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# A novel method for the Approximation of risk of Blackout in operational conditions

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UNIVERSITÉ PARIS EST

THÈSE DE DOCTORAT

PAR

URREGO AGUDELO Lilliam

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A novel method for the approximation of  
risk of blackout in operational conditions

---

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November 2016

## *Abstract*

### **A novel method for the Approximation of risk of "Blackout" in operational conditions.**

The electricity industry can be characterized by several risks: regulatory, adequacy, human error, etc. One of the most outstanding aspects, because of their impact, is related to not supply demand (DNS).

To avoid these DNS problems: cascading failures or blackouts, much has been done on equipment reliability, security of the electrical systems, asset management, the learned lessons of the big events, contingency plans, and development of monitoring systems etc.

To prevent cascading failures, particularly in reliability studies, determinist criteria were applied, such as N-1, which allows to avoid the initial event of failure in the planning and operation of the system. In general, analysis tools for these preventive actions are applied separately for the planning and for the system operation of an electric power. After a cascading failure, considerable efforts must be done to analyze faults to minimize the possibility of a similar event.

In spite of all these efforts, blackouts or large cascading failures still happen, although events are considered to be rare due to the efforts of the industry. Indeed, it is a challenge from the point of view of analysis and simulation, due to the large number of possible interactions and their diversity and complexity, to obtain a good prediction of a situation. Moreover, effective methods for understanding this phenomenon, and to mitigate the cascading failures are not developed yet.

In our work, a new methodology is proposed to estimate the blackout risk using complex systems models. This approach is based on the use of variables that can be precursors of a DNS event. In other terms, it is based on the study of the dependence or correlation

between the variables involved in the blackout risk, and the self-organized criticality (SOC) property of complex systems.

Once the SOC conditions are determined, a direct current statistical power flow model DC SPFM was executed to simulate the behavior of the system and its variables for the performance of the electrical system. Simulations results were compared to the real operation behavior of the electrical power system.

The DC power flow is a simplified model, which represents the complex phenomenon in a simple way, however neglects some aspects of the events of operation of the system that can happen in blackouts. The representation of cascading failures and evolution of the network in a simple model allows the analysis of the temporary relations in the operation of electrical networks, besides the interaction between reliability of short-term and long-term (with improvements network). The process of network improvement can be understood like a response or reaction of the system to its reliability requirements. This methodology is focused on the operational planning of the following day (day ahead market), but it can be applied to other time scales, example expansion planning.

The proposed method for analyzing the risk of blackout is a technical based approach that does not include external variables like human factors, information technology, and communications or procedural failures that can cause the blackout. Keep in mind that the events that cause blackouts often are a combination or the sequence of causes associated with different factors, the proposed method could be complemented by other elements that analyze the external variables to include in addition to the technical issues.

The results show that the complex behavior with a power law and the Hurst index is greater than 0.5. The simulations based on our model have the same behavior as the real behavior of the system.

For using the complexity theory, the SOC conditions must be established for the day ahead analyzed market. Then an inverse simulation is executed, where the endpoint of the simulation is the current situation of the system, and allows the system to evolve and meet the requisites of criticality auto-organized in a desired point of operation.

After simulating the criterion of reliability used in the operation of the electrical system for cascading failures, they are validated by historical failures obtained from the electrical

system. These results, allow the identification of lines with the biggest probability to fail, the sequence of associate events, and what simulations of actions of operation or expansion, can reduce the risk of failures of the transmission network.

In the power system, the possible advantage of this methodology in the operative process is to include the risk information in decision making. Advantages expected for the electrical network are the appropriate evaluation of the risk of the network, the increase the reliability of the system (probabilistic analysis), and a progress of the planning of the risk of the day ahead (holistic analysis) and situational awareness.

Future work should be focused on better modeling and evaluation of cascading outages from the steady-state and transient stability points of view.

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## Resumen

### Metodología de estimación del riesgo apagón en la operación de los sistemas eléctricos

La industria eléctrica se puede caracterizar por varios riesgos, el regulatorio, suministro errores humanos etc. Uno de los más importantes, debido a su impacto es el relacionado con la demanda no suministrada (DNS).

Para evitar la DNS: fallas en cascada o apagones, se ha realizado bastante en la confiabilidad de los equipos, seguridad de los sistemas eléctrico, gestión de activos, en las lecciones aprendidas de los grandes eventos, planes de contingencia y desarrollo de sistemas de monitoreo etc

Para prevenir las fallas en cascada en los estudios de confiabilidad, se aplican los criterios determinísticos, tales como el N-1, el cual permite evitar el evento inicial de falla en la planeación y operación del sistema. En general, las herramientas de análisis para las acciones preventivas son aplicadas de forma separada para la planeación y operación del sistema en los sistemas de potencia. Después de una falla en cascada, se deben realizar esfuerzos considerables para analizar las fallas y minimizar la posibilidad de eventos similares.

A pesar de todos estos esfuerzos, los apagones o grandes fallas en cascada aun ocurren, aunque los eventos son considerados raros debido a los esfuerzos de la industria. En efecto, es un reto para el análisis y la simulación, debido al gran número de posibles iteraciones y su diversidad y complejidad para obtener una buena predicción de la situación. Además aún no han sido desarrollado métodos efectivos para el entendimiento y la mitigación de las fallas en cascada, en forma holística.

En este trabajo, una metodología es propuesta para estimar el riesgo del apagón usando modelos de sistemas complejos, está basado en el uso de variables que pueden ser precursoras de un evento que ocasione DNS. En otras palabras, está basado en la dependencia entre algunas variables involucradas en el riesgo apagón usando las propiedades de los sistemas complejos auto-organizados críticos (SOC).

Una vez que las condiciones SOC son determinadas, con un modelo de flujo de carga estadístico se simula el comportamiento del sistema y el desempeño de las variables del sistema eléctrico. Los resultados de las simulaciones fueron comparados con la operación real del sistema eléctrico colombiano.

El flujo de carga DC es un modelo simplificado, que representa un fenómeno complejo de una manera simple, sin embargo deja de lado algunos aspectos de los eventos de falla que pueden suceder en los apagones. La representación de las fallas en cascada y la evolución de la red en un modelo simple, permite el análisis de la relación temporal de las redes eléctricas, además la interacción entre la confiabilidad de corto y mediano plazo. El proceso de mejora de la red puede ser visto como una respuesta a los requerimientos de confiabilidad del sistema. Esta metodología está focalizada en la planeación de la operación del siguiente día, pero puede ser aplicada a otras escalas de tiempo, por ejemplo la planeación de la expansión.

La metodología propuesta para analizar el riesgo de apagón está basada en aspectos técnicos, no incluye variables externas como factores humanos, tecnologías de la información, comunicaciones o fallas de procedimientos que puedan causar los apagones. Estos eventos causales a menudo son una combinación o secuencia de causas asociadas con diferentes factores. Esta metodología puede ser complementada con otros elementos que analicen éstos factores adicionales a los técnicos.

Los resultados muestran un comportamiento complejo con una ley de potencia y un índice de Hurst mayor a 0.5. Las simulaciones realizadas tienen un comportamiento similar al comportamiento real histórico del sistema eléctrico.

Para usar la teoría compleja, las condiciones SOC deben ser establecidas para la planeación de la operación del día siguiente. Una simulación inversa es realizada, donde el punto final de la simulación es la situación actual del sistema, se le permite al sistema evolucionar y encontrar los requisitos de la criticidad auto-organizada en un punto de operación deseado.

Después se simula el criterio de confiabilidad usado en la operación de sistemas eléctricos para las fallas en cascada, se valida con la información histórica obtenida del sistema de potencia. Estos resultados permiten la identificación de líneas que tienen la más alta

probabilidad de fallar, la secuencia asociada a los eventos y que acciones de la operación o de la expansión pueden reducir el riesgo de fallas en la red de transmisión.

En el sistema de potencia, la posible ventaja de esta metodología en el proceso operativo es incluir la información de riesgo en la toma de decisiones. Las ventajas esperadas en la red eléctrica en una valoración del riesgo apropiada, el incremento de la confiabilidad del sistema (análisis probabilísticos) y una mejora en la planeación de la operación del día siguiente (análisis holístico) y de la conciencia situacional.

Los futuros trabajos debe focalizarse en mejorar el modelamiento y evaluación de las fallas en cascada de un estado estacionario a uno de estabilidad transitoria.



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## Résumé

### Une nouvelle méthode d'estimation des risques de Blackout en conditions opérationnelles

L'industrie électrique est généralement caractérisée par plusieurs risques : la réglementation, la capacité à transporter et distribuer, les erreurs humaines, ... L'un des aspects les plus remarquables et perceptibles, en raison de l'impact engendré, est lié à la « demande non desservie », c'est à dire, le « blackout ».

Afin d'éviter ces problèmes de défaillances en cascade ou blackouts, beaucoup de travaux, en particulier fondés sur les enseignements des événements majeurs historiques, ont permis de dégager des solutions pour fiabiliser les équipements, sécuriser au mieux les systèmes électriques. La maintenance prédictive des matériels, la gestion des contingences en situation d'urgence, le développement de systèmes de surveillance représentent de telles solutions.

Prévenir un phénomène de mise en cascade de pannes dans les études de fiabilité, passe par l'expression de critères déterministes comme la contingence (N-1) et permet d'éviter la défaillance initiale dans la planification du système et en mode opérationnel. En général, les outils d'analyse servant à définir ces actions préventives traitent de manière séparée la planification et l'exploitation d'un système électrique. Après une défaillance en cascade, des efforts considérables doivent en effet être déployés pour analyser les causes et minimiser la possibilité d'un événement similaire.

En dépit de tous ces efforts, des blackouts ou des grandes défaillances en cascade peuvent encore se produire, même si ces événements peuvent être considérés comme rares. Le défi alors à relever, tant en analyse qu'en simulation, est d'essayer d'estimer le risque d'un tel événement compte tenu de la complexité des interactions possibles dans un réseau électrique. De telles méthodes, permettant d'appréhender les phénomènes précurseurs et les prévenir ne sont pas encore complètement opérationnelles.

Dans notre travail, une méthodologie nouvelle est proposée pour estimer le risque de blackout en utilisant une approche issue de la modélisation des systèmes complexes. Cette approche est basée sur l'utilisation de variables qui peuvent être des précurseurs d'un événement de « demande non desservie ». En d'autres termes, l'étude de la dépendance ou des corrélations entre les variables impliquées dans le risque de blackout et la caractéristique de Criticalité Auto-Organisée (CAO ou SOC, « Self Organized Criticality ») des systèmes complexes permet d'envisager une estimation du risque de blackout.

Après avoir établi les conditions de mise en régime de criticalité auto-organisée, un modèle statistique de gestion des flux de puissance active (DC SPFM) est développé afin de simuler le comportement du réseau électrique et de ses variables environnementales et étudier ses performances. Une comparaison théorie / expérience a été réalisée en se basant sur des conditions de fonctionnement opérationnel d'un réseau électrique réel.

Le modèle DC SPFM est un modèle simplifié représentant l'interaction du réseau avec son environnement. Il néglige cependant certains aspects des événements pouvant se produire lors de blackouts. La représentation des défaillances en cascade et le modèle d'évolution simplifié du réseau électrique permet l'analyse des relations temporaires dans l'exploitation des réseaux électriques, tout en décrivant l'interaction entre la fiabilité à court terme et la fiabilité à long terme (avec une politique d'amélioration planifiée). Le processus d'amélioration du réseau peut alors être comprise comme une réponse ou une réaction du système à ses exigences de fiabilité. Cette méthodologie est axée sur la planification opérationnelle du lendemain (marché « day-ahead »), mais elle peut être appliquée à d'autres échelles de temps, comme la planification de l'extension du réseau par exemple.

La méthode proposée pour analyser le risque de blackout est une approche essentiellement technique et n'inclut pas les variables externes comme les facteurs humains, la technologie de l'information, les communications ou les défaillances de procédure qui peuvent être à l'origine de blackout. Il faut garder à l'esprit que les événements à l'origine des pannes sont souvent une combinaison ou une séquence de causes associées à différents facteurs. La méthode ainsi proposée pourrait être complétée par d'autres éléments analysant ces facteurs en vue de les inclure dans la description.

Les résultats expérimentaux montrent un comportement complexe en loi de puissance avec une mesure de l'exposant de Hurst supérieur à 0,5 de la distribution des pannes. Les simulations basées sur notre modèle retrouvent ce comportement et proposent de le quantifier.

En utilisant la théorie de la complexité, les conditions SOC doivent être établies pour l'analyse du marché du jour suivant. A la suite, une simulation inverse est exécutée où le point final de la simulation devient la situation actuelle du système et permet au système d'évoluer et de répondre aux conditions requises par la caractéristique de criticalité auto-organisée en un point de fonctionnement souhaité.

Après avoir simulé le critère de fiabilité utilisé dans l'exploitation du système électrique en condition de mise en cascade, l'analyse des défaillances historiques du système électrique permet de valider la démarche. Ces résultats permettent alors l'identification des lignes avec la plus grande probabilité de défaillance, la séquence des événements associés et quelles actions en exploitation ou en planification peuvent réduire le risque de défaillance du réseau électrique de transmission.

Un des avantages potentiels de cette méthodologie est d'inclure, en conditions opérationnelles, l'information liée aux risques du processus décisionnel. Les bénéfices attendus pour les opérateurs de réseau électrique sont l'évaluation appropriée des risques du réseau, l'augmentation de la fiabilité du système (analyse probabiliste) et une meilleure planification du risque pour le « jour suivant » (analyse holistique) et une meilleure connaissance de la situation.

Les travaux futurs se concentreront sur une meilleure modélisation et évaluation des défaillances en cascade en condition de régime établi et de stabilité transitoire.

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## List of Abbreviations

AC	Alternating Current
AGC	Automatic Generation Control
CAMS	Computing and Analytical Methods Subcommittee
CDF	Cumulative Distribution Function
CIGRE	International council on large electrical systems
CREG	<i>Comisión de regulación de energía y gas</i>
DC	Direct Current
DC	Direct Current
DC SPM	Direct Current Statistical Power Flow Model
DNS	Demand non supply
EPRI	Electric Power Research Institute
EPS	Electrical power system
GB	Great Britain
H	Hurst Index
HOT	Highly optimized tolerance
HPC	High Performance Computing
IEEE	Institute of Electrical and Electronics Engineers
KPI	Key Risk Indicator
LDA	Aggregate Loss Distribution Function
LDR	Long Range Dependence
LRD	Long Range Dependence
LT	Long Term
NERC	North American Electric Reliability Corporation
OPA	Oak Ridge-PSERC-Alaska
OPF eco	Optimal Power Flow Economical
ORNL	Oak Ridge National Laboratory
PDF	Probability Distribution Function

PES	Power & Energy Society
PSERC	Power System Engineering Research Centre
SOC	Self-Organized Criticality
TransCARE	Transmission Contingency Analysis and Reliability Evaluation
TRELSS	Transmission reliability evaluation of large scale systems
TSO	Transmission System Operator
UPME	<i>Unidad Planeación Minero Energética</i>
US	United States
USD	Dollar of United States
VaR	Value at Risk
XM	System Operator and Market Manager in Colombia

# Contents

<i>Abstract</i> .....	ii
Acknowledgements.....	xi
List of Figures .....	xvii
Introduction .....	xxi
1. Power system and blackout risk.....	1
1.1    Complexity of the electric power system .....	2
1.2    A cascading failure .....	4
1.3    Industry practice .....	7
1.4    Methods of analysis .....	8
1.4.1.    Power flow based analysis.....	9
1.4.2.    The hidden failure.....	12
1.4.3.    Resilience .....	12
1.4.4.    High-level probabilistic models .....	13
1.4.4.1.    CASCADE model .....	13
1.4.4.2.    Network theory approaches .....	14
1.4.5.    Critical components and high risk multiple contingencies.....	15
1.4.6.    Recognizing patterns .....	15
1.4.7.    Conventional reliability methods .....	16
1.5    Risk approach .....	16
1.5.1.    Emerging technologies .....	18
1.5.2.    Risk quantification approach.....	19
2. Design power network model based in Self Organized Criticality .....	22
2.1    Self-Organized Criticality.....	22
2.1.1.    In power systems .....	23
2.1.2.    In Colombian power systems. ....	28
2.1.2.1.    Colombian power system description.....	28
2.1.2.2.    Colombian database.....	29

