Investigation of the Blackouts Complexity Regarding Spinning Reserve and Frequency Control in Interconnected Power Systems

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Abstract— **The dynamics of power system blackouts and the associated Self-Organized Criticality (SOC) behavior is a subject that receives continuous attention in view of its inherent complexity and relevant consequences. Within this context, the paper focuses on the short-term dynamic and, more specifically, aims at studying the role of the spinning reserve and frequency control on the blackout mechanism. The main contribution is to study the influence of the power system interconnections on the pre and post blackout system behavior. For this investigation, a statistical procedure, based on the Monte Carlo Simulation (MCS) method, is proposed to perform a blackout risk analysis considering cascading outages and generators frequency responses. The proposed procedure is then applied to the IEEE 118 bus system as an interconnected network characterized by three areas. The distribution of the blackout size and the number of component outages are assessed for the whole system as well as for each area.**

Keywords-component: Blackout Analysis, Power Law Distribution, Self-Organized Criticality, Cascading Outages, Monte Carlo Simulation.

I. INTRODUCTION

Power transmission networks are large and complex systems that have experienced wide blackouts in the recent two decades (i.e. the Northeast and Italy blackouts in 2003). Although large cascading blackouts are relatively rare events, the investigation of their mechanism calls for significant efforts in view of the relevant consequences. Understanding the complex dynamics of power systems components through their interactions with different control methods, are the main challenges to comprehend a blackout mechanism. In this respect, several investigations have been performed in the literatures [1]–[14]. An additional aspect that increases the complexity of the problem is the operation of single power systems within an interconnected supergrid (e.g. interconnected networks in continental Europe – ENTSOE and North America – NERC). The areas of an interconnected power system generally profit of increased security and mutual economically efficient generation where higher security margins are a consequence of shared active power reserves. However, the security of the interconnected power system could decrease with the increase of the interconnection and consequently increase of the system complexity.

The blackouts data of the power system in North America and China have been studied in [1]–[2] and [3]–[5], respectively. These analysis have shown an overall power law distribution of the blackout size. This peculiarity demonstrates that the dynamic of blackouts can be associated to complex systems with Self-Organized Criticality (SOC) feature. In the system with the SOC characteristic, there are different types of variables with opposed driving forces that, in certain conditions, could drive the system into a critical operation state. In this state, after the occurrence of an initial fault or disturbance, cascading outages could cause a blackout (e.g. [6]). An important consequence of the SOC is that occurrences of small and large blackouts are associated each other (e.g. [7]). Therefore, the delivery of required control actions should be carefully evaluated because of counter-intuitive effects of opposing forces in the dynamics of complex systems.

The different aspects of the blackouts complexity could be investigated in different time scales, namely, long-term, short-term, and transient dynamics [6]. Concerning the long-term dynamic, in [8]–[10] it has been investigated the role of load growth and engineering responses (including upgrades of generation and transmission systems) as external opposing forces to evaluate the system margins from critical loading in monthly or yearly time scales. The short-term dynamic in the range between several minutes to an hour, represents the internal system driving forces and can be associated to the load flow calculation [9]–[11]. The transient dynamics from milliseconds to seconds represents the inductive factor initiated by transient instability subsequent to large disturbances. The successive transient dynamics may cause abrupt outages [12].

Various methods have been proposed to model and analyze different aspects of blackouts in long-term, short-term and transient dynamics, such as, hidden failure model [8], OPA (ORNL-PSerc-Alaska) model [9], CASCADE model [13], Manchester model [11], Optimal Power Flow (OPF) based model [10] and OPF Transient Stability (OTS) model [12].

