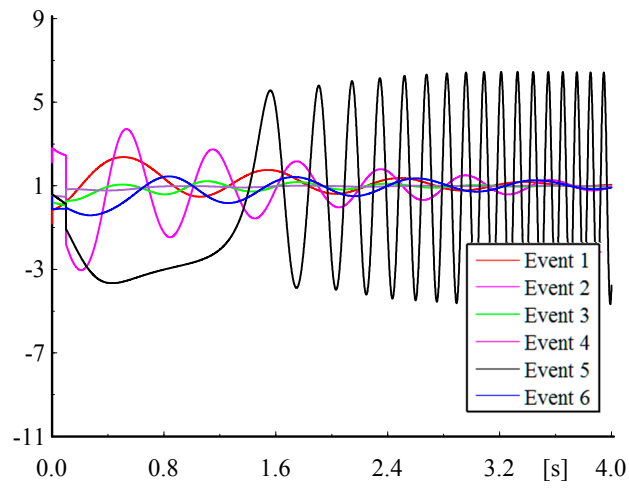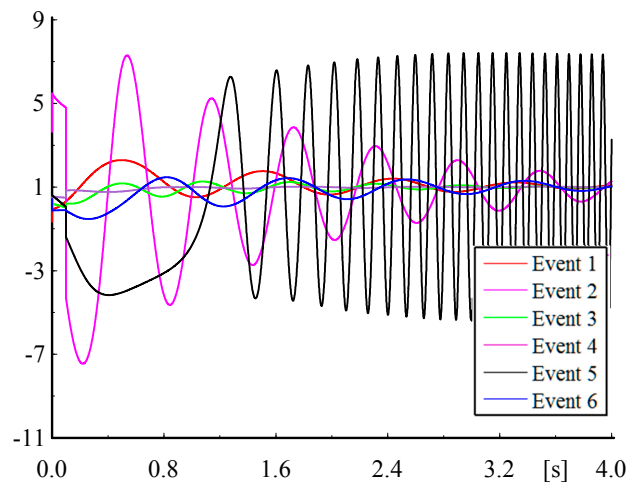

(**a**)

Figure 6. *Cont.*

(**b**)

(**c**)

(**d**)

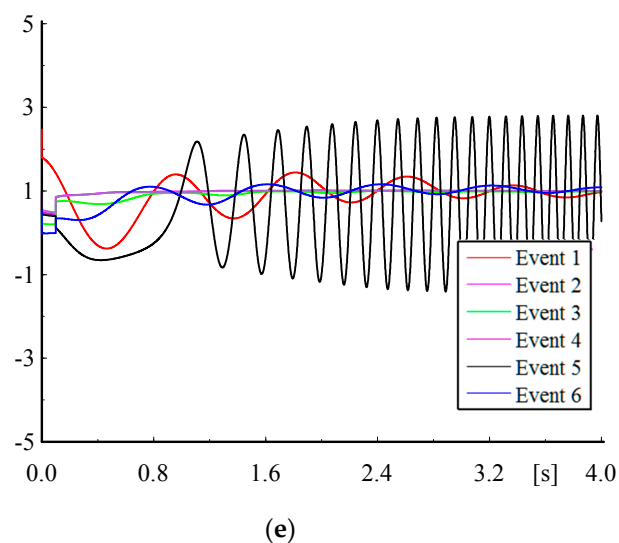**Figure 6.** *Cont.*

(**e**)

Figure 6. Normalized active power of Line 4–6 per steady-state value for events with a new fault location in various operation scenarios: (**a**) Scenario 1; (**b**) Scenario 2; (**c**) Scenario 3; (**d**) Scenario 4; (**e**) Scenario 5.

5. Conclusions

Power systems may have so many events and their nonlinear behavior may cause complicated conditions. Hence, this paper was arranged to study not only steady-state, but also dynamic behavior in event conditions as a novel approach for the purpose of ranking. Ranking of the events according to their effects on the system modes and frequency responses could be a way of improving dynamic security assessment, operation analysis, and controller design. This paper proposed a new approach for polytopic LPV modeling of the power systems during event occurrences based on transient operating points using WAMS concepts and presented new and enhanced time-domain and frequency-domain indices for event ranking purposes.

Simulations of base case conditions illustrated that the proposed approach can help to distinguish between two events with the same steady-state effect on the power system while the traditional steady-state indices such as loading could not provide this benefit. This fact showed that the proposed approach is more useful for security assessment with respect to the conventional methods. On the other hand, simulation results of various operation scenarios showed that FREAE as a proposed novel index is useful and powerful for detecting and predicting the worst event among some events by using a stable response in base case condition while other proposed or traditional indices (such as NTDSITAE, MP and loading) could not achieve the mentioned purpose. The simulation results verified that an event with a low priority by conventional indices may have a high priority using the proposed indices in this paper and even destabilizes the overall system.

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