2.2	Statistical analysis .....	32
2.2.1.	$\alpha$ -stable Laws Properties.....	32
2.2.2.	Particle Swarm Optimization for estimation of $\alpha$ -stable laws.....	33
2.2.3.	$\alpha$ -stable distribution for Colombian power system data.....	34
2.3	Estimation of VaR of demand not supplied in electric power systems .....	37
3.	Design of a simulation process to fit a power network behavior .....	47
3.1	Model general structure.....	48
3.2	Slow dynamics: Power network evolution.....	48
3.2.1.	Power demand and generation power evolution .....	49
3.2.2.	Network improvement strategy .....	51
3.2.2.1.	Immediate strategy approach.....	52
3.2.2.2.	Delayed strategy approach.....	52
3.2.3.	Generation economic dispatch (OPF eco).....	53
3.2.4.	Final load power demand shedding and/or generation power re-dispatching	54
3.2.5.	Identification of “power demand shedding” event .....	56
3.3	Fast dynamics: Cascade phenomena .....	56
3.3.1.	Line trip initial occurrence .....	56
3.3.1.1.	Overloaded line condition .....	56
3.3.1.2.	Overloaded line trip occurrence .....	57
3.3.2.	Power demand load shedding and/or generation power re-dispatching process .....	57
3.4	DC SPFM inputs and outputs summarize.....	58
3.4.1.	DC SPFM input parameters summarize .....	58
3.4.2.	DC SPFM outputs summarize .....	58
3.5	DC SPFM inputs from Colombian system.....	61
3.5.1.	Parameter for Transmission DC SPFM Model: .....	61
3.5.2.	Parameter for Demand DC SPFM Model: .....	64
3.5.3.	Parameter for generation DC SPFM Model: .....	66
3.5.4.	Parameter for line fault DC SPFM Model:.....	68
3.6	SOC Conditions Settings .....	69
3.6.1.	Cellular automata.....	71



3.6.1.1.	Local Phase.....	71
3.6.1.2.	Accumulation phase .....	72
3.6.1.3.	Transmission evolution capacity .....	72
3.6.1.4.	Determination of coefficient (local phase and accumulation phase) with respect to the observable (historical data).....	73
3.6.2.	Parameter associated with SOC conditions setting .....	74
3.6.2.1.	Physical point of view of SOC for power grid .....	75
3.6.2.2.	Assumptions from the Colombian power system.....	76
4.	Applications in day-ahead market in real power system. N-1 criteria.....	82
4.1	General results .....	83
4.2	Reliability criteria model .....	87
4.3	Other interesting results .....	90
4.3.1	Critical lines .....	91
4.3.2	Probability of fault on particular line .....	92
4.3.3	Sequence of events .....	93
5.	Conclusions.....	96
	References.....	98

# List of Figures

Figure 1-1 Electrical power system composed of several interacting between them.....	4
Figure 2-1 SOC Model – Sand Pile .....	24
Figure 2-2 Colombian transmission capacity evolution .....	27
Figure 2-3 Demand non supply (MWh) of each event.....	30
Figure 2-4 Distribution function of outages per hour.....	30
Figure 2-5 Cumulative Distribution Function of time restoring .....	31
Figure 2-6 Cumulative Distribution Function of DNS (KWh).....	31
Figure 2-7 Probability density function for different $\alpha$ .....	33
Figure 2-8 Kolmogorov Smirnov Criteria.....	34
Figure 2-9 Frequency distribution of events monthly .....	35
Figure 2-10 Real data & $\alpha$ -stable law, $\Delta t=30$ days, $\alpha=1.7$ .....	36
Figure 2-11: VaR and CVaR diagram. ....	37
Figure 2-12 Cost for the power losses level $k - C^k$ (UMPE).....	41
Figure 2-13 Monte-Carlo simulation process .....	42
Figure 2-14 Probability Distribution of Demand Not Supplied (MWh) .....	43
Figure 2-15 Probability Distribution of blackout cost monthly (US \$).....	43
Figure 2-16 Estimation of VaR for DNS cost versus $\Delta t$ .....	46
Figure 3-1 DC SPFM general algorithm .....	49
Figure 3-2 Evolution of mean power demand (a) and daily power demand (b) .....	50
Figure 3-3 Illustration of maximal power margin (a) and operational power margin (b) ....	51
Figure 3-4 Evolution of network total transmission capacity for immediate and delayed strategies .....	53
Figure 3-5. Example of a line loading rate dependent probability function $pfr1 = fLr$ ....	57
Figure 3-6. Parameters associated with transmission evolution.....	61
Figure 3-7 Evolution of the generation associated with system constraints against total ....	62
Figure 3-8. Transmission expansion evolution.....	63
Figure 3-9 combined effect of improve short-term and long-term network.....	64

Figure 3-10. Parameters associated with demand evolution .....	65
Figure 3-11. Evolution of demand and forecast .....	65
Figure 3-12 Parameters associated with generation evolution .....	67
Figure 3-13 Generation capacity evolution .....	68
Figure 3-14. Parameters associated with line fault.....	69
Figure 3-15 SOC regime of transition .....	70
Figure 3-16 Sand pile evolution: from ideal network to SOC regime network .....	70
Figure 3-17 Accumulation phase.....	72
Figure 3-18 Transmission capacity evolution in semi log.....	73
Figure 3-19 Local phase and accumulation phase respect to historical data.....	73
Figure 3-20: Evolution of total load power demand, total available generation and total transmission capacity power for day 1 .....	78
Figure 3-21 CDF of shed power demand Network Dispatch and for historical data .....	79
Figure 3-22 Evolution SOC parameter, $\tau$ and $\gamma$ . (a) Network lines mean loading rate and (b) its normalization with network total transmission capacity. (c) Ratio total transmission capacity over total power demand and (d) its normalization with network total transmission capacity.....	80
Figure 4-1 CDF of shed power demand for N-k contingency, three dispatches and for historical data.....	85
Figure 4-2 Model reliability criteria for electric power system .....	88
Figure 4-3 CDF of shed power demand during the 4 trajectories N-1 contingency simulation .....	88
Figure 4-4 Comparison between deterministic assumption and probabilistic criterion .....	90
Figure 4-5 Ratio between line capacity SOC limitation and line capacity thermal limitation: high ratio relative to line more often involved in power demand shed cascading phenomena during SOC condition setting process .....	91
Figure 4-6. Initial evidence of system reaction for improvements on critical lines .....	92
Figure 4-7 Sequence of cascading failure for Colombian power system .....	94

# List of tables

Table 2-1 Analogy between physical model and electrical model .....	25
Table 2-2 Statistics for frequency of events .....	34
Table 3-1 DC SPFM slow dynamics related input parameters .....	59
Table 3-2 DC SPFM fast dynamics related input parameters .....	59
Table 3-3 DC SPFM slow dynamics related outputs .....	60
Table 3-4 DC SPFM fast dynamics related outputs .....	60
Table 3-5 DC SPFM main input parameters .....	78
Table 4-1 One sequence of cascading failure for line 166 Colombian power system .....	94

*To my family in special to David*

# Introduction

Identification and quantification of operational risk is now a major issue for businesses and the academic community. Operational failures caused by people, internal or external fraud, human or technical error, have consequences for all types of businesses and potentially cause economic losses. External factors such as regulatory changes, social, political, and market are also a source of risk, therefore, identification and quantification of events that could lead to catastrophic losses are now a management challenge.

There are several risks that in the electricity sector characterize it such as, regulatory, power supply, equipment failure, human error etc. One of the results, for the impact they cause to materialize risks are associated with demand not supply (DNS) events, economic valuation and impact on customers, are the subject of multiple investigations. This research has three lines of work; the first attempts to model the performance of the power system using physical models (Dobson, et al., 2000; Carreras B. A, 2004)(I. Dobson, 2000; Dobson I., 2004; Doorman G., 2004; S. Mei, 2010). The second seeks to quantify customer interruption costs following different methodologies (CIGRE, 2001; M. Sullivan, 2009; UPME, 2004a; UPME, 2005; Eto J., 2008; R. Hickling, 2011). The third line of development is to integrate all corporate information risk management processes based on risk-Enterprise Risk Management - ERM (AS / NZS 1999, ISO 2009, ISO 2009).

Electrical power systems have worked hard to avoid DNS, cascading failures or blackouts, from equipment reliability, safety of electrical systems, asset management, lessons learned from major events, contingency plans, development of monitoring systems etc.

In preventing cascading failures, deterministic criteria are applied particularly in reliability studies, such as N-1 that help prevent the initial event of the failure in the planning and operation of the system; they analyze and mitigate failure caused by the overload and instabilities, and reliability of the individual components is improved. Overall analysis tools and simulation for these preventative actions are applied separately to planning and operation of electric power systems (EPS). After a cascading failure or power outage occurs, considerable efforts are made to analyze particular fault detail and improve the power system to minimize the possibility of a similar event.

Even with all these efforts to plan the SEP operation, blackouts or large cascading failures still happen. The events are considered rare in part because of the efforts of the industry. They present a challenge for the analysis and simulation, due to the large number of possible interactions and the diversity and complexity of these interactions that make it difficult to obtain a good prediction of the situation. The analysis of DNS records in several countries show that outages of all sizes can occur, in addition there is a substantial risk of the occurrence of large cascading failures. Additionally, current methods for direct understanding of the phenomenon and mitigating cascading failure are not yet fully developed.

The major blackouts typically involve many separate processes. Current tools focus on a single process or some of them and do not capture all possible interactions that can result. Although a complete detailed analysis of all possible processes and interactions is methodologically not feasible because of its complexity. The question is how to systematically simulate the possible interactions and also to cope with the huge number of unlikely interactions necessary to develop and test methods modeling and analysis, including probabilistic risk-based approaches that capture in cascading failures with the appropriate level in modeling detail. Some advances have been made in the simulations for a sample of initial failures, with an emphasis on causes associated with overloading of equipment and protective systems and have developed simple models for other processes, such as voltage collapse. Methods of incorporating events whose cause is the dynamic stability, operator actions and the effects of complex systems remain a challenge.

This document proposes a methodology to estimate the blackout risk using complex system models to improve decision making in the management of electrical power systems in operative conditions. The use of variables that may be precursors of a DNS event, is dependent or correlated between variables involved in the blackout risk. The use of complex systems, specifically self-organized criticality (SOC), can contribute in this regard with the statistical analysis of the data series of the DNS.

The VaR is done using the cost of rationing data from the Colombian system to estimate the cost of a blackout including economic variables that are put into the technical variables.

In addition, traditionally the risk grows with the root square of the time, but with a data series that has complex behavior, the grow rate is higher.

After complying with the SOC conditions regarding data independence and compliance with the complex behavior of the system, modeling the topology is carried out in detail the EPS in a direct current statistical power flow model (DC SPFM) in the complex area. These simulations provide information on the complex behavior of the variables of the electrical system management involved as well as some additional variables used in the operation thereof. Simulations are adjusted with real-time EPS behavior and some applications of the methodology proposed in some aspects of electric power systems.

This proposal developed a blackout risk from a technical approach and does not include external variables such as human factors, information technology, and communications or procedural failures that can cause the blackout. Keep in mind that the events that cause blackouts are often a combination or sequence of causes associated with different factors. This methodological proposal should be complemented with other analyses or with modified assumptions to include more than technical reasons.

Even from a technical point of view the present work is part of a DC load flow which is a general model that represents a complex phenomenon in a simple, fast, and traceable way. However neglected aspects of system operation such as power, time events, and other types of disturbances that can occur in blackouts (hidden failures in the protection system, dynamic voltage stability, transient stability and small signal, etc ..)

The work aims to represent of cascading failures and network evolution in a simple model to analyze the temporal relationships in the operation of power systems, interaction between reliability of short-term and long-term (with improvements network). The process of improving the network can be understood as a response or feedback, which adjusts system reliability.

For decision-making related to risk failure, it is necessary to take into account the time scales in which the evaluation is done, there are three major scales: 1) system operation time in real time; 2) operational planning, ie the day, week, or the month before operation day; and 3) long-term planning, in which changes to infrastructure or regulation are feasible. In the vicinity of real time, there is a limited set of actions available to manage



risk, but the consequences of bad decisions can be enormous. This work focuses on the operational planning of the previous day (day ahead market) but can be applied to other scales, which are well correlated.

The thesis is organized into four chapters, the first and second are a framework of the background and how the SOC system is done, in the third chapter the methodology used is documented. The fourth shows some application to N-1 criteria in day-ahead market in Colombian power system and finally the conclusions and recommendations

# 1. Power system and blackout risk

In large blackouts usually a complicated cascading chains of events is involved. Although not common they are very expensive for society. Estimates of direct costs of millions of dollars. There is also potential indirect costs such as social problems and propagation of failures to other infrastructure (communications, water supply, natural gas, and transportation). For example, Aug. 14, 2003 began as a fairly normal day in the eastern United States and Canada, unseen by nearly everyone, the grid began to degrade, starting with several isolated plants and line failures. Through a combination of unlikely events, in 23 minutes, nearly 50 million people in eastern North America lost power. The cost and human toll from the blackout was staggering. Millions of New York commuters walked home across the bridges out of Manhattan; millions elsewhere drove through traffic stopped by an absence of lights and signals. Hospitals and homes for the elderly scrambled to find temporary power. Businesses shut down, incurring an estimated \$6 billion in losses (Fox-Penner, 2005).

Due to this event a task force was formed between the United States and Canada, to establish the causes and recommendations (Liscouski, 2004) . The main causes were found to be, inadequate system understanding, inadequate situational awareness, inadequate tree trimming, and an inadequate level of support from the reliability coordinator.

For others big blackouts (Andersson, et al., 2005) Sweden and Eastern Denmark, September 23, 2003 the system was moderately loaded before the blackout but several system components were out of service due to maintenance. Even taking these scheduled outages into account the system was not stressed, after a cascading failure, in seconds, this islanded system collapsed in both voltage and frequency and thus resulted in a blackout. A total of 4700 MW of load was lost in Sweden (1.6 million people affected) and 1850 MW in Denmark (2.4 million people affected). In an Italian blackout on september 28, 2003 the primary cause was a tree flashover caused the tripping of a major tie-line between Italy and Switzerland.

The main recommendations were about:

- Regulation: Reliability standards should be made mandatory, enforceable and reviewed periodically, taking into account experiences from major system incidents. At a regulatory body level, the need for expenditure and investment for bulk system reliability (including investments in new technologies), and to continued promotion of ongoing industry and government funded research in the discipline of power systems engineering to meet the challenges of the ever growing and complex power grids around the world
- Technical: a improve reliability, use automatic load shedding , improve training for operators, evaluate and adopt better real-time tools, reevaluate its existing reliability standards, resolving issues related to zone 3 relays.

Latest blackouts have been analyzed by the CIGRE working group C2-21 (Ben, et al., 2014), in which the main causes associated with these natural phenomena, communications failures, errors in design and applications, operator errors and primary equipment failure.

Among the lessons learned from studying blackouts is that one of the main causes is a lack of understanding of the power system due to its complexity, and that the recommendations given after a blackout are related to reliability standards. Complexity and reliability are two key concepts in this methodology, and they will be used to identify blackout risk in operational conditions.

This chapter will explore the definitions of complexity, as well as cascading failures, as an explication of blackout risk. In addition, we will review industry practice and methods of analysis related to managing cascading failures. Finally, a focus of this work is to describe the risk analysis approach.

## **1.1 Complexity of the electric power system**

For better power system understanding, in systems operating in several time scales, like power systems, land and air transport schemes or production line, the quantification of risk has been generally done from a technical point of view, as the reliability of system, or the mechanisms of protection, defense plans, investments in monitoring and diagnosis, improved maintenance processes or network expansion (Cepin, 2011;

Vaiman, et al., 2012) and there is few evidence that these assessments are integrated with other systems and support optimal decisions from the system for risk management which can be so efficient for the complete system (Mei S., 2010 ).

Electrical power systems (EPS) in particular can be considered complex systems, which have traditionally been analyzed as the sum of the behavior of individual elements, in different time scales, with some relationships to each other, the overall system analysis related to both the behavior of components internally, (the various processes that develop the system) with external components that influence it, are issues in development (Mei S., 2010 ; Anderson G et, 2004; Dobson, et al., 2002).

An electrical power system is composed of several subsystems (Mei S., 2010 ) interacting with each other, The first takes place where energy conversion, transformation, transmission, distribution and consumption, the chain supplying EPS, the second consists of the control systems for safe operation and economic stability and the third market associated with energy, and hedging transactions whose underlying is the price, margins, availability, reliability or capacity of energy, Figure 1-1.

There have been several efforts to assess the cost of power interruptions for customers. A bottom-up approach for estimating the cost of power interruptions (Hamachi & Eto, 2006), the estimate is based on a survey of selected customer groups asking these customers to estimate costs for several distinct power-outage scenarios. (Wenyuan, 2006).