In this paper we focus on the short-term dynamics and specifically investigate the complexity of blackouts concerning the spinning reserve and frequency control. The main idea is to study the complexity of blackouts regarding the counteraction of the spinning reserve and the load shedding (including load curtailment and under-frequency load shedding) and their impacts on the cascading outages. In traditional approaches, regardless cascading outages, it is considered that the higher amount of the spinning reserve leads to the higher system security. Whereas, in one hand, less amount of spinning reserve may cause successive actions of under-frequency load shedding which increase the number of small blackouts. On the other hand, excessive amount of spinning reserve avoids the operation of the under-frequency load shedding and decreases the probability of small blackouts. However, it can increase the probability of line overloads triggering cascading outages and consequent large blackouts.

In order to study the aforementioned phenomena, a blackout risk analysis method based on Monte Carlo Simulation (MCS) is proposed. It takes into account the following aspects: a) the effects of cascading outages due to the overloading and hidden failure of transmission system, b) the response of primary frequency control of generation units to the power imbalance in each step of cascading outages.

In view of what above, the proposed model aims at effectively show the interaction between spinning reserve and load shedding as opposing forces in short-term dynamics criticality.

The structure of the paper is the following: section II describes the blackout risk assessment methodology, section III illustrates and discusses the simulation results with reference to the IEEE 118 bus test system considered as an interconnected network with three main areas.

II. BLACKOUT RISK ASSESSMENT METHOD

The evaluated blackout risk should demonstrate the power law distribution in different measures of the blackout size [7]. For this purpose, this section describes a statistical method aimed at numerically evaluate the risk of cascading blackouts regarding the spinning reserve and the frequency control in the power systems. The method considers the following elements: a) the effects of cascading outages due to overloads and hidden failure of protection systems, b) the response of primary frequency control of the generating units to power imbalance (i.e. frequency deviation). It must be noted that this model represents some of the main important mechanisms associated to blackout dynamics. The other concomitant mechanisms, such as voltage excursions and collapse, transient instability, are not taken into consideration. Generally, these mechanisms don’t impose high impact on the spinning reserve and the frequency control procedure.

The flowchart of the proposed procedure for the blackout risk assessment is shown in Fig. 1.

For the blackout risk assessment purpose, the MCS is applied to provide contingency scenarios containing both generation and transmission outages. The system states are derived by sampling the state of each component based on the probability of its availability [15]. One of the merits of the MCS method is that it has the ability to look beyond the probable contingencies taking into account rare, but significant, events [16]. Moreover, the dagger sampling is used as a variance reduction technique to simulate the rare event cases and to improve the performance of the MCS [17]. This method is appropriate for two state variables and small probability events [18]. In this sampling method, for each component with failure probability p, a single failure is randomly selected within each $1/p$ trials. Hence, only one random number determines the state of the component for $1/p$ trials.