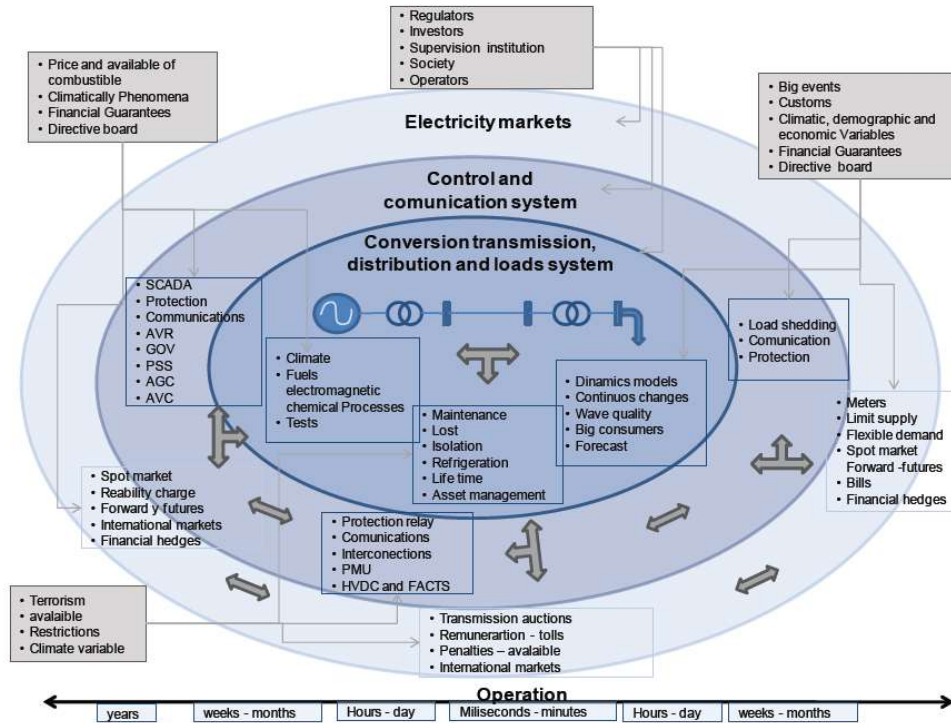


Figure 1-1 Electrical power system composed of several interacting between them

## 1.2 A cascading failure

A cascading failure can be define as a sequence of dependent failures of individual components that successively weakens the power system (Dobson, et al., 2008), including failures in the software, procedures, people whom planning, operate, and regulate the power system.

Exist several challenges for asses a cascading failure, a power system has thousands components than could failure, consider checking combinations of failures in a power system model with  $n$  components of  $k$  successive failures, requires  $n - k$  cases to be checked, which rapidly becomes infeasible even with the fastest computers for modest values of  $k$  (single failures like N-1 criteria requires only  $n$  cases to be checked).

A cascading failure occurs during all periods, although could be a tendency that all blackouts happen during peak load days (because it is the maximum system stress), the reality is that many blackouts occur during other periods because the grid has facilities that are out of service for maintenance, repair, new construction or replacement. A

probability of a large cascading failure (blackout) can be increase by the combination of these outages and dynamic characteristics of the system.

As observed in Figure 1-1, a cascading failure analysis is complicated because it could be diversity of failures and the many different mechanisms by which failures can interact. Modeling requirements and timescales (milliseconds for electromechanical effects and tens of minutes for voltage support and thermal heating) is a big challenge, which may be increased by the development of new technologies.

A cascading failure has uncertainties associated with the initial events, the sequence of dependent events after the initial event and the impact of a blackout with a known size. The cause of initial evens can be many different, in (Ben, et al., 2014), propose a set of categories, primary equipment failure, design and application error, secondary equipment failure, communication and/or control system failures, natural phenomena, operator error, error in maintenance, security related, inadequate investment, excessive risk taking and/or inappropriate risk management and others. The initial event, can be considered at random, nevertheless the report found that the most of event analyzed were caused by natural phenomena, followed by communication failures, design and application error, operator error and primary equipment failure.

The sequence of dependent events are a combinations of several of types of failures and interactions, including cascading overloads, failures of protection equipment, transient instability, reactive power problems and voltage collapse, rotor angle stability, frequency stability, rare and unusual failures or combinations of failures.

The power industry has worked in power system security analysis has so far focused on only one of these aspects of cascading failures, and so hard to avoid cascading blackouts, with a measurements for the causes and some of them for consequences (Ben, et al., 2014; Bell, et al., 2010). While this approach has made possible impressive advances in understanding of each aspect, it does not provide a framework for understanding the overall phenomenon.

An underlying question is whether you can vary the approach does not prevent blackout and evaluate the course with some probability and focus efforts on investment and maintenance paths greater impact and frequency in a simulation.

Properties of cascading failure can be found by analysis; some blackout statistics show that the probability distribution from blackout data exhibits a power law region with an exponent between  $-1$  and  $-2$  (Carreras, et al., 2000, Carreras, et al., 2004). The power law implies that blackouts of all sizes can occur. Similar power law dependences of blackout probability with blackout size are observed in U.S. (Carreras, et al., 2004), Sweden (Holmgren & Molin, 2006), Norway (Bakke, et al., 2006), New Zealand (Ancell, et al., 2005), and China (Weng, et al., 2006). The power law data suggests that large blackouts are much more likely than might be expected from the common probability distributions that have exponential tails. The heavy tails in distributions of blackout size can be qualitatively attributed to the dependency of events in a cascading blackout. As the blackout progresses, the power system usually becomes more stressed, and it becomes more likely that further events will happen. This weakening of the power system as events occur makes it more likely that a smaller blackout will evolve into a larger blackout (Dobson, et al., 2008).

The criticality, cascading blackouts become more likely as the power system becomes stressed. As the load increases, the average blackout size increases very slowly, until, at a loading called the critical loading, there is a sharp change and average blackout size starts increasing much more quickly. In critical loading, there is a power law in the probability distribution of blackout size (Carreras, et al., 2002)(Nedic, et al., 2006). The critical loading defines a reference point for increasing risk of cascading failure; there have been several approaches to assess the probability of cascading blackouts as load increases. The average propagation of failures and the size of the initial disturbance from simulated or real data and then using these estimated parameters in branching process models to predict the distribution of blackout size (Dobson, et al., 2008). Some probabilistic techniques are used for give a more reliable indication of the level of stress in a power system, calculating a probabilistic indicator of the level of stress in a power system, uses correlated sampling and Monte Carlo simulation to develop a calibrated reference scale of system stress that relates (Kirschen, et al., 2004).

In the operation a power systems is explain with increase the stress by increase due to load growth and the stress decrease due to the system upgrades, network improvements or engineering responses. The power systems evolving power system inspired by theories of self-organized criticality systems in statistical physics suggests that these opposing forces tend to slowly shape the power system towards criticality (Carreras B.

A, 2004), (Dobson, et al., 2007), (Bak, 1996). This has been demonstrated with a simple model of these opposing forces shaping the evolution of a power system model of cascading line overloads at the level of DC load flow and LT (long term) dispatch (Carreras, et al., 2004). Additional, based on the NERC (North American electric reliability corporation) data on North American blackouts analysis has concluded that the dynamics of blackouts have some features of self-organized criticality systems, (Carreras B. A, 2004; Dobson, et al., 2008).

Mechanism for generating power law distributions, focused on optimized systems, suggest that power law is a tradeoff between yield, cost of resources and tolerance to risks. In comparison with SOC (self-organized criticality) models, the HOT (highly optimized tolerance) states exist for densities higher than a critical density and the power law are not restricted to special values of the density (Carlson & Doyle, 1999). Is a way of understanding engineered complex systems and applied electric power systems (partially optimized by design). HOT is a constrained optimization problem that minimizes the expected cost of cascading events subject to a bound on the cost of the resources required to limit their propagation, but requires an a priori knowledge of the event probabilities, a functional relationship between the size of the events and the resources, and the number of dimensions of the space over which the events propagate (Dobson, et al., 2008).

### **1.3 Industry practice**

The main current approaches are applying deterministic criteria such as the N-1 criterion that help to suppress cascades, additional practices are used to analyzing and mitigating failures and efforts to improve the reliability of individual components. The analysis are more or less standard for several phenomena that can affect the security of the system and lead to cascading outages. These phenomena have different timescales and generally require different tradeoffs of modeling detail and simulation time, and it is usually studied separately and interactions between phenomena are often ignored. Some of them are: static security assessment, transient security assessment, voltage security assessment, small signal analysis, available transfer capacity analysis (Dobson, et al., 2008).



Most of these analysis are done with commercial tools than evaluate the consequences for a given contingency. It is hard to model and analyze successive combinations of the some phenomena. After a large blackout occurs, considerable efforts are made to analyze the detail of that particular cascade and improve the power system to minimize a similar cascade happening again.

In face the regulation, in North America NERC standards, the Balancing Authorities (BA) require consider contingency four different categories A, B, C, and D. Category D covers resulting extreme events in two or more elements or cascading removed out of service. The standard states that: "A number of extreme that contingencies are listed under category D and judged to be critical by the transmission planning entity (-ies) will be selected for evaluation. It is not expected that all possible facility outages under each listed contingency of category D will be evaluated". In Great Britain, in GB-wide security standard there was a clarification that, following any power system disturbance, protection and control equipment may normally be expected to respond automatically. In Europe there is increasing focus on minimization of the extent to which the network acts as a barrier to inter-area trades of electrical energy, this has led to increasing adoption of system integrity protection schemes to facilitate automatic post-fault actions and reduce pre-fault constraint of power transfers. (Papic, et al., 2011).

In the case of Colombia, the regulator CREG (*comision de regulacion de energia y gas*) defines a simplified probabilistic method "for the analysis of reliability by means of this method you should use the criteria N-1 and N-2, considering the probability of occurrence in the evaluation of costs and benefits. In applying these criteria, the national transmission system must be able to transport steady state energy from generation centers to substations load in case of normal operation ". (CREG, 2012)

## 1.4 Methods of analysis

Probabilistic and deterministic approaches are used after a blackout, the analysis is a sequence of largely deterministic and causal events. However, to predict or simulate the events of a blackout before it happens is necessary to use probabilistic models (for high number of cases to be analyzed).

The deterministic criteria have served the power industry for years. The basic weakness is that they do not respond to the probabilistic nature of power system behavior, load variation, and component failures (Wenyuan, 2006). However, given the dynamic nature of a power system, the outcome of the multiple contingency depends not only on the combination but also on the sequence in which the outages occur for a large system with tens of thousands of components, estimating the impact of each  $N - x$  contingency with even  $x = 3$  will require more than  $10^{11}$  simulations, which is computationally infeasible for a simulator with any fidelity (Vaiman, et al., 2012).

In steady-state modeling we can find several type of analysis: power flow based analysis, hidden failures, and resilience. Additionally high-level probabilistic models including cascade models and network theory approach can capture some generic characteristics of cascading failures but power flow is not used. Below these analyzes are described with more detail:

#### **1.4.1. Power flow based analysis**

N-1 contingency analysis is an essential part of industry practices in anticipating potential failures in a power grid (Cepin, 2011; Morante, et al., 2006). In the case of failures cascade a series of power flows is calculated by considering related events sequentially. There may be generating re-dispatched or operator actions in response to these analyses. Each disconnection event result in a case of power flow. This analysis ensures a single credible contingency will not spread in a blackout cascade, in order to ensure that not a single contingency cuts in cascade, network operators operate continuously contingency analysis to study "what if" with credible cases and check intolerable consequences. Though it has been a common industry practice, analysis based on the N-1 criterion may not be adequate to assess the vulnerability of cascading failures, there are multiple unrelated events may occur in a system and result in cascading failures. Is necessary analyzed, N-2 and even higher order of contingency events. But  $N - x$  contingency analysis is very challenging due to the combinatory number of contingencies and the extremely large amount of computational time. A practical solution is identify the credible  $N - x$  contingencies from a system-wide perspective forming a contingency list, based on substation configuration obtained from topology processing data and probability analysis of protection system failures (Chen &

McCalley, 2005) and apply high performance computing techniques and hardware to check a maximum number of contingencies within time constraints taking advantage of parallel computing platforms (Huang & Nieplocha, 2008).

An industrial tool, for identify cascading failure situation, TRELSS (transmission reliability evaluation of large- scale systems) is a reliability assessment of composite generation and transmission systems developed by EPRI in cooperation with Southern Company Services (Koenig, et al., 2010). The solution algorithms include fast power flow, unit margin, user participation factor and full or fixed-loss economic generation dispatch, a robust mixed-integer linear programming function for remedial actions, user specified remedial actions (Huang, et al., 2009). The user can prepare a list of thousands of initiating events which TRELSS will evaluate each of them separately. A set of threshold values such as the loading level at which a transmission line trips, and the threshold low voltage at which a load is dropped, are set. A unique feature in TRELSS is the modeling of the protection system actions to realistically simulate potential cascading failures. User specified remedial actions can be selected such as circuit switching, load transfer or load curtailment when contingencies or system problems occur, and the specification of both study and remedial action areas (Papic, et al., 2011). TRELSS computes three types of reliability indices: system problem indices; load curtailment indices and customer indices. Better modeling and sequencing of cascading steps have been identified for further development (Hardiman, et al., 2004). Recently EPRI is working on a new program called Transmission Contingency Analysis and Reliability Evaluation (TransCARE) to replace TRELSS. All of the algorithms, models and calculations in TRELSS will have been carried over to TransCARE without sacrificing the modeling and mathematical rigor of TRELSS (Papic, et al., 2011).

A model used in research, is the Oak Ridge-PSERC-Alaska (OPA) for a fixed network represents transmission lines, loads and generators approximate DC load flow. From a solved base case, power outages are initiated by random line cuts. Whenever a line out, generation and load are re-dispatch using standard methods of linear programming. The cost function is weighted to ensure that the load shedding is avoided where possible. If the lines are overloaded during optimization, then these lines are drawn with a fixed probability. The process of re-dispatching and blackouts test is repeated until there are no more.

The OPA model (Dobson, et al., 2001; Carreras, et al., 2002; Carreras, et al., 2002) proposed in this context is a simplified model jointly studied by the Oak Ridge National Laboratory (ORNL), the Power System Engineering Research Centre (PSERC) at Wisconsin University and the Physics Department at Alaska University. In fact, OPA, the name of the model, consists of the first letters of the names of the three institutes

This model was developed in order to understand and simulate the dynamics of an evolving power system in the presence of a continuous increase in load demand. The model tries to capture the SOC dynamics. It makes use of the DC load flow assumptions and therefore the model does not take into account issues such as voltage stability (Fitzmaurice, 2010).

Models exist that increase the level of detail, using AC (alternating current) load flow analysis (Mei, et al., 2011), but they take more time to resolve the power flow problem. The initial research must be done with DC model, because the simplification of the power system, within the model, does not necessarily reduce the model's validity, in addition, in the thesis, we want develop models to include voltage stability as a constraint in the optimization problem.

The main idea is that as generations and loads increase continuously, line power flows grow accordingly, which results in breakdowns in some overloaded transmission lines that in turn lead to the power flow increase in other lines and further overloads and breakdowns until finally the cascading failure happens. The OPA model contains two loops. The inner loop corresponds to the fast dynamics that simulates the cascading failure; the outer loop corresponds to the slow dynamics that simulates the upgrades and improvements in power systems including the increase of generations in response to the growing loads and the improvement in transmission capabilities, (Mei, et al., 2011). This model can show the application of SOC theory to the analysis of power systems. It leads to the promising approach of using simulations to obtain data for system evolutions and blackouts and accordingly carrying out research on the fault distributions and their SOC

Other model used is Manchester model is set for AC power representing a series of cascading failures interactions, including cascade and transmission lines shot, heuristic representation generator instability, loss per low frequency, re-dispatch, post-

contingency active and reactive sources, and pressure drop emergency to avoid complete system failure caused by a voltage collapse.

### **1.4.2.The hidden failure**

It refers to permanent defects that would cause a relay or a relay system to incorrectly and inappropriately react to disturbances (Tamronglak, et al., 1996). The hidden failures in a power system are usually triggered by other events, and don't frequently occur, but they may have big consequences (Phadke & Thorp, 1996). A hidden failure is a failure in relay protection equipment that has not been detected under normal working conditions and might be exposed in abnormal situations and cause the malfunction of the relay system. A hidden failure model is developed in (Phadke & Thorp, 1996) to simulate cascading failures and blackouts. The process starts from a random initial line outage. If the power flow through a line adjacent to the faulted line is above a pre-set threshold value, that line is tripped as well. Otherwise, the hidden failure mechanism is used to decide whether the line should be tripped. Power flows are recalculated after each tripping action until the end of the development of the cascading failure (Mei, et al., 2011).

### **1.4.3.Resilience**

The concept of resiliency can be applied to events of substantial risk, including those with low probability but high consequence. Some utilities include a selection of N-2 events and common mode events in their security analyses. The resilience is the capacity for a self-healing power grid. A self-healing grid would determine the actions to take to recover from a vulnerable operating condition by itself. A good example of self-healing actions is adaptive load shedding (Dobson, et al., 2008). Also there is an estimation of the annual cost of power outages caused by severe weather between 2003 and 2012 and strategies for modernizing the U.S. grid and increasing grid resilience (energy, 2013).

## 1.4.4. High-level probabilistic models

There are models that are not based on power flows such as high-level probabilistic statistics describing the cascading failures, but show no flow of energy or network modelling. These models capture some of the generic characteristics of the cascade process, but do not represent details of the mechanisms in cascade. Power grids are not the only types of systems experiencing cascading failures. This phenomenon also occurs in computing systems with fault tolerance, which have very high reliability requirements (eg banks). These probabilistic models provide analytical formulas for the total number of failures as functions of parameters easily understood in quantifying the overall progression of cascading failure. High-level probabilistic models describe the cascading process but do not model any power systems physics. These models are useful for understanding cascading failure in more detailed models.

### 1.4.4.1. CASCADE model

The CASCADE model consists of  $n$  identical components that are all initially in their normal states with independent initial loads that are randomly chosen in the range. A random disturbance is then exerted on all the loads. If the load of some component is above its threshold value, then a fault takes place at that component, whose load is then redistributed to other components that are working under normal conditions. This process may cause cascading failures (Dobson, et al., 2002; Dobson, et al., 2003; Dobson, et al., 2005).

When the load levels of all components are low, the failures are more or less independent and the blackout distribution satisfies the exponential distribution. The system is less likely to experience large cascading failures, when the load levels increase to some critical values, the fault distribution exhibits the power-law tail characteristics and when the load level keeps increasing, large-scale blackouts may happen. Some limitations of the model are that all the components and their interactions are identical and it ignores the network topology when computing load redistribution and it doesn't consider the changes in power generation (Mei, et al., 2011).

Branching process models can approximate the CASCADE model (Dobson, et al., 2005). It takes the average failure probability as the cascading failure propagation

speed. It is further shown that there is a linear relationship between the fault propagation speed and the system's load level.

#### **1.4.4.2. Network theory approaches**

The dynamics of cascading are related to statistical topological properties of networks inspired by the Internet. The cascading failure has similar features to a power system grid, but the models usually differ. The importance of links or nodes is measured by betweenness, which is proportional to the number of least distance paths through the link or node. Several graph analysis techniques have been applied to power grid vulnerability assessment, including small-world networks, scale-free networks, and centrality (Dobson, et al., 2008).

The small-world network model was first proposed by Watts and Strogatz in 1998. It is a breakthrough in the study of complex networks, (Mei, et al., 2011). The small-world network concept has the properties of a relative big clustering coefficient and relative small characteristic length path. The theory reveals that a few remote connections greatly decrease the path length. The loss of those remote connections will increase the characteristic path length, decrease the transfer capacity of power grid, cause partial power shortage and ultimately lead to cascading failures. The model assumes that a node will fail if a given fraction  $\gamma$  of its neighbors have failed. Starting with initial failures on a few isolated nodes, the process will become cascading when these initial failures lead to subsequent failures due to exceeding the fraction  $\gamma$ . Those lines with remote connections would have the initial failures and are the vulnerable lines according to the small-world network theory (Huang, et al., 2009).

The scale-free network model was proposed by Barabasi and Albert in 1999 (Huang, et al., 2009). They incorporated two critical notions in the formation of scale-free networks, growth and preferential attachment. Growth means that new nodes are added sequentially to the existing network, and preferential attachment means that a newly added node has a tendency to be linked to the nodes in the network with higher degrees preferential (Mei, et al., 2011). Scale-free networks have important properties such as that the degree of distribution follows the power-law distribution and a few nodes have a large number of links but most nodes have only a few links. Simultaneity scale-free networks have other properties, like resistant to accidental attacks but are extremely

vulnerable to coordinated ones. Power networks have a number of highly-connected hub buses and can have important implications for the reliability and security of power networks (Huang, et al., 2009).

The centrality of a vertex is used to determine the relative importance of a vertex within the network. A network may have a set of center nodes. Then centrality is a property determined by each vertex's topological position. The distribution of centrality reflects the level of centralization in the whole network. Some of these include degree centrality, closeness centrality and betweenness centrality (Freeman, 1977). A degree centrality is the degrees of nodes that are related to the importance of the node in the network. A node with a higher degree is connected to more nodes (only immediate links). A closeness centrality, is concerned with the shortest distance between a node and all other nodes that are reachable from it. Here, distance can be defined differently and once a definition is picked, the distance between any two nodes can be calculated. Then the distance distribution shows the centrality of the network (Mei, et al., 2011). A betweenness centrality indicates the topological importance and capability of this node. If the node is often located in the shortest paths of other node pairs, then it is highly influential on information propagation in the network (Freeman, 1977). The betweenness approach is further improved by the introduction of an efficiency index.

### **1.4.5.Critical components and high risk multiple contingencies**

The identification of critical components and high risk multiple contingencies can be used to estimate the vulnerability of the network. Dynamic decision trees and fast simulation are used in the Practical estimation of high-risk N-k contingencies (Chen & McCalley, 2005). Several methods for the identification of critical multiple contingencies have been proposed to identify vulnerabilities to deliberate attack or worst-case scenarios (Dobson, et al., 2008).

### **1.4.6.Recognizing patterns**

Recognizing patterns in major blackouts and then studying how they combine into cascading sequences of events (including line tripping, overloading of other lines,



malfunctions of protection devices, power oscillations and voltage instability, and system splitting and collapse) can give key information to the operator to use to manage the blackout risk. Common characteristics of blackouts are clarified by analyzing the cascaded events of the major blackouts (Yamashita, et al., 2009).

### **1.4.7. Conventional reliability methods**

There is extensive literature and assessment tools on power system reliability (Cepin, 2011), including component reliability and maintenance, generation adequacy and assessments of transmission system reliability, the effects of weather, and common cause failure. These methods are useful and commonly used in the electrical industry, but they are based on underlying assumptions of independent events and do not apply to cascading failure because the successive weakening of the system as the cascade proceeds makes the cascading events dependent (Dobson, et al., 2008).

Severe power outages let us realize that the single-contingency criterion (the N-1 principle) that has been used for many years in the power industry may not be sufficient to preserve a reasonable system reliability level. However, it is also commonly recognized that no utility can financially justify the N-2 or N-3 principle in power system planning. Obviously, one alternative is to bring risk management into the practice of planning, design, operation, and maintenance, keeping system risk within an acceptable range (Wenyuan, 2006).

## **1.5 Risk approach**

A comprehensive risk analysis should contain a combination of probability and consequences (technical, business, and social costs). The risk evaluation of power systems should recognize the likelihood of failure events and the severity and degree of their consequences. Utilities have dealt with system risks for a long time. The criteria and methods first used in practical applications were all deterministically based, such as the reserve percentage in generation capacity planning and the single-contingency principle in transmission planning.

Suppressing all blackouts is not possible. But think about joint solutions for the risk of small, medium, and large blackouts, allows tradeoffs between small and large blackouts to be assessed (Dobson, et al., 2007; Carreras, et al., 2003).

Large cascading blackouts, although rare due to industry efforts, are a challenge to analyze and simulate in a predictive way due to the huge number of possible rare interactions and the diversity and complexity of these interactions. Analyses of blackout records in a number of countries show that although large blackouts are rarer than small blackouts, blackouts of all sizes can occur, and there is a substantial risk of large cascading blackouts. A catastrophic failure, defined as one that results in the outage of a sizable amount of load, may be caused by dynamic instabilities in the system or exhaustion of the reserves in transmission due to a sequence of line tripping leading to voltage collapse. Therefore one cannot dismiss large cascading blackouts as so unlikely that they should be neglected. At the same time it should be recognized that the current methods for directly understanding and mitigating cascading failure are not well developed.

Vulnerability is a measure of the system's weakness with respect to a sequence of cascading events that may include line or generator outages, malfunctions or undesirable operations of protection relays, information or communication system failures, and human errors.

In most cases the power failure is not caused by a single event (it has been covered by the criteria of reliability in the operation of the electrical power system) and are caused by a series of events related to each other. After the first event a sequence of other related events producing a cascade occurs that often result in non-supply demand for end-users of EPS. In more general terms, it can be said that a number of factors cause cascading failures that cause a blackout as a result.

Electrical systems maintain a good level of robustness and reliability due to the implementation of multiple control systems and protection. These systems include risk management measures for the risk of a blackout, and influence the system's response to internal or external disturbance to which it is subjected to some time scale.

When electric power systems fail they greatly impact the final consumers and the supply chain of the electricity market, and indirectly impact the welfare of the citizens

due to the inconvenience in transportation, security, communications, system health and the country's productivity chain.

The network impacts caused by blackouts can be complex and the risks should be analyzed using a more systemic approach. This approach allows for optimization and prioritization of network investments and operating policies that reduce the likelihood and impact of a blackout to society.

### **1.5.1. Emerging technologies**

Some additional elements that could increase the likelihood or severity of cascading failures are: the interconnection function to facilitate large electrical energy trades across wide areas, increased difficulty in building new overhead lines (ambient difficulties, or stakeholder), increased dependency in power system operation on a greater number of individual independent actors (difficulties of information), limited flexibility of new generations plants (solar and wind plants, or combines cycle gas turbine), decreased clarity of responsibility in disaggregate industries and between different interconnected systems, increased size of interconnected grids and additional difficulties in the operation coordination of different industries of transmission and generations (Bell, et al., 2010).

For electric power systems the impact of some emerging technologies can help estimate the vulnerability of the network. These include phasor technology, advanced visualization, high-performance computing (HPC), and how data mining in cascading failure analysis influence the evaluation of the vulnerability of the electric power system (Huang Z. et al. IEEE PES CAMS Task Force on Understanding, 2009).

New trends in the development of electrical systems are bringing more complexity to the operation. Developments in smart grid as demand response, distributed generation or inclusion of large batteries in the generation or transmission systems will be a challenge in terms of predicting the behavior of these new system agents. Large variability in variables such as demand and power generation is expected, requiring many more real-time systems. This trends increase the chances of a blackout, especially when the system is limited by a lack of network expansion.

## 1.5.2. Risk quantification approach

This proposed methodology is based on the complex behaviour of the power system as demonstrated in several theoretical works (Carreras B. A, 2004) and applied to some actual power systems (watts & Ayala, 2014). First, the consolidation and analysis of the databases of electric power systems failures are carried out. Next, a statistical model of behavioural data is performed using SOC models. Then an electrical model is developed using a DC power flow for networks. Finally, the results for a real power system with databases of daily operation of the Colombian electrical system (day ahead market) are calculated comparing the use of the deterministic criterion N-1 with the probabilistic model simulations result.

The deterministic criteria N-1, is frequently applied to help to suppress cascades from the initial event. There are a range of industry practices devoted to analyzing and mitigating failures caused by a variety of processes, such as overloads and various types of instabilities, as well as efforts to improve the reliability of individual components. Indeed there are analysis and simulation tools that apply separately for each of these processes.

It would be too restrictive to plan or operate the system generally beyond conventional N-1 or N-D security. However, it is important that the tools are available such that high impact/low probability events can be managed in the control room and in planning to reduce the system's exposure to risk. It is beneficial to have a real-time view of risk in power systems to alert the user to the occurrence and characteristics of a particular risk issue. It is also useful to quantify risk in relation to the operational planning timeframe to aid decision making by highlighting critical system states and elements in the power system that are vulnerable. With this information, targeted guidance reports enable operators to move away from high-risk states. A measurement-based approach can be used to validate the operational action and provide notifications to operators that the system has moved to a lower risk state as a result of the action.

This proposal manages the risks of widespread disturbance in electrical power systems for decision-making in a day-ahead market. International literature on blackouts, as well as research on the Colombian power system, shows that large-scale disturbances occur much more frequently than deterministic reliability criteria suggest. The use of

conventional N-1 or N-D contingency analyses does not address high impact events adequately. Furthermore, it is noted that the more congested a power system becomes the more likely it is for hidden weaknesses to be exposed and wide area collapse is increasingly likely.

It is important that high impact risks are addressed without over-constraining the network, which would result in higher costs. In this respect, understanding the risks, observing when they occur, and enabling a prompt response is valuable for balancing the requirements for security with market efficiency.

This proposed analysis seeks to be complementary to traditional analysis of the electrical industry. By estimating the risk in some network components more detailed studies of network reliability can be made. A deep analysis focusing on the most likely problems that limit the size of  $N - k$  criteria may prevent or limit the blackouts more efficiently.

Some of the detail simulations can produce likely or high risk cascading sequences and others sample more broadly from all the cascading sequences to approximate the overall cascading risk. Controlling the high risk sequences is one possible tactic to mitigate cascading failures (e.g. (Wang & Thorp, 2001) (Mili, et al., 2004), and finding the overall cascading risk is important for evaluating the benefits of mitigation efforts.

## In conclusion

A complicated chain of cascading events are usually involved in large blackouts. Although not common, they are very expensive for society (direct costs of millions of dollars). The power industry and academic teams have worked hard to analyze and avoid cascading blackouts. Several corrective measures and improvements taken place after of a blackout, however they can still occur.

The power systems operates in several time scales, and it is analyzed in detail in each one, but these scales are rarely integrated to provide support for optimal decisions. Traditionally it has been analyzed as the sum of the behavior of individual elements, in different time scales, with some relationships to each other.

An electrical power system is composed of several subsystems interacting with each other and is considered a complex system. A power system has thousands of components that can fail and checking every combination of failures becomes infeasible even with the fastest computers.

A good way to focus on risk is to analyze the events from a systemic point of view since the possible impacts from blackouts are complex. This focus allows for optimization and prioritization of network investments and operating policies that reduce the likelihood and impact of a blackout to society.

## 2. Design power network model based in Self Organized Criticality

Complex systems have been successfully developed in other disciplines and are formed by several components whose collective behavior emerges from the interaction of each individual component. The long-term memory and power law properties such as self-organized criticality is studied. These properties are present in the power system and can serve to explain the probability of extreme events in systems, such as blackouts, extreme events that are unlikely, but have a high economic and social impact.

After a description of the SOC theory and its application in power systems it is shown that the Colombian power system has SOC behavior. An estimate of the long-term memory and power law properties is performed with different techniques, and adjustment is performed to an alpha stable distribution.

Then a Value at Risk (VaR) is estimated using a Monte Carlo simulation to obtain the profile of the aggregate lost distribution function. The VaR increase rate is larger than the Gaussian case (0.5) for the blackout risk. The risk is underestimated using traditional tools than assume Gaussian distribution.

### 2.1 Self-Organized Criticality

On the edge of chaos (cellular automata) is where the dynamic system expresses its optimal performance (being ultra-sensitive, subtle and having a complex order) and where the phenomenon of self-organized criticality (SOC) is manifested. It has led to an explosion of research in a growing number of disciplines including cultural anthropology, archeology and art history (Reynoso, 2006).

In classical physics, a critical point is a point at which a system radically changes its behavior or its structure; there is a control parameter that can be varying for that change. In self-organizing, however the system reaches a critical point in accordance with its own internal dynamics, irrespective of the value of any variable control. A self-organized critical system is a simple pile of sand. Dropping a trickle of sand slowly a pile is formed, as the stack grows, avalanches transporting sand from top to bottom

occur. In theoretical models the slope of the stack is independent of the speed at which the sand is thrown. This slope is self-organized; a minor event (a grain of additional sand) can trigger a chain reaction and lead an avalanche (nonlinear function) (Bak, 1999; Bak, 1996; Bak & Kan, 1991).

The behavior of the pile of sand depends on the interaction between the elements, and not on any external control. Since the state of the pile determines how much more sand is needed to modify it, a grain of sand can have an excessive influence or not have any; the magnitude of the influence is determined by the state, but the next state is determined by a grain of sand. Avalanches involve interacting elements in the pile, according to complex interactions. This same concept is presented in complex cellular automata at the edge of chaos.

The size and frequency of avalanches seems to follow a power law distribution, small events are the most frequent and large are the least. When the power-law distributions are plotted with both axes logarithmic (log-log) is a straight line. A power law means a number  $N$  can be expressed as proportional to the power of another quantity  $r$ .

$$N = \frac{C}{r^D}$$

Where,  $C$  is a constant, and  $D$  is the exponent. The distribution of the power law is a fractal feature found in many different areas such as economics, biology, physics and apparently culture, without there even being a universally accepted theory to explain its occurrence. A critical system is also scale independent: there is no typical or unique avalanche size, nor is there a relationship between the grain size that triggers an avalanche and its magnitude (Kauffman, 1995; Paczuski, et al., 1996). Mathematically this is expressed as a power spectrum  $1/f^D$ , which involves a self-affinity similar to that of fractals processes.