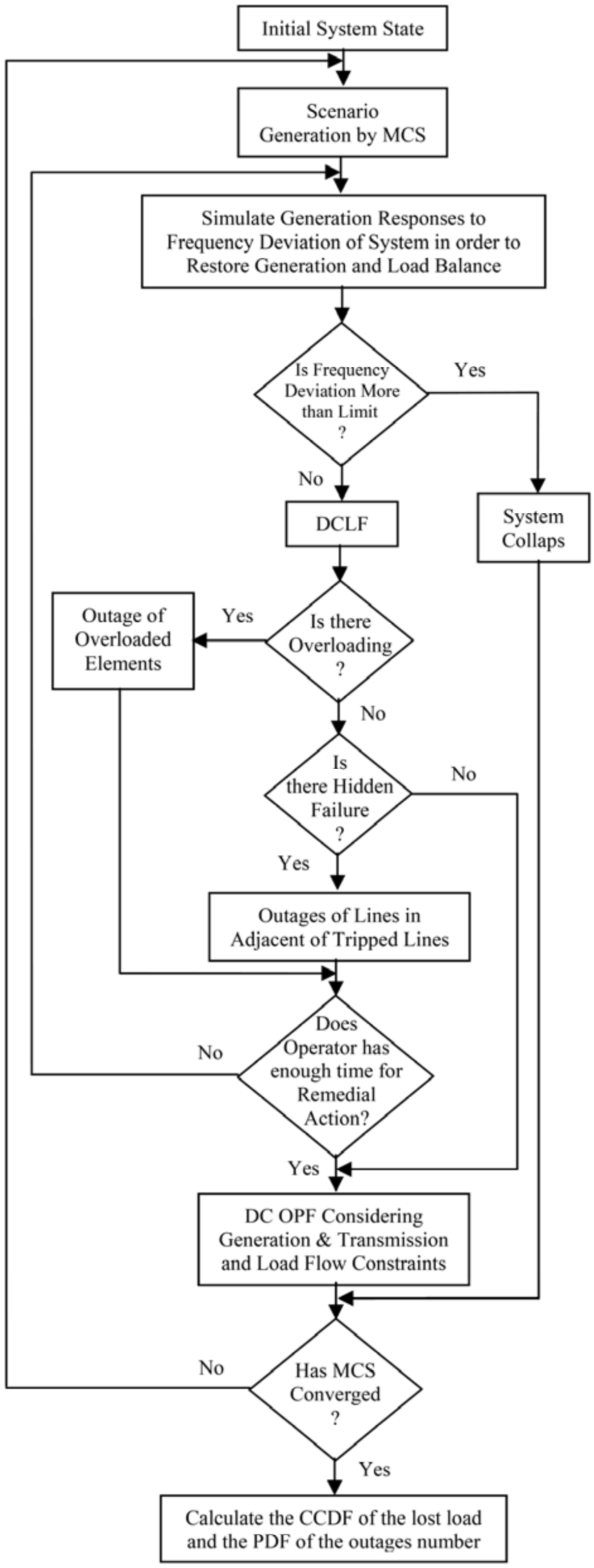

Figure 1. Flowchart of the proposed blackout risk assessment method.

The contingency scenarios construct the system states and model the initial event. In the simulation procedure, after the initial event or after each step of cascading outages, there may be a power imbalance and consequently a frequency deviation in the system. The frequency deviation spreads uniformly in the system and all the generators with primary frequency control respond to this power imbalance. A distributed slack bus model is considered in such a way that all of the remaining dispatched generating units share the power imbalance according to their droop frequency-control characteristics. It is noteworthy that, when the frequency deviation in the system (or in each island of the system after cascading outages and system separation) exceeds or drops 5% of the nominal frequency (±2.5 Hz in 50 Hz), all the generators in this area trip and the system collapses [19].

Whenever the frequency deviation is in the allowed range (i.e. for a 50 Hz system between 47.5 Hz and 52.5 Hz), but the available capacities of the synchronized generating units are unable to satisfy the load, a frequency load shedding scheme uniformly disconnects the amount of the load to reach a new power balance. After the generation and load balance is restored, a linearized load flow (DCLF) is applied to calculate the power flow and the transmission loading in each step of the cascading outages.

The outage of overloaded lines is one of the most important mechanisms in the power system blackouts. Moreover, the protection system has an undetected defect that remains dormant until an abnormal operating condition is reached. This state is often referred as 'hidden failure'. In order to consider the effect of hidden failure in cascading outages, it is assumed that each transmission line has a different flow-dependent probability of incorrect trip. This characteristic is modeled as an increasing function of the line flow which is seen by the line protective relay. As shown in Fig. 2, this probability (P_r) is small and equal to 0.01 for line flow lower than the line limit. This probability increases in proportion to the line flow between 1 and 1.4 times of the line limit [8]. The lines that loaded more than 1.4 times of the line limit (overloaded lines) trips. It worth to mention that the hidden failures can only occur whenever there is not any overloaded line. Also, the lines which are connected to the last tripped lines are exposed to the hidden failure of protection system according to the obtained probability from Fig. 2.