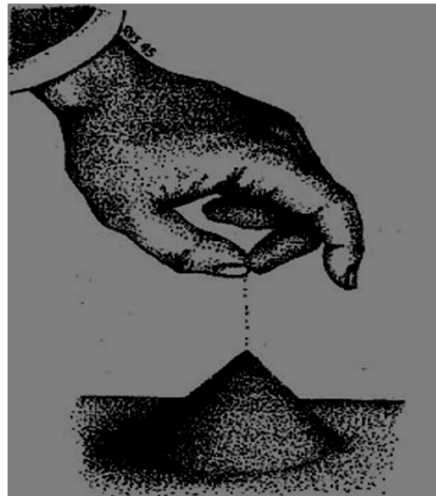
### **2.1.1. In power systems**

The electrical system is a complex system consisting of a large number of subsystems with characteristics widely studied throughout the development of power systems. In 2000 initial evidence was presented (Carreras, et al., 2000; Carreras, et al., 2004) that the behavior of the electric system, with respect to blackouts and its response, has



similarities with the behavior of a self-organizing physical system in a critical situation. This system is known as a Self-Organized Criticality -SOC- system, and is particularly evident in a sand pile, see Figure 2-1.

The SOC model: grains of sand are continuously added to a pile of sand varying the location at random (slow dynamic). When the local gradient becomes too large sand located in this region is more likely to collapse and cause an avalanche (fast dynamic). The system state is the vector of maximum gradients for all locations of the sand pile. The driving force is the addition of sand grains and the relaxing force of gravity causes the sand to collapse and reduce the maximum gradient. The SOC system is the dynamic equilibrium in which avalanches of all sizes occur and in which there is a long-term correlation between avalanches.



*Figure 2-1 SOC Model – Sand Pile*

The analogy to the electric power system is shown in the Table 2-1. There are some differences too, for example in the time scale. For a power system a black out is in fast scale and It takes time to determine the causes of a blackout and for the relaxation of the system to happen. On the other hand, with a sand pile, the avalanches are coincidental with the relaxation of high gradients.

<b>Variables</b>	<b>Power System</b>	<b>Sand Pile</b>
System state	Loading pattern	Gradient profile
Driving Force	Customer demand	Addition of sand

Relaxing force	Response to blackout	Gravity
Event	Limit flow or trip	Sand topples
Cascade	Cascading failure	Avalanche

*Table 2-1 Analogy between physical model and electrical model*

In a power system the term self-organized criticality contains two ideas:

- "Criticality", meaning that the system is correlated over large distances and long time scales. (A system can be criticality without being self-organized).
- "Self-organized" means that the system has a critical behavior without the need for an operator to fine tune or control parameters.

The system tends to dynamically adjust the parameter. This leads to a steady state and dynamic attractor of evolution. This is the case of sand pile that starting from its critical slope undergoes an avalanche to return to a dynamically stable slope. Considering an electrical network under self-organized criticality regime is therefore necessary when one takes into account the grid in its environment, i.e. we consider the necessary reaction (or feedback reaction) for its operation. "Feedback" reaction to any dysfunction can be operational policy control (control room), human intervention, maintenance operations, planning policy and can be quantified. The grid is then a dynamic system, managed by two opposing forces (load plan and "Response to incident"), in the critical regime (subcritical, critical, super-critical). The power law behavior observed experimentally finds its origin in this competition (universal behavior).

In Dobson et al (Carreras, et al., 2000; Carreras, et al., 2004), on the basis of observations (number of black-out, number of customers affected, restoration time after outage), the presence of power laws were shown on the marginal distributions, correlations or long-term persistence: Two statistical techniques are used for a long-term correlation in the data series of demand non supply; that of re-scaling range statistics (R / S) statistics and the scale windows variance technique (SWV).

The R/S technique considers successive data blocks  $m$  integrated time series and measures how fast the range or standard deviation of the block grows as  $m$  increases. The associated series is built to Brownian motion, if the series has a self-correlation

function, scales where  $H$  is the Hurst exponent; if  $H$  are between 1 and 0,5 the data series time has a long term correlation.

Scale is the possible explanation of how a power system can be self-organized. Power systems have short time scales where actions are taken such as the dispatch of resources or the same re dispatch and long-term actions such as improving the capacity of transmission lines. The operation of this system seeks to satisfy demand at minimum cost; customers have consumption demands with daily and seasonal cycles that have long-term secular increases. Events associated with the power system occur with a probability that depends on a load component, that is, the probability increases with the load. A blackout is defined as an event that limits the capacity of the line or trigger, and has non-supply demand (Carreras, et al., 2004).

The system has two opposing forces; on the one side there is the increase of the load due to demand and on the other side the improvement in the capacity of transmission lines or the generation capacity produced by supply. Outages come as a relaxing force when system conditions reach a stress that the system cannot manage by itself (by the laws of the system).

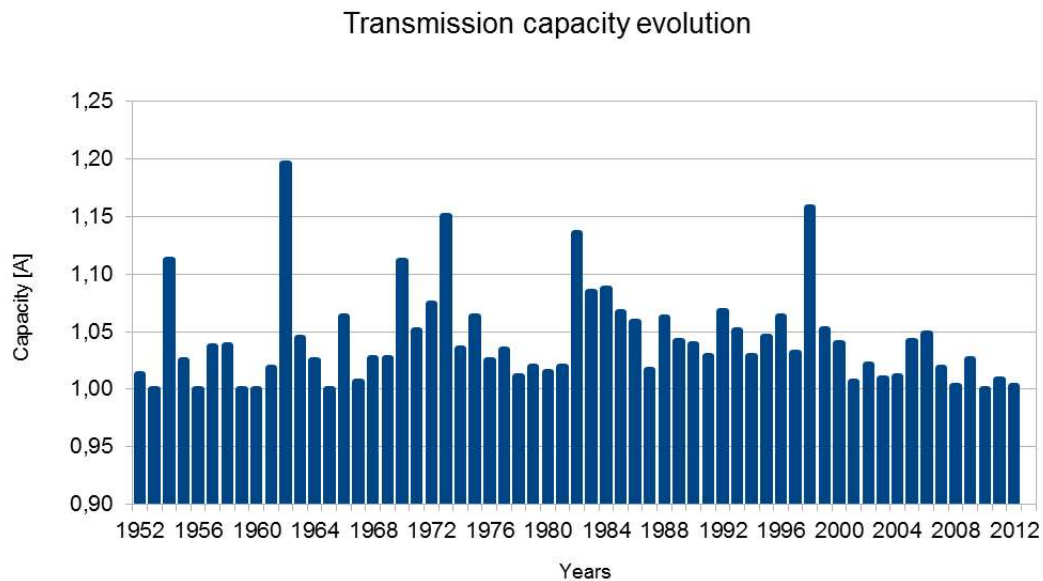
These opposing forces operate in different time ranges and spatial scales, and suggest that the electrical system is similar to the SOC model. The systems that operates close to criticality shows power tail characteristic of the dynamic equilibrium. The efforts to mitigate blackout risk can move the system to a new dynamic equilibrium (near to criticality point and conserve the tail) but a complex system shows a strong nonlinear coupling between mitigation and frequency, the reduction of one kind of disruption can increase others disruptions (Dobson, et al., 2002) this result could be worse for risk management.

An electrical transmission model, called OPA, was proposed (Carreras, et al., 2001; Dobson, et al., 2002) to study electrical behavior (similar to the sand pile), the model sets generator, loads, transmission line network as their operational limits in a DC power flow. This model lets us identify the critical point of the power system (the existence of power tail). In theory the electrical power system has two types of transitions; the first one is because generator capability is limited and the second one is due to transmission line capacity limits (Carreras, et al., 2002).

Using this model a network can be analyzed to find the trigger of the elements that can start a blackout event and the cascading failure. This allows us to identify the lines or group of lines that has a major probability of failure (Carreras, et al., 2012). It can be used to identify specific assets that in some special conditions could have more failures.

DC SPFM (direct current statistical power flow model) is used in the approach of this thesis, it considers both the feedback force immediate restoration (i.e. engineering responses as improvements in operating policies, maintenance & equipment, controls and all responses tending to increase the margins of transmission lines) and delayed restoration. Immediate restoration is equivalent to Dobson's model proposed in (Carreras, et al., 2001; Dobson, et al., 2002). For delayed restoration, the idea is to consider the time evolution of transmission lines. Figure 2-2 gives the time evolution of Colombian Transmission Capacity.

Generally speaking, it's considers only the iterative process with a sequence of events, without taking time and time evolution into consideration.



*Figure 2-2 Colombian transmission capacity evolution*

## **2.1.2. In Colombian power systems.**

The first step is to estimate if the Colombian system may have self-organized critical behavior. A short description of the Colombian electric system is made, as well as an explanation of the work with databases non-demand supplied events.

### **2.1.2.1. Colombian power system description**

Colombia is a country with an estimated 45 million inhabitants, with coverage of over 99,2% and approximately 12,7 million subscribers (Asocodis, 2013), to the electrical service (including residential, commercial and industrial end users). It has an area of 1,141,748 m<sup>2</sup>.

The power sector in Colombia is highly dependent on hydro resources. On December 31st, 2015 it had a net effective capacity of 16.420 MW, comprising 10.892 MW of hydroelectric generation capacity (66,6% of the total installed capacity), 4.743 MW of thermoelectric generation capacity, 698,4 MW of generation capacity of resources below 20 MW (hydro, thermal and wind) and 86,6 MW of cogeneration capacity (XM ESP, 2015).

Thermal generation is mostly gas-based generation (3.404 MW) exploiting gas reservoirs located in the Northwestern region. Coal-based generation (1.339 MW), on the other hand, is expected to increase over time because new coal reserves have recently been found in the northeast region (Cesar and Boyacá). It has been estimated that Colombia has roughly 100 GW of potential hydropower. However, most of the hydro projects face serious development constraints due to the evolution of the environmental laws.

The energy demand of the national interconnected system in the year 2015 was 66,2 TWh, with a peak power demand of 10.095 MW in early december.

There are four major wholesale market participants, i.e., generators, distributors, transmission companies, and retailers in Colombia. No new companies created after the Electricity Act of 1994 are allowed to participate in the four activities, yet the retail activity may be combined either with generation or distribution. Companies created before 1994 were allowed to retain their vertical integration but they must keep separate accounting.

Generators can participate in the day-ahead market or establish bilateral contracts with retailers. They are obligated to provide ancillary services and are paid for it. The only current ancillary service market in Colombia is that of secondary frequency control.

By the end of 2015 there were 47 generators and 68 Retailers with commercial activity in the Colombian electricity market, as well as 29 Distributors and 10 National Transmission Companies<sup>1</sup>. The national interconnected system had 24,989 km of high voltage lines, over 110 kV

The largest transmission company in Colombia is Interconexión Eléctrica S.A. -ISA, a company of which the government owns 52.94% of the total shares. ISA owns 73.87% of the national transmission system. ISA also has operations and owns transmission assets in Ecuador, Peru, Bolivia and Brazil.

### **2.1.2.2. Colombian database**

The database of the Colombian power system of demand not supply was used. The list includes information about small and big events of DNS since 1996 to 2013. The database has information about energy loss, duration, region, equipment failure, and the initial hour of the event. There are close to 20,000 events of DNS outages. The initial classification are for transmission, distribution supply limitation (program demand not supplied due to credit risk or non-pay risk) and terrorism attack. This analysis is centered on the transmission system failures (over 110 kV) it has 11,129 events, but when the possible causes were analyzed 1,757 outages were programmed by the operator and haven't been considered. The final data used shows 9,372 events in the transmission system that permits us obtain different distribution functions, Figure 2-3. Size of events is characterized through the DNS (MWh).

Some of the causes of events found were natural events; lightning strikes, terrorism, equipment failure, maintenance activities, excessive customer-load demand or operating conditions, etc.

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<sup>1</sup> Transmission is defined in Colombia for voltages equal or above 220 kV and Distribution for voltages below that threshold.

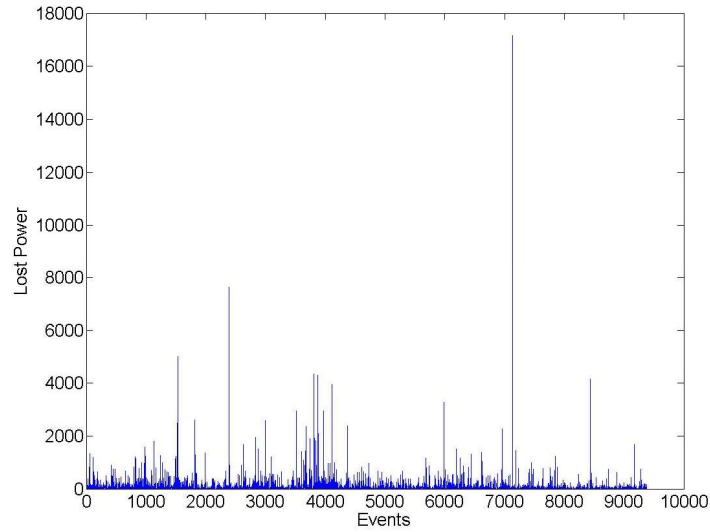


Figure 2-3 Demand non supply (MWh) of each event

The fault events are drawn respective of their start time. Figure 2-4 shows the outages probability distribution per hour. It has a similar pattern to the typical daily load demand the Colombian power system (shape).

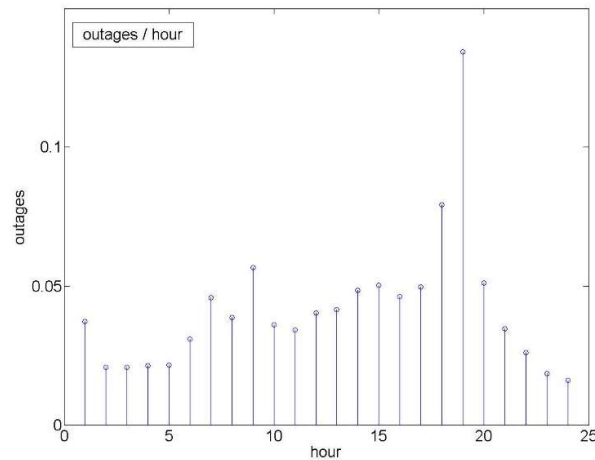


Figure 2-4 Distribution function of outages per hour

The cumulative distribution function –CDF– of time restoring in Figure 2-5 shows that around 65% of events have a duration of less than 0.1 day (2.4 hours).

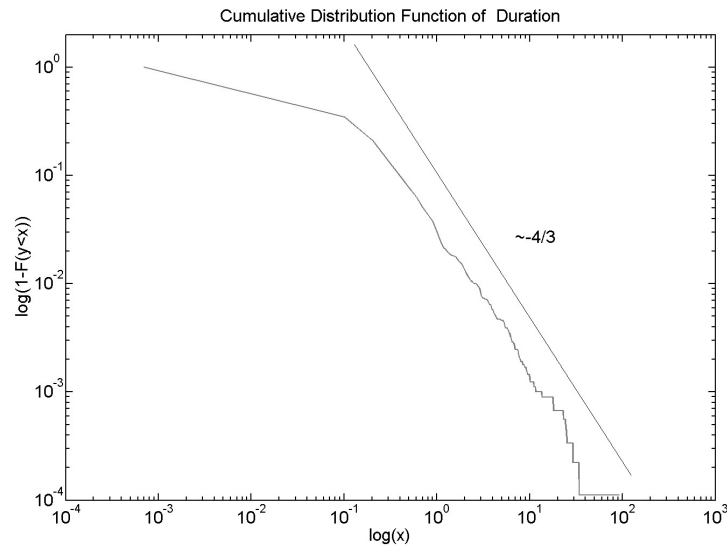


Figure 2-5 Cumulative Distribution Function of time restoring

CDF of Demand Not Supplied (DNS) is presented on Figure 2-6. As expected, power law regime can be showed and may be related to SOC regime, commonly accepted for this systems type (Carreras, et al., 2004). It can be observed that power law behavior also describes duration of events, Figure 2-5.

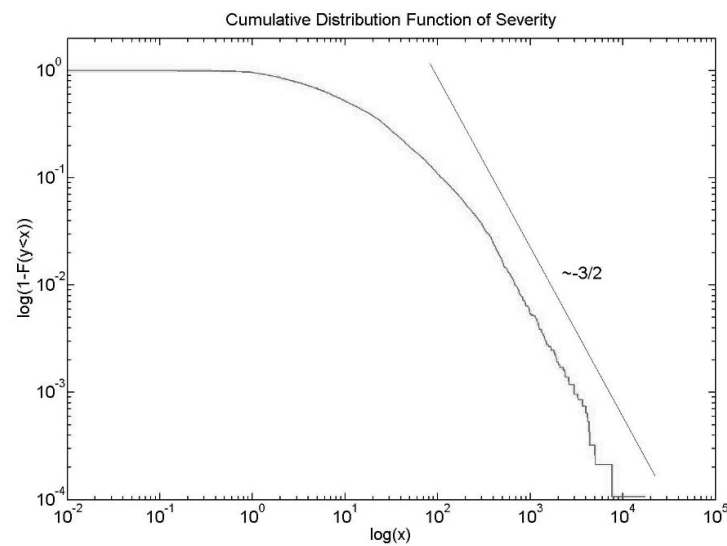


Figure 2-6 Cumulative Distribution Function of DNS (KWh)



## 2.2 Statistical analysis

### 2.2.1. $\alpha$ -stable Laws Properties

When a linear combination of random variables of the same law is also a random variable of identical probability distribution, this law is known as “stable”. The random variable  $X$  is stable if  $\forall a, b$  positive constants,  $X_1$  and  $X_2$  independent copies of  $X$ ,

$$aX_1 + bX_2 \stackrel{d}{=} cX + d \quad c, d \in R \quad \text{Equation 2-1}$$

The symbol  $\stackrel{d}{=}$  means equality in distribution, i.e. both expressions have the same probability law. The shape of  $X$  is preserved (up to scale and shift) under addition. This family of  $\alpha$ -stable distribution is also known as L-stable, Levy-Pareto distribution. it requires four parameters to describe (Figure 2-7).

- shape parameter (index of stability)  $\alpha \in [0, 2]$
- skewness parameter  $\beta \in [-1, 1]$
- scale parameter  $\gamma > 0$
- location parameter  $\delta \in R$

(symbol  $\sigma, \mu$  are respectively reserved to standard deviation and mean).

A random variable  $X$  of stable law has a characteristic function  $\varphi(t)$ , (Nolan, 2012; Voit, 2003). And the probability distribution  $f(x)$  is determined by:

$$\varphi(t, \alpha, \beta, \gamma, \delta) = e^{it\delta - |t|^\alpha (1 - i\beta \text{Sign}(t)\Phi)}$$

$$\text{with } \begin{cases} \Phi = -\left(\frac{2}{\pi}\right) \cdot \log|t| & \text{if } \alpha = 1 \\ \Phi = \tan\left(\frac{\pi\alpha}{2}\right) & \text{otherwise} \end{cases} \quad f(x) = \frac{1}{2\pi} \int_{-\infty}^{\infty} \varphi(t) e^{-itx} dt \quad \text{Equation 2-2}$$

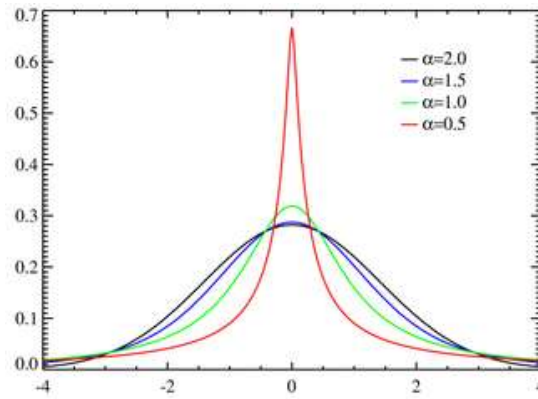


Figure 2-7 Probability density function for different  $\alpha$

For special cases,:

- $\alpha=2$ , the probability distribution is a Gaussian distribution  $\mathcal{N}(\mu = \delta, \sigma = 2\gamma^2)$ ,
- $\alpha=1$  and  $\beta=0$ , the probability distribution is a Cauchy distribution with scale and location parameters  $\gamma$  and  $\delta$ ,
- $\alpha=1/2$  et  $\beta=1$ , the probability distribution is a Levy distribution with scale and location parameters  $\gamma$  and  $\delta$ .

## 2.2.2. Particle Swarm Optimization for estimation of $\alpha$ -stable laws

A particle swarm algorithm with Kolmogorov-Smirnov criteria is used to estimate the parameters of  $\alpha$ -stable law (Ismail, et al., 2013). Kolmogorov-Smirnov statistic is a non-parametric test that could be used to compare sample with a reference probability distribution (adequation). A distance  $D_n$  is quantified between empirical and reference PDF (Figure 2-8).

Hypothesis  $H_0$  (sample comes from reference distribution) is rejected when  $\sqrt{n} \cdot D > K_\alpha$  ( $K_\alpha$  is a quantile from Kolmogorov-Smirnov tabulation table).

$$D_n = \sup_x |F_n(x) - F(x)| \quad \text{Equation 2-3}$$

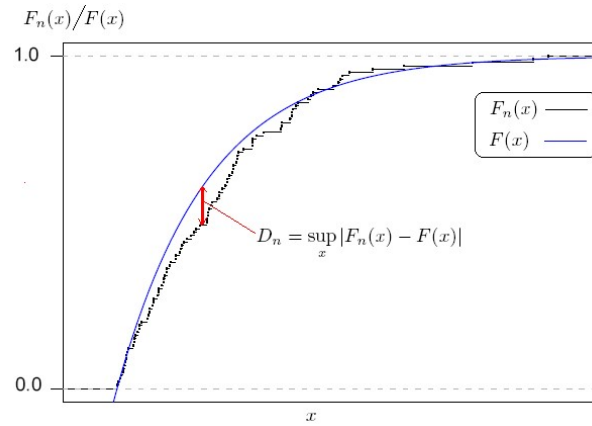


Figure 2-8 Kolmogorov Smirnov Criteria

### 2.2.3. $\alpha$ -stable distribution for Colombian power system data

Empirical distribution can be parameterized by an  $\alpha$ -stable distribution, characterized by 4 parameters:  $\alpha$ ,  $\beta$ ,  $\gamma$ ,  $\delta$  (Nolan, 2014), (Voit, 2003). All parameters were estimated using Particle Swarm Optimization (PSO) with Kolmogorov-Smirnov criteria (Ismail, et al., 2013)

The  $\alpha$ -stable distributions are heavy-tailed with infinite variance and in some cases infinite first moment ( $\alpha < 1$ ). For month resolution ( $\Delta t = 30$ ), we found the statistics shown in Table 2-2, and Figure 2-9 Frequency distribution of events monthly:

$\alpha = 1.70, \beta = 1.00, \gamma = 12.15, \delta = 51.90$					
Statistics	Mean	SD	Median	Max	Min
Real data	50,71	31,75	59	114	4
A-stable law	51,2	38	103	185	4

Table 2-2 Statistics for frequency of events

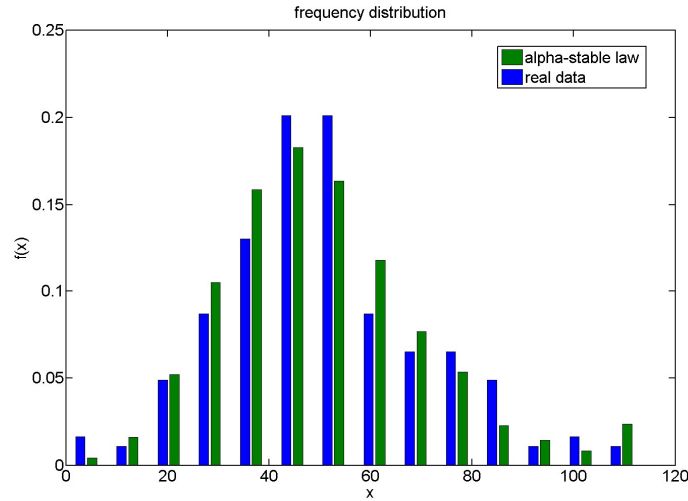


Figure 2-9 Frequency distribution of events monthly

If it is taken (Heliodore, 2012):

$$\gamma = 0.8(\Delta t)^H \quad \text{with} \quad H = 0.8 \quad \text{and} \quad \delta = 1.73.\Delta t \quad \text{Equation 2-4}$$

Self-similarity test related to  $\alpha$ -stable law implies:

$$\gamma = \gamma_0(\Delta t)^{\frac{1}{\alpha}} = \gamma_0(\Delta t)^{\frac{1}{1.7}} \neq 0.8(\Delta t)^H \quad \text{Equation 2-5}$$

These results address the existence and definition of long range dependence (LRD) in the dynamics of the power grid, it was observed initially by (Chen, et al., 2006) (Carreras, et al., 2000) (Weron & Simonsen, 2005), that the distribution of outages showed long range time correlations and power law tails.

Long range time correlations is deduced from self-similarity exponent  $H$  (Hurst index),  $H \in [0,2]$ ,  $\frac{1}{2} < H < 1$  persistent regime. From time series, numerous techniques were developed to estimate  $H$ , among them, the rescaled range statistics - R/S (Mandelbrot & Wallis, 1968), (Teverovsky, et al., 1999) , the Scaled Window Variance - SWV (Cannon, et al., 1997) or the Diffusion Entropy Analysis - DEA, (Nicola, 2001). Considering stationary or not of series, regular or irregular sampling, results can be slightly different and must be used carefully (Courteille, 2011).

Starting from  $d$ , the LRD exponent and  $H$ , the self-similarity parameter, a stochastic process  $X_t$  is  $H$ -self similar if  $\forall \lambda > 0$ , the processes  $X(\lambda t)$  and  $\lambda^H X(t)$  have the same law:

Equation 2-6

$$X(\lambda t) \stackrel{d}{=} \lambda^H X(t)$$

Two aspects can contribute to the self-similarity of a process (Cont, 2005; Franzke, et al., 2012; Mandelbrot & Wallis, 1968; Watkins, et al., 2005):

- the first term,  $J$ , associated to persistence and called “Joseph Effect”,
- the second one,  $L$ , representative of large discontinuities (heavy tail) and called “Noah Effect”.

The self-similarity parameter becomes ( $\alpha$ , stable index):

$$H = d + \frac{1}{\alpha} \quad H \in [0,1] \quad \text{Equation 2-7}$$

With sub-structures ( $J, L$ ):

$$J = d + \frac{1}{2} \quad L = \frac{1}{\alpha} \quad \text{Equation 2-8}$$

In the Gaussian case,  $\alpha=2$  :

$$H = J + L - \frac{1}{2} \Rightarrow H = J = d + \frac{1}{2} \quad \text{Equation 2-9}$$

The assumption states that both phenomena lead to this value of self-similarity parameter. The Figure 2-10 shows the heavy tail deduced from asymptotic regime. Time increasing, empirical distribution will converge to this one.

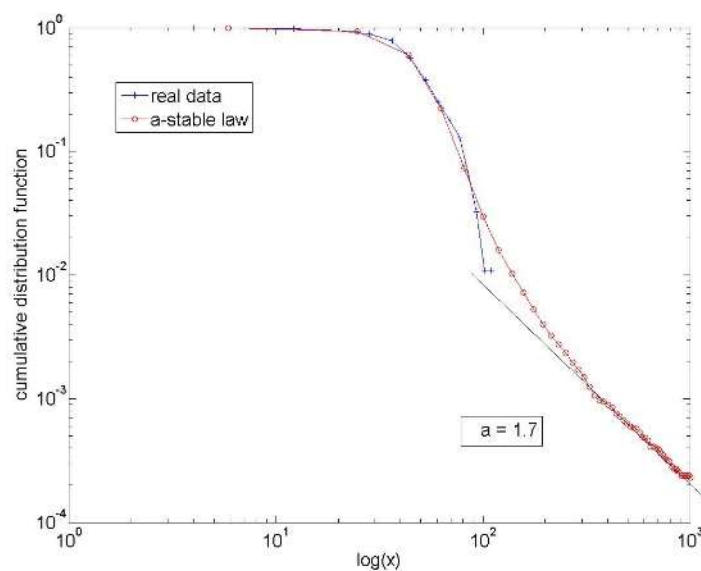


Figure 2-10 Real data &  $\alpha$ -stable law,  $\Delta t=30$  days,  $\alpha=1.7$

## 2.3 Estimation of VaR of demand not supplied in electric power systems

The financial sector commonly quantifies the market risk or potential economics loss of portfolio using the *VaR* index, initially proposed by J.P. Morgan Bank (J.P.Morgan & Reuters, 1996), *VaR* is a risk index and it is based on the continuous returns (*R*) of each position into portfolios, the general *VaR* model is indicated below (Jorion, 2007):

$$VaR = -W_0 (R^* - \mu) \tag{Equation 2-10}$$

Where,  $W_0$  is the portfolio value,  $R^*$  is critical return given a confidence level,  $\mu$  is expected return.

*VaR* summarizes the maximum expected loss over a time horizon with a given confidence level (Figure 2-11). In the more general form, it can be derived from the probability distribution function of future portfolio value  $f(x)$ . At a given confidence level  $c$  and significance level  $1 - c$ , one can find the worst possible realisations or losses (*VaR*) such that the probability of exceeding this value is  $c$ :

$$VaRc = \{x \mid P(x > VaR) \leq 1 - c\} = \{x \mid F(x) \geq c\} \tag{Equation 2-11}$$

Or

$$c = \int_{-\infty}^{VaR} f(x).dx \tag{Equation 2-12}$$

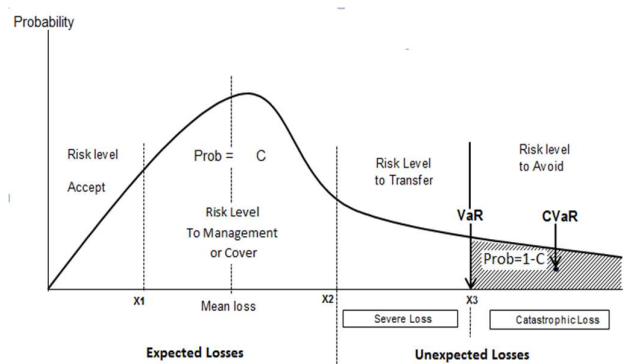


Figure 2-11: VaR and CVaR diagram.

Depending on the probability distribution function of returns  $R$ , the relation (3) can take different forms. For instance, if  $R$  has a normal distribution in the simplest case, then:

$$VaR_p = W_0 q_c \sigma_p \sqrt{t} \quad \text{Equation 2-13}$$

With  $W_0$ , the portfolio value;  $q_c$ , is value of standard normal distribution (at 95% confidence level,  $q_c = 1.64$ );  $\sqrt{t}$ , the square root of time describing portfolio volatility for different time periods (time scaling property);  $\sigma_p$ , the standard deviation of portfolio defined by  $\sigma_p = \sqrt{[w_i]^T \cdot [\Omega] \cdot [w_i]}$ ;  $w_i$ , the proportion of each asset in portfolio;  $\Omega$ , the Variance - Covariance matrix between asset of portfolio.

The conditional value-at-risk ( $CVaR$ ) is well-known as a more consistent risk measure. It is defined as the loss expected when the losses are greater than  $VaR$ , that is called expected shortfall or expected tail loss.  $VaR$  and  $CVaR$  depend on the underlying probability distribution function of the risk factors. If a loss  $L$  is in excess of  $VaR$  (the event is in the tail of the loss distribution), the conditional value-at-risk tells us how much we may expect to lose. This concept looks like the gravity centre applied to the tail of the probability distribution function of losses, formally:

$$CVaR = E[L | L > VaR] \quad \text{Equation 2-14}$$

In general form,  $CVaR$  is defined as:

$$CVaR = (1-c)^{-1} \int_{VaR}^{\infty} x \cdot f(x) \cdot dx \quad \text{Equation 2-15}$$

Since  $CVaR$  is the average loss weighted by probability beyond  $VaR$ , it is relatively easy to calculate: we slice the tail of the aggregate loss distribution above the  $VaR$  ( $X > VaR$ ) into  $N$  slices and then calculate the weighted average loss by probability. Figure 2-11 represents this concept.

$VaR$  and  $CVaR$  can be applied to measure the operational risk, in this regard we speak of operational  $VaR$  ( $OpVaR$ ). We are focused on quantifying the potential economic expected loss due to failure in a power system, with the purpose of hedging them or making management decisions. In general form, the potential loss is the product of the probability that a failure occurs (frequency) with its associated cost (severity),

expressed with Equation 2-16. Frequency and severity are both stochastic processes previously identified and represented by mean of Probability Distribution Functions which must be added to obtain the aggregate loss distribution function (LDA). It is not easy to get a simple relation for LDA and it is necessary to apply numerical methods. A frequently used method is the Monte-Carlo simulation (Chavez, et al., 2006; Chernobai & Rachev, 2006; CRUZ, 2004; Vose, 1996) in order to aggregate PDFs and estimate *LDA*.

$$LDA_s = \sum_{i=1}^N X_i \quad \text{Equation 2-16}$$

Where  $N$  represents the number of fault events (frequency of events) and  $X_i$  is the economic loss of each event (severity of event), implies that the total losses are the result of two sources of randomness, frequency and severity. The Equation 2-16, is useful in financial markets however depending of the application context, additional risk factors must be identified and integrated into the Equation 2-16, in this point we must identify which risk factors allow us to quantify the blackout cost and how it will be integrated.