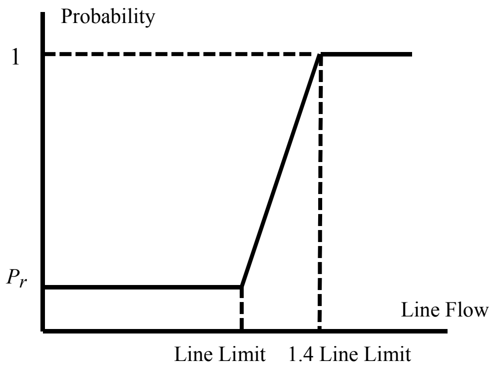

Figure 2. Probability of incorrect line tripping [8].

As above-mentioned, after each step of cascading outage, power generation and consumption balance would be restored mainly through the generators primary frequency response. These generating units reach their new operating points typically in tens of seconds. Therefore, the operator has the opportunity to implement some remedial actions and minimize the amount of lost load, after several steps of cascading outages. Investigation on the cascading dynamics of the power system blackouts in [8] shows that this model is appropriate to demonstrate the power law distribution of the blackouts size. Hence, the model of operators' response to contingencies is considered as a linearized OPF (DC OPF). The aim of the DC OPF is the minimization of the lost load through re-dispatching the generating units and shedding some loads. This DC OPF is performed once after the third step of cascading outages. The DC OPF is accomplished using simplex algorithm of Linear Programming (LP).

In each step of lines outage, if the system is divided into multiple islands, the simulation would be separately performed for each island. It is assumed that each island continue its operation under this condition considering its own constraints.

After simulating each scenario, the obtained amount of lost loads and the number of transmission component outages are utilized to evaluate the risk of blackout. For this purpose, the Complementary Cumulative Distribution Function (CCDF) of the lost load is calculated simply by ranking the lost load data and then scaling the ranked data. Also, the Probability Distribution Function (PDF) of the number of transmission component outages, as a discrete random variable, is calculated simply by assigning a probability to each possible value such that the total probability for all number of outages is equal to 1.

It is worth noting that, in general, for the cumulative probability associated with a particular quantity (e.g. lost load), sufficient number of the MCS samples should be calculated to ensure a specific level of accuracy ($\pm\delta$) associated to a confidence level (α). The accuracy level is used as the stopping criteria for the MCS. The percentiles closer to the 50^{th} percentile of an output distribution will reach a higher level of accuracy relatively far quicker than percentiles towards the tails. The proposed method in [20] ensures the required level of accuracy associated with a value x by determining what fraction of the samples fell at or above x. If so far we have had n samples of MCS and s have fallen at or above x, the cumulative percentile (P_x) can be estimated as $P_x=s/n$. Then, by using (1) and monitoring s and n we can determine whether the required level of accuracy is obtained. The variable x could be considered for the lost load as well as the number of outages.

$$\delta = z.\sqrt{\frac{P_x.(1-P_x)}{n}} \tag{1}$$

where z is 1.96, 2.56 and 3.29 for 95%, 99% and 99.9% of the confidence level, respectively.

III. Simulations and Discussions

The aforementioned complexity in the spinning reserve and frequency control is investigated in the IEEE 118 bus system as an interconnected system with three areas, shown in Fig. 3. The detailed data of generation, load, and the transmission system are given in [21]. The proposed blackout risk analysis method is applied for each area separately as well as for the interconnected system. Different amounts of spinning reserve are specified for each one of the four study cases. Then, the risks of blackout in each area and in the interconnected system are compared using the distribution of the blackout size and the number of transmission component outages. For this purpose, the CCDF of the lost load data and the PDF of the number of transmission outages are calculated. The CCDF of the lost load and the PDF of the outage numbers are plotted in the log-log and log-linear axes, respectively, to effectively illustrate the power law region in the distributions. For the convenience of comparing different systems, the outage power divided by the total load, as a normalized blackout indicator, is used in this study.