The PDF of the number of outage events (frequency) and the PDF of the DNS (severity) can be calculated by analysing the events from historical data. A scaling time factor was previously defined for frequency analysis (daily, weekly or monthly). In general terms, Equation 2-16 can be rewritten for the electric context as:

$$LDA_s = \sum_{i=1}^N f(DNS_i, C, \theta) \quad \text{Equation 2-17}$$

Where  $N$  is the number of outages events occurred in a time period (daily, weekly or monthly). *DNS* is the demand not supplied for each event “ $i$ ” (MWh). It can be used for information of the complete system, by regions, by customer type, by cause, etc.  $C$  is the customer cost and different methodologies are available to estimate (CIGRE, 2001; Sullivan, et al., 2009).  $\theta$  are other variables in relation with the outages in the power system, such as customer type, power lost, outages duration, geographic regions, equipment type, origin or causes, etc. Finally,  $f(\cdot)$  is a functional relationship which must be identified and implies a multidimensional modelling, more complex than the



financial modelling of operative risk which is a simple aggregation of frequency and severity of failures.

The following general assumption was made: (i) the outage events are independent and identically distributed (*i.i.d.*). (ii) The frequency and the severity are independent random variables. (iii) The DNS costs depends on power loss, we use the methodology from the Colombian Energetic planner (UPME, 2004a) in order to assess the outages in power systems according to the power loss. (iv) The ratio of power loss of each outage is computed using the peak power demand within the hour that the outage is occurring, without consideration for the failure duration, (v) spatial relationships amongst events are not considered.

Concerning the transmission system outages, we propose a more specific model  $f(.)$  defined as follows:

$$LDA_s = f(N, DNS, h, t, C) \quad \text{Equation 2-18}$$

And

$$LDA_s = \sum_{i=1}^N DNS_i^h \cdot C^k \quad \text{Equation 2-19}$$

Where,  $LDA_s$  is the aggregate loss distribution for the DNS, “s” is the simulation index, is the output variable.  $N$  is the PDF of monthly outage events (Figure 2-9).  $h$  is the hour when outages occur and a discrete PDF is used to quantify power loss ratio.  $k$  identifies the cost ranking for the power loss level.  $DNS_i^h$  is the PDF of Demand Not Supplied for each event  $i$  (Figure 2-6), happened in the hour  $h$  (MWh) (Figure 2-4).  $C^k$  is the cost of energy not supplied for the power loss level (Figure 2-12). The cost of energy not supplied  $C^k$  for different power loss levels  $k$ , is defined by:

$$P_i^h = \frac{DNS_i^h}{t_i} \quad \text{Equation 2-20}$$

$$R_i^h = \frac{P_i^h}{PS^h} \quad \text{Equation 2-21}$$

$$\text{if } R_i^h \in R^k \Rightarrow C^k$$

Equation 2-22

with:  $t_i$ , the duration PDF of each outage  $i$  occurred in hour  $h$  (hour) (Figure 2-5),  $P_i^h$ , the power loss of each simulated outage  $i$ , in the hour  $h$  (MW),  $PS^h$ , the total system peak demand, estimated for each hour  $h$  (MW),  $R_i^h$ , the power loss Ratio of each outage  $i$ , in the hour  $h$ . The Figure 2-12 shows the different ratios of power losses  $R^k$  with their associated cost  $C^k$  in US\$/KWh. As you can see all the variables have associated PDFs, which must be aggregated in order to get the LDA profile as an estimation of blackout cost by means of the Monte Carlo simulation.

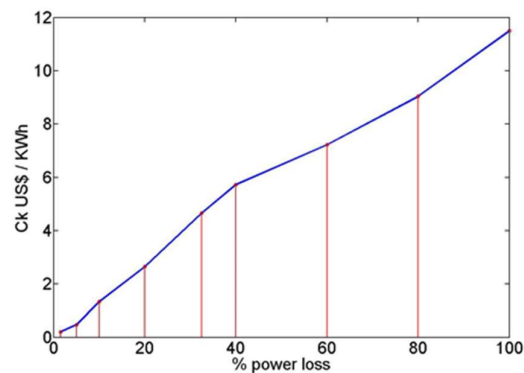


Figure 2-12 Cost for the power losses level  $k$  -  $C^k$  (UMPE)

The Monte-Carlo Simulation is presented in Figure 2-13 to obtain the profile of LDA. Normally the operative risk profile (LDA) has a heavy tail and the range of economic losses can be divided in different categories in order to make operations, management and hedging decisions (in Figure 2-11 marked with point X1, X2, and X3). It could be important information for the risk managers of all the different agents operating in the electricity market: energy suppliers, transmission & distribution operators, traders, as well as to utilities regulators. The losses can be classified into two categories, the expected and the unexpected losses. In turn, the unexpected losses can be classified as severe or catastrophic. The expected losses can be compensated for by consuming a proportion of the utilities' profits, while the severe or catastrophic losses will be covered by a proportion of the economic equity, insurance contracts or derivatives (Hull, 2008). The model presented in the Equation 2-19 can be associated with making decisions with the profile of estimated economic losses, moreover the model can be rewritten depending on one's particular interests, such as making a decision about

maintenance programmes, defining equipment inventories policies, define KPIs, investment policies or insurance coverage strategies to name a few.

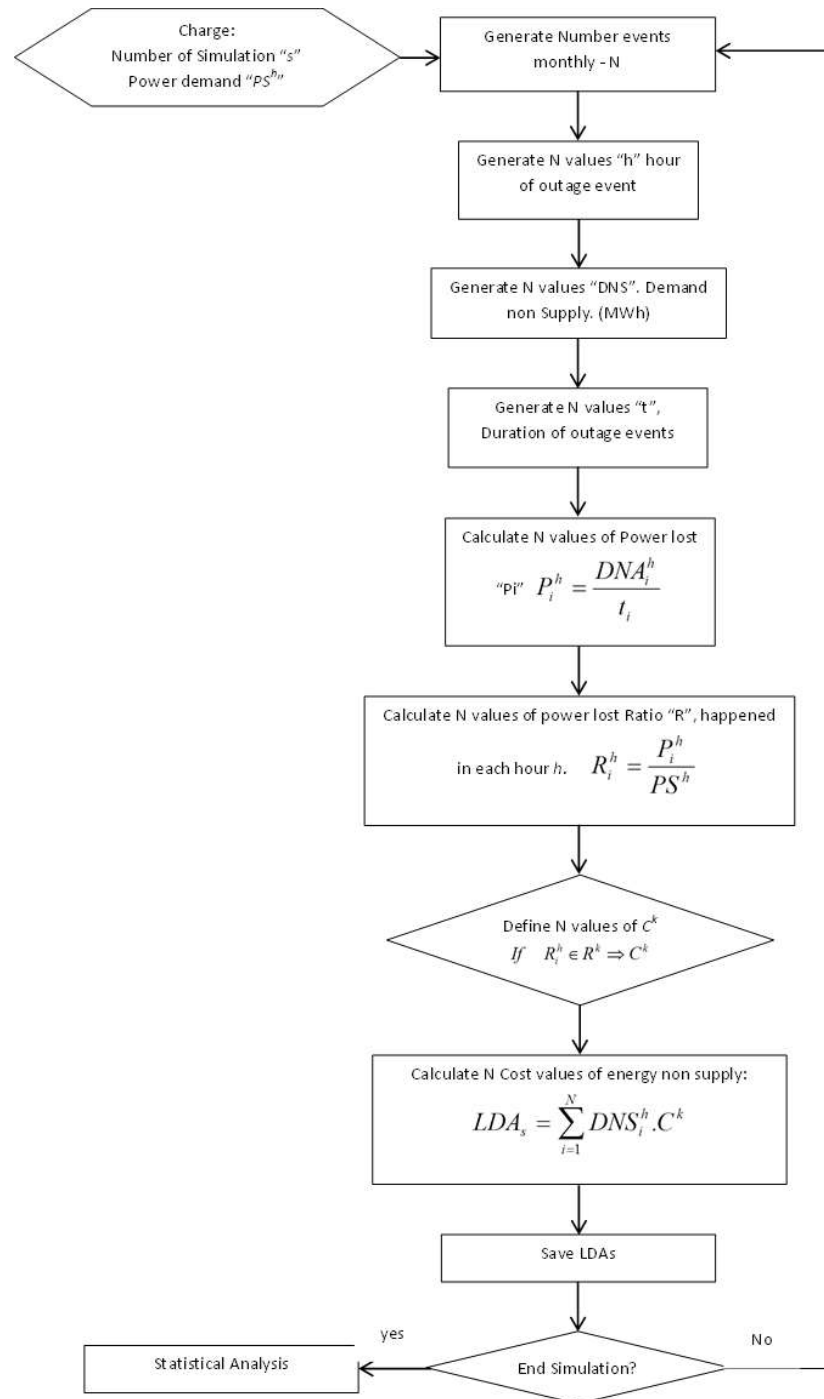


Figure 2-13 Monte-Carlo simulation process

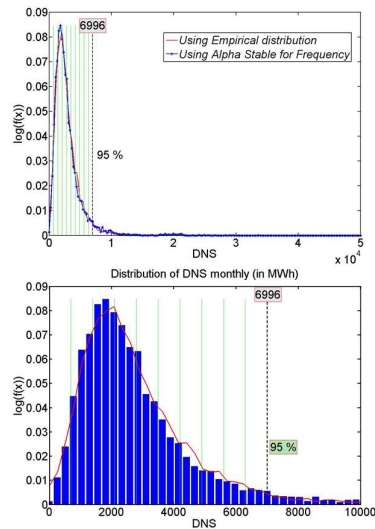


Figure 2-14 Probability Distribution of Demand Not Supplied (MWh)

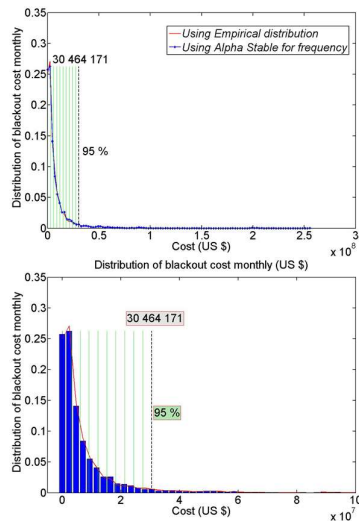


Figure 2-15 Probability Distribution of blackout cost monthly (US \$)

9,372 cases of demand not supplied (DNS) in the transmission system allow us to obtain different distribution functions. The Figure 2-14 and Figure 2-15 show respectively the probability distributions of the DNS and Blackout Cost (monthly) obtained after the simulation process for the Colombian electricity market, using both empirical, and  $\alpha$ -stable distributions. The average value of demand not supplied is around of 2,900 MWh with a mean cost of 8 million USD monthly. The percentile 95% of the DNS is around 6.996 MWh and the maximum economic expected loss at 95% confidence (VaR) is around 30 million USD monthly. The CVaR reaches around 63 million USD monthly.

As shown on the Figure 2-11, there are different regions in the distribution of the operational risk profile, i.e. one region for expected losses between 0 and  $X_2$  and one for unexpected losses (over the expected losses) between  $X_2$  and  $\infty$ . But how can these regions of probability distribution of demand not supplied cost shown in Figure 2-15 be identified? There is no standard methodology to extract these values directly as it depends on the characteristics of each type of agent (transporter, distributor, trader or regulator), on the risk-taking propensity of each board of directors, and on each available equity level or the cost of the insurance policies to name a few.

The different limits must be identified ad-hoc. The limits  $X_1$ ,  $X_2$  and  $X_3$  can be identified in the Figure 2-15 with different approaches such as a constant value, a financial/economic analysis or a technical analysis. For instance, the level  $X_3$  is usually the value at risk for the 95% or 99% confidence level (or CVaR) and the levels  $X_1$  and  $X_2$  could be the limits associated with the standard deviation around the mean. Let us take a technical criterion from a regulator point-of-view (Pacheco & Rios, 2010) which defines the values  $X_1$ ,  $X_2$  and  $X_3$  as functions of demand not supplied, of the event durations, and of the power lost. The classification based on DNS is used in order to obtain the PDF of monthly DNS for each ranking, allowing us to read their percentiles from the probability distribution functions of monthly DNS. Note that later this can also be used to read the outage cost. The economical interpretation of these limits from a regulator's point of view becomes:

- Loss <  $X_1$ : faults are considered as “minor” or moderate for the system. They are considered a common load loss with low frequency variation and recovering without load shedding. They have a short duration and quick recuperation time (or staggered). The cost is understood like an acceptable risk level for the system. In our case this value sits around 4 million US\$ per month. This category includes the first two categories proposal by (Pacheco & Rios, 2010) because common practices suggest that high frequency events will not make the system vulnerable (Doorman, et al., 2004) (< 250 MWh).
- $X_1 \leq$  Loss <  $X_2$ : the faults are “major” with middle frequency variation with load shedding or generation lost. The events' durations are more than one hour and their restoration goes up to a few hours. The causes and consequences of failures must be managed. This interval can include the expected average value of faults. In our work

this value sits around 12 million US\$ per month (< 900 MWh).

- $X2 \leq \text{Loss} < X3$ : level known as “critical” with a strong frequency variation and load shedding or generation loss and restoration of the system to operations is difficult: it can take more than two hours when part of the electrical system, an electrical area, is lost. The system operator must perform a deeper analysis for determining the causes and consequences for the market and review operations security compliance for utilities that do not meet the levels of system availability. The cost of DNS could be transferred by securitisation, future contracts, or being covered by other agents within the market. The value sits around 19 million USD per month (< 2,500 MWh).
- $\text{Loss} \geq X3$ : level known as “catastrophic loss”. The event has a high probability to being a total blackout because of very strong frequency variations with actuation of load shedding schemes in several stages, generation unit’s outset. Restoring operations in an acceptable time presents many difficulties. The maximal economic loss (value-at-risk) at the 95 % confidence level sits around 30 million USD per month. (6.996 MWh)

Furthermore, from equation 6 we observe VaR growing with a square root of time in Gaussian case (it assume that asset returns are normal). An  $\alpha$ -stable behaviour of frequency distribution implies infinite value for variance and volatility. In this case, the generalisation of  $VaR$  is defined through the scale parameter  $\gamma$  of a  $\alpha$ -stable law (Levy-Vehel & C., 2002; Peters, 1994):

$$VaR \approx W_0 q_c^\alpha \gamma_0 (\Delta t)^{\frac{1}{\alpha}} \quad \text{Equation 2-23}$$

The value-at-risk (reading the 95% percentile) of the energy not supplied cost for periods of 1-day to 90-days was calculated (Figure 2-16) in a similar form to the analysis for doing the monthly period. We find that the VaR increase rate is larger than the Gaussian case (0.5) for the blackout risk; and, in a first approximation, we can consider that  $VaR \approx (\Delta t)^{0.8}$  but we propose a more detailed study in the future on each probability distribution function (energy not supplied, duration, frequency of events) in order to identify long range dependence. Usual Hurst exponent estimation (through

index  $J$ ) must be distinguished from  $\alpha$ -stable estimation and techniques such as diffusion entropy analysis (Scafetta, 2001) may be good candidates.

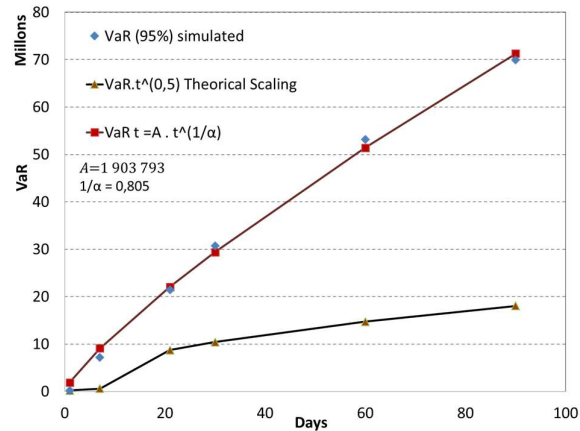


Figure 2-16 Estimation of VaR for DNS cost versus  $\Delta t$

## In conclusion

The phenomenon of self-organized criticality (SOC), shown in a simple pile of sand, can be applied to a power system explaining the behavior of the electric system to blackouts and its response. For a long-term correlation in the data series of demand not supply statistical techniques are used to estimate the Hurst index in 0.8 (confirm than data series time has a long term correlation).

The CDF of Demand Not Supplied (DNS) in the Colombian power system, as expected, follows a power law regime, and may be related to SOC regime. In the statistical analysis the real data were adjusted to  $\alpha$ -stable distribution that characterize complex phenomenon.

When an estimation of VaR of demand not supplied data is done the growth rate VaR in time is greater than the root 0.5. This implies that the risk is growing at a higher rate than the data with Gaussian behavior. The growth rate measured by VaR and Hurst index are related.

### **3. Design of a simulation process to fit a power network behavior**

The DC SPFM is used in order to understand and simulate the dynamics of an evolving power system in the presence of a continuous increase in load demand. The intent of the model is to capture the hypothesized SOC dynamics of real world power systems in a manner that is tractable in terms of simulation length and therefore most of the details of real world systems are not included (Carreras *et al.*, 2004a; Carreras *et al.*, 2004b). One primary method of reduction is that the model makes use of the DC load flow assumptions and therefore the model does not take into account issues such as voltage stability. Despite reducing the complicated details of real world power system the model does produce very complex behavior. These mimic the power law and other statistics of observed blackout time series for power systems and therefore the model achieves its intended goals (Carreras *et al.*, 2004a).