The amount of generation and the maximum available spinning reserve for each area is given in Table I. The simulations are performed for the four study cases with different amount of spinning reserve. The spinning reserves (R) are presented in percentage of the total capacity of generators. The spinning reserve is allocated based on the remained capacity of each generator.

It should be noted that for each area, the neighboring areas' network beyond the interconnections are modeled by an active power injection. In this way, each interconnection line is modeled by a consumption or generation.

In order to provide the stopping criteria for the MCS using (1), the value x should be defined for any output quantity. The value of x shows the percentile of the data which ensured us about the accuracy level. Since in this paper we derive the CCDF of the lost load and the PDF of the outages number, two different values are specified x_c and x_p, respectively. These values for each study case are obtained through sensitivity analysis and the results are given in Table II. x_c is given in the lost load divided by the total load and x_p is given in the number of outages. Note that all the simulations come with 99% of the confidence level.

TABLE I. GENERATION AND SPINNING RESERVE OF EACH AREA

	Generation (MW)	Maximum Available Spinning Reserve (MW)
Area A	1076	500
Area B	1866.53	1024.20
Area C	1547.84	700

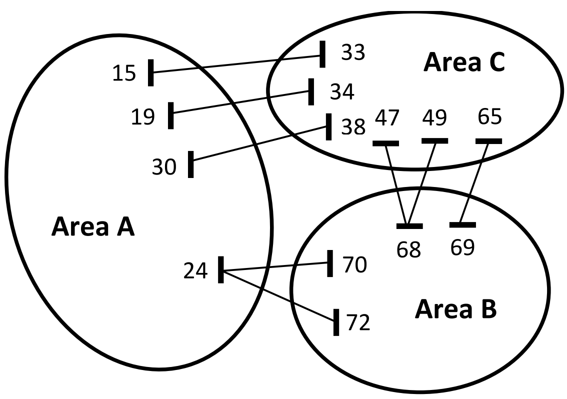

Figure 3. IEEE 118 bus system with three areas.

Moreover, the power law distribution of the lost load CCDF and the number of outages PDF could be effectively demonstrated by obtaining accuracy level (δ) lower than 0.001 and 0.0005, respectively. The required samples of the MCS to obtain the requested accuracy level are given in Table III. As an example, in the interconnected system case study with R_{max}, for the CCDF of the lost load, the confidence interval associated with this accuracy level is shown in Fig. 4. The results have been obtained with 940000 MCS iteration according to Table III. It should be noted that this case is the worst case for the accuracy level among the other case studies.

The obtained results of the PDF of the number of outages for Area A, B, C and the interconnected system are given in Fig.5, Fig. 6, Fig. 7, and Fig. 8, respectively. These figures effectively demonstrate the power law distribution of the PDF of the number of outages. Generally, as the amount of reserves increase, the probability of higher number of outages increases. This behavior is more explicit in Area B in comparison with the other areas. The reason is the higher amount of the spinning reserve in Area B. However, the interconnection of the areas intensifies this complex behavior as depicted in Fig. 8. Thus, in the interconnected system this complexity should receive more consideration.

The CCDF of the lost load data for Area A, B, C and the interconnected system are given in Fig. 9, Fig. 10, Fig. 11, and Fig. 12, respectively. As it can be seen, the obtained CCDFs show the power law distribution behavior.

TABLE II. THE ENSURED PERCENTILE

x	Lost Load / Total Load (x_c)				Number of Outages (x_p)			
R	*Area A*	*Area B*	*Area C*	*Interc*	*Area A*	*Area B*	*Area C*	*Interc*
5%	0.6	0.5	0.53	0.38	16	10	16	10
25%	0.54	0.4	0.6	0.43	16	9	16	16
max%	0.45	0.45	0.48	0.43	16	11	16	16

TABLE III. NUMBER OF SAMPLES TO OBTAIN THE REQUIRED ACCURACY

$\times 10^5$	Lost Load				Number of Outages			
R	*Area A*	*Area B*	*Area C*	*Interc*	*Area A*	*Area B*	*Area C*	*Interc*
5%	5.3	3.8	4	8	5.3	5.3	6.5	6.4
25%	4.7	2.2	1.8	0.6	5.3	5	6	6.4
max%	3.2	0.1	0.2	9.4[a]	3.1	7	6	7

a. The interconnected system case study with R_{max} requires 0.00008 accuracy level.

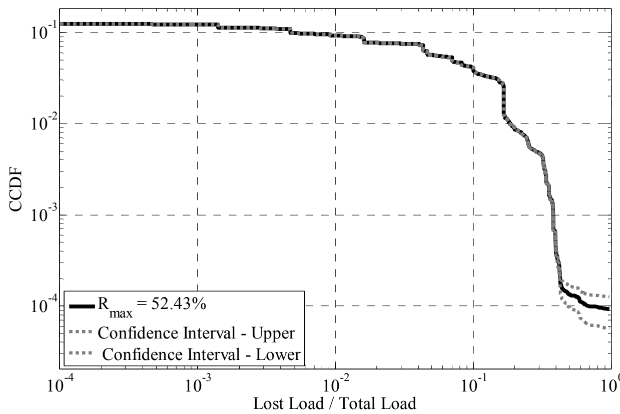

Figure 4. The confidence interval of the interconnected system case study.

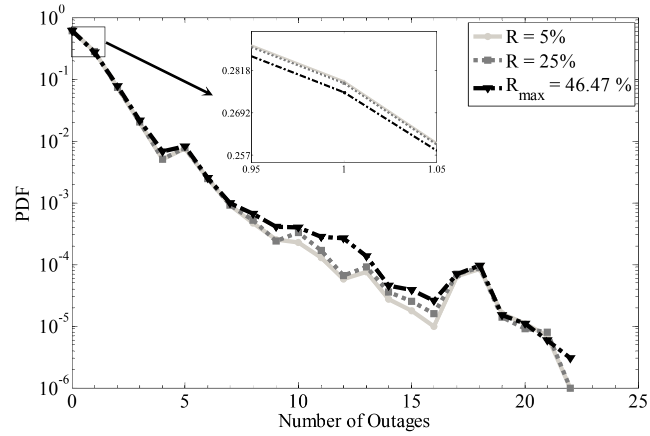

Figure 5. PDF of the number of outages for Area A.

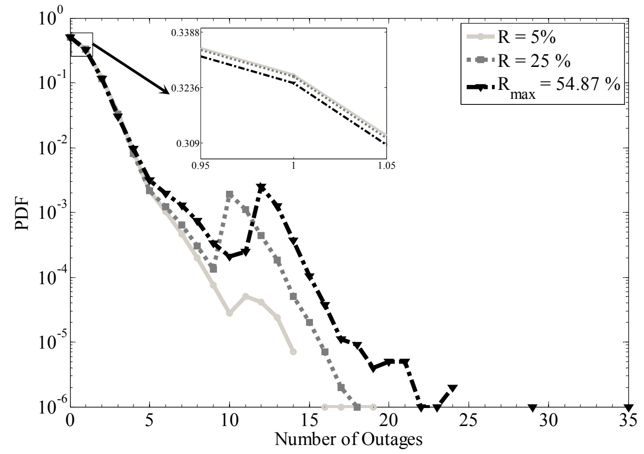

Figure 6. PDF of the number of outages for Area B.

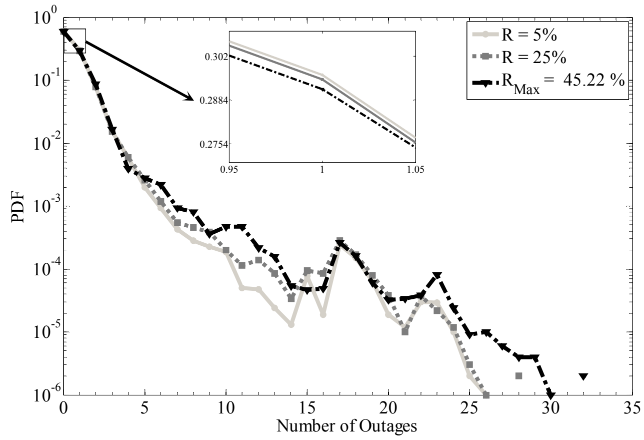

Figure 7. PDF of the number of outages for Area C.

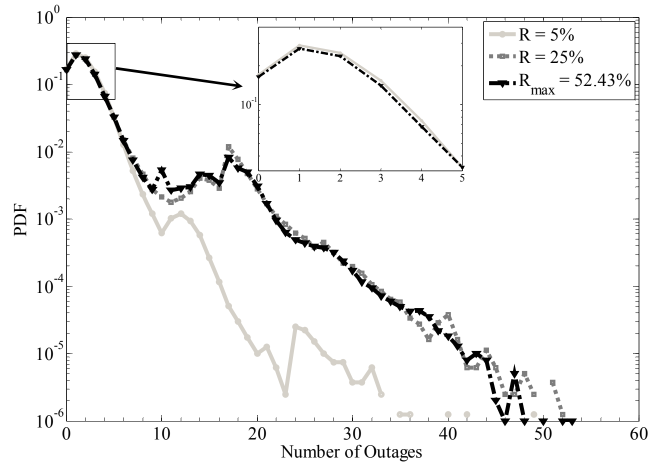

Figure 8. PDF of the number of outages for interconnected system.

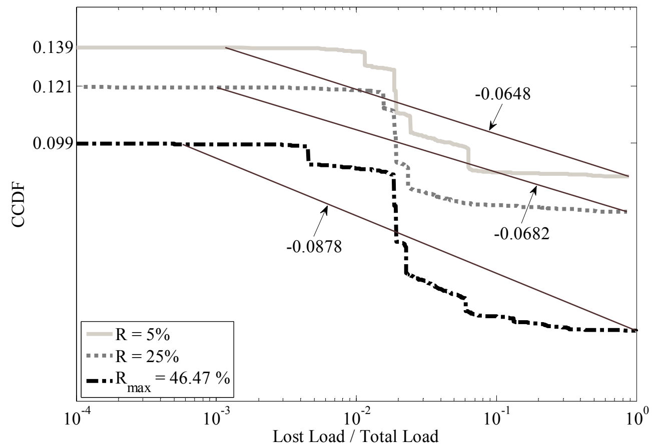

Figure 9. CCDF of the lost load for Area A.

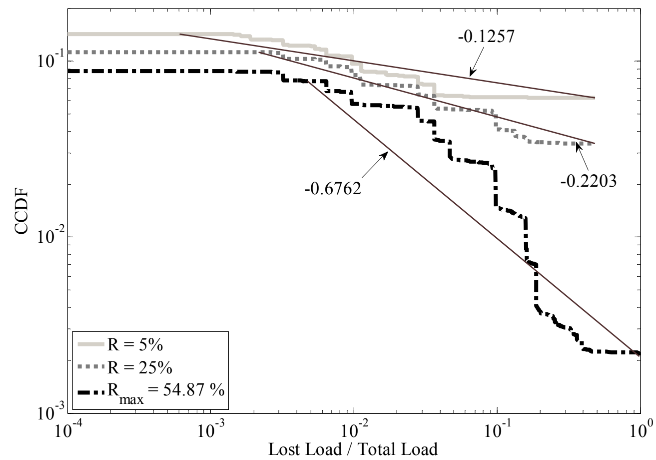

Figure 10. CCDF of the lost load for Area B.

The slope of the CCDF could be used to show the number of events in the power law region. The higher slopes demonstrate the higher number of events. According to Fig. 9–12, the higher amount of the reserve leads to higher slope of CCDF in the power law region and consequently increases the probability of large blackouts. This behavior becomes more significant in the interconnected system as illustrated in Fig. 12. These results confirm the obtained results from the PDF of the number of outages.

It should be noted that the CCDF of the lost load starts at different values. This value shows the total number of scenarios with lost load per total number of scenarios (probability of scenarios with lost load). For instance in Fig. 9, the probability of scenarios with lost load considering the reserve 5%, 25% and 46.47% are 0.139 , 0.121 and 0.099,

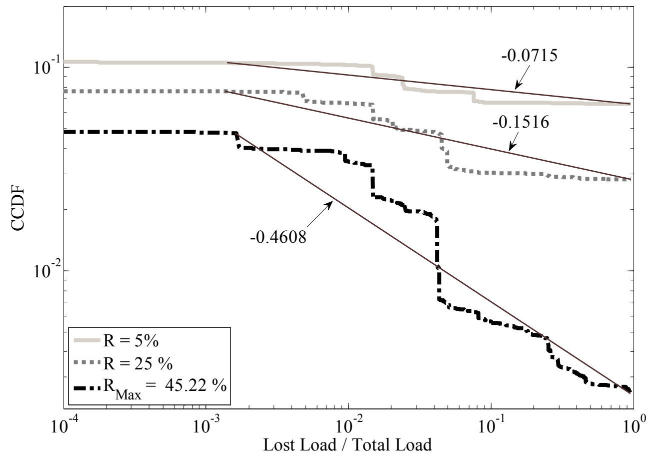

Figure 11. CCDF of the lost load for Area C.

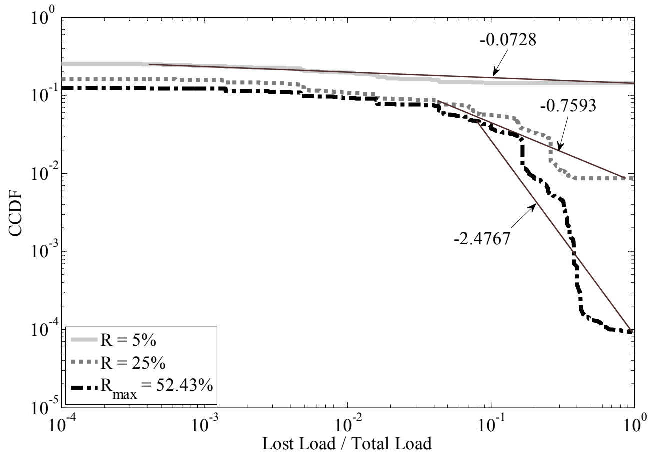

Figure 12. CCDF of the lost load for interconnected system.

respectively. In all the study cases, as illustrated in Fig. 9–12, the higher amount of the spinning reserve decreases the number of scenarios with lost load. It means that the higher spinning reserve decreases the number of small blackouts, because previously it is demonstrated that the higher spinning reserve increases the number of large blackouts.

IV. CONCLUSION

The paper has investigated the dependency of blackouts regarding the spinning reserve and frequency control in the system. At first, it is shown that the complexity exists in short-term dynamics between under-frequency load shedding and spinning reserve, as the opposing forces. Secondly it is shown that this complexity becomes more significant in the interconnected power system. Moreover, it is illustrated that the decrease of the amount of spinning reserve increases the number of under-frequency load shedding which increase the number of the small blackouts. As a counter effect, the higher amounts of spinning reserve increase the probability of overloading and cascading outages and consequently large blackouts.

The main conclusion of the paper is that this specific complex behavior should be considered in the spinning reserve allocation of interconnected systems to prevent the risk of large blackouts. In particular, additional constraints should be taken into account in the operation of interconnected power systems in order to control the participation of each area in the spinning reserve provision.

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