The simplification of the power system, within the model, does not necessarily reduce the model's validity. The aim is to model certain characteristics of the system and not the system in its entirety. Models exist that increase the level of detail over the original OPA, specifically reducing the DC load flow assumptions and using AC load flow analysis (Mei *et al.*, 2008). However due to large increases in running time for the AC problem over the DC problem, it would seem sensible to investigate the behavior of the original DC model before a full AC analysis is carried out. A full AC analysis is beyond the scope of this work.

This section is dedicated to the presentation of DC Statistical Power Flow Model (DC SPFM). This model shows that the network general simulation tool can be used for different applications such as network expansion analysis or operational day-ahead risk analysis. In addition the Colombian database will be modeled with the DC SPFM, and the condition setting will be estimated because the power system in the short term should have the same behavior as the long term (historic data).



### 3.1 Model general structure

The model general structure introduces two-time scale dynamics (slow and fast) and is built on the association of:

- A physical model, consisting here in a DC optimal power flow model, which determines power flow balance in any network operating condition (even fault condition and possible associated power demand shedding), taking into account physical constraints inherent to the network.
- Statistical variables such as functions characterizing the failure probability of network components (e.g. lines) depending on network operating conditions.

The general algorithm of the proposed DC SPFM is presented in Figure 3-1, where yellow and green parts are respectively relative to slow and fast dynamics. The DC SPFM model is an iterative model, i.e. the network evolution is simulated through a succession of events. No specific time scale (or time step) is attached to the model structure. It is then appropriate to any time scale (e.g. days, hours). Selected time scales must then be specified by setting the appropriate input parameters of the model. A typical use of DC SPFM could be with a daily time scale based study, i.e. input parameters must be related to a daily evolution of the network.

### 3.2 Slow dynamics: Power network evolution

Power network evolution first involves load power demand increases associated with power generation capability increases. Then in response to demand evolution network improvement is introduced, mainly to keep a minimum and realistic power transmission capacity margin.

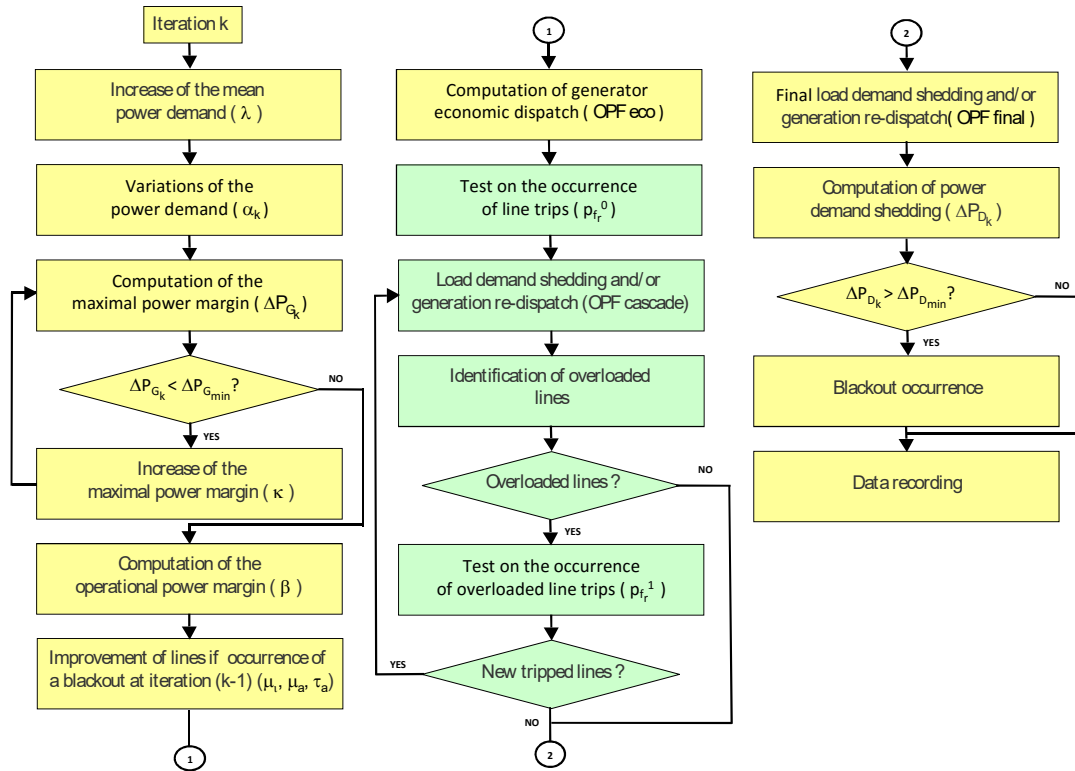


Figure 3-1 DC SPFM general algorithm

### 3.2.1. Power demand and generation power evolution

Load power demand evolution is done on an iteratively based demand increase. Considering active mean power demand vector on iteration  $k - 1$ ,  $\bar{P}_{D_{k-1}}$ , active mean power demand vector on iteration  $k$ ,  $\bar{P}_{D_k}$ , is determined by using a constant increase rate  $\lambda$ . Then, active actual power demand vector on iteration  $k$ ,  $P_{D_k}$ , is computed introducing variations around mean power demand through a random coefficient  $\alpha_k$  (Equation 3-1). The dimension of power demand vectors is equal to load node number  $N_L$ .

$$\begin{cases} P_{D_k} = \lambda P_{D_{k-1}} \\ \bar{P}_{D_k} = \alpha_k \bar{P}_{D_k} \end{cases} \quad \text{Equation 3-1}$$

Figure 3-2 shows typical evolution of both mean and actual power demands (computed on a daily time basis).

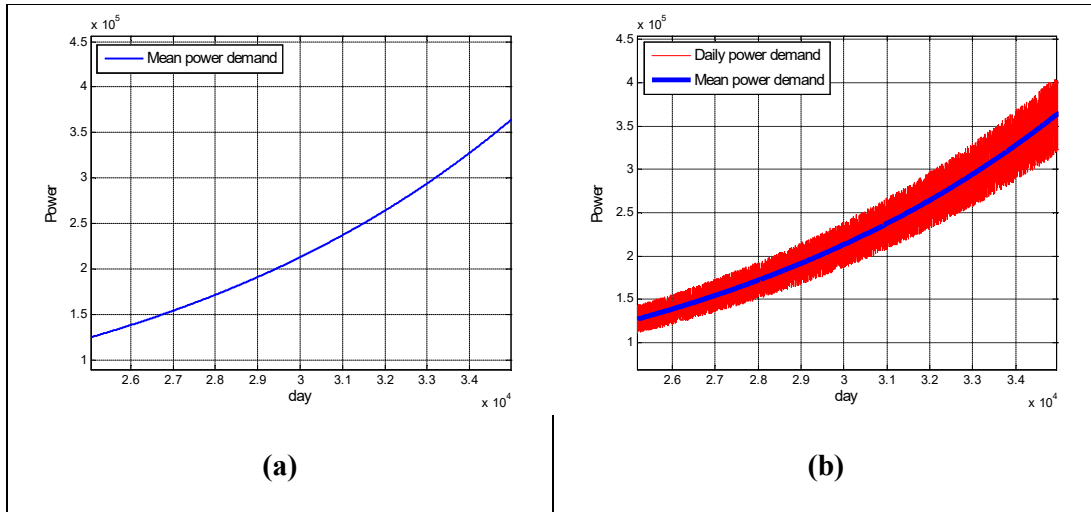


Figure 3-2 Evolution of mean power demand (a) and daily power demand (b)

Power generation capability evolution is introduced with the idea of keeping a constant minimal Power Margin,  $\Delta P_G^{min}$ . On iteration  $k$ , the “whole generators” available power margin  $\Delta P_{G_k}$  is defined by Equation 3-2.

$$\Delta P_{G_k} = \sum_{i=1}^{N_G} P_{G_{max_i}} - \sum_{j=1}^{N_L} \bar{P}_{D_{kj}} \quad \text{Equation 3-2}$$

Where  $P_{G_{max_i}}$  is the maximum active power that can be generated at node  $i$ ,  $\bar{P}_{D_{kj}}$  is the mean active power demand at load node  $j$ , and  $N_G$  is the generator nodes' number. Then, power margin  $\Delta P_{G_k}$  is kept over a minimal margin such that:

$$\Delta P_{G_k} = \Delta P_G^{min} \quad \text{Equation 3-3}$$

by increasing, if necessary, active power margin  $\Delta P_{G_k}$  using:

$$P_{G_{max_i}} = P_{G_{max_i}} + \kappa \sum_{j=1}^{N_L} \bar{P}_{D_{kj}} \quad \text{Equation 3-4}$$

Where generator  $i$  is randomly chosen in  $[1 \dots N_G]$  until condition Equation 3-3 is verified, and  $\kappa$  is a constant increase rate.

Generation power margin  $\Delta P_{G_k}$  is introduced to simulate the evolution of the network in terms of maximum capacity generation and could be referred to the network expansion planning strategy.

Regarding network operation, it seems interesting to take into account an operational generation power margin, i.e. an available generation margin (which could be seen as AGC generation reserves). Such an available generation margin is introduced in DC SPFM through a constant coefficient  $\beta$ . At iteration  $k$ , generator  $i$  operational available generation capacity  $P_{G_{max}k_i}^{op}$  is computed introducing equations Equation 3-5 and Equation 3-6. Figure 3-3 gives an example of both maximal and operational power margins.

$$\varepsilon = \beta \frac{\sum_{j=1}^{N_L} P_{D_{kj}}}{\sum_{i=1}^{N_G} P_{G_{max}i}} \quad \text{Equation 3-5}$$

$$P_{G_{max}k_i}^{op} = \min \left( \varepsilon P_{G_{max}i}, P_{G_{max}i} \right) \quad \text{Equation 3-6}$$

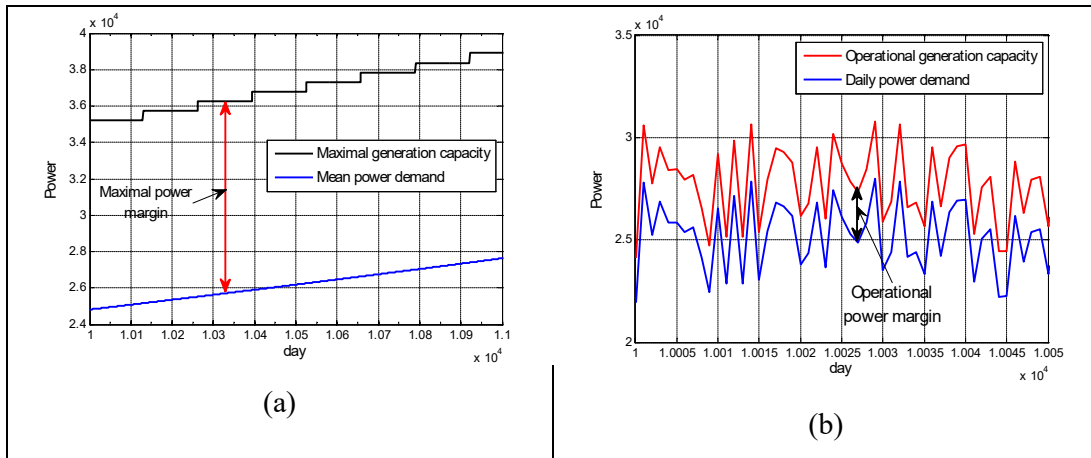


Figure 3-3 Illustration of maximal power margin (a) and operational power margin (b)

### 3.2.2. Network improvement strategy

Network improvement strategy refers to feedback actions done to improve the behaviour of the network, i.e. feedback energy that has to be provided to the network in order to keep it operating well. In DC SPFM network improvement actions are relative to the increase of line transmission maximal capacities and are introduced as follows:

- An immediate feedback strategy, which characterizes the “sum” of all actions that are done, on a continuous way, to maintain a well operating network.

- A delayed feedback strategy, which could be referred to as a network expansion strategy.

### 3.2.2.1. Immediate strategy approach

Immediate strategy consists in increasing the line's maximum transmission capacity that has been declared overloaded when a blackout occurs at iteration  $k$ . Maximal power transmission capacity of such identified lines is immediately modified at the iteration after the blackout occurs (i.e. at iteration  $k + 1$ ) as proposed by Equation 3-7, where  $T_{Lmax_\gamma}$  is the maximal active power that line  $r$  can transport and  $\mu_i$  is a constant improvement rate.

$$T_{Lmax_\gamma,(k+1)} = \mu_i T_{Lmax_\gamma,k} \quad \text{Equation 3-7}$$

In addition, line impedances are modified in order to be coherent with the line's maximum flux improvement as follows:

$$\begin{cases} Z_r = Z_r / \mu_i \\ B_{sh_r} = \mu_i B_{sh_r} \end{cases} \quad \text{Equation 3-8}$$

Where  $Z_r$  and  $B_{sh_r}$  are respectively the series impedance and the shunt susceptance of line  $r$ .

### 3.2.2.2. Delayed strategy approach

In the delayed strategy approach the above mentioned immediate strategy (refer to equations Equation 3-7 and Equation 3-8) is associated with a delayed improvement of lines.

Lines that have been declared overloaded when a blackout occurs on iteration  $k$  are also improved after a delay, here referenced as  $\tau_a$ .

Maximal power transmission capacity of such identified lines is then modified at iteration  $\kappa + \tau_a$  as proposed by Equation 3-9 where  $\mu_a$  is a constant improvement rate.

$$T_{Lmaxr,(k+\tau_a)} = \mu_a T_{Lmaxr,k} \quad \text{Equation 3-9}$$

In addition, line impedances are modified in order to be coherent with a line's maximum flux improvement as follows:

$$\begin{cases} Z_r = Z_r / \mu_a \\ B_{sh_r} = \mu_a B_{sh_r} \end{cases} \quad \text{Equation 3-10}$$

Figure 3-4, gives an illustration of typical network total transmission capacity evolution for immediate and delayed case studies.

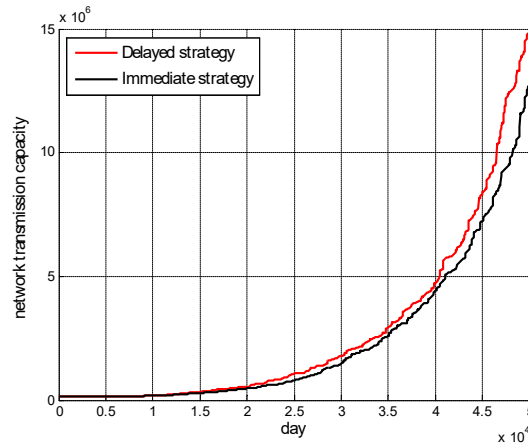


Figure 3-4 Evolution of network total transmission capacity for immediate and delayed strategies

### 3.2.3. Generation economic dispatch (OPF eco)

In order to simplify notations, indices  $k$  and  $k-1$  are removed from equations. This is motivated by the fact that the following computations are all related to iteration  $k$  of the model process.

The generator economic dispatch step is performed in order to determine, on the basis of generation costs, the generator dispatch that will be considered during the following cascade phenomena step. This is done by carrying out an optimal power flow (OPF eco) calculation aiming to minimize a given cost objective function, here given by Equation 3-11 while respecting network physical constraints, which are given by Equation 3-12.

$$J_{eco}(X_{eco}) = \frac{1}{2} P_G^T H P_G + C^T P_G + D \quad \text{Equation 3-11}$$

With cost coefficient constant matrices  $H$ ,  $C$  and  $D$ .

$$\begin{cases} P(\theta) - P_G + P_D = 0 \\ T_L(\theta) - T_{Lmax} \leq 0 \end{cases} \quad \text{Equation 3-12}$$

where  $\theta$ ,  $P_G$ ,  $P_D$ ,  $P(\theta)$ ,  $T_L(\theta)$  and  $T_{Lmax}$  are vectors respectively representing node voltage phases, generator node active powers, load node active powers demands, active power flows converging to nodes, line active power flows and line maximal active power flows. Associated optimization variables are then defined as follows:

$$X_{eco} = [\theta \quad P_G]^T \quad \text{Equation 3-13}$$

and constraint limits on optimization variables are introduced through Equation 3-14.

$$\begin{cases} \theta_{min} \leq \theta \leq \theta_{max} \\ P_{Gmin} \leq P_G \leq P_{Gmax} \end{cases} \quad \text{Equation 3-14}$$

Where  $\theta_{min}$ ,  $\theta_{max}$ ,  $P_{Gmin}$  and  $P_{Gmax}$  are vectors respectively representing voltage phase minimum/ maximum limits, generator node active power minimum / maximum limits.

The result of the economic dispatch step is the initial generation map, here referenced as  $P_{G_0}$ .

If the generation economic dispatch  $P_{G_0}$  has been previously computed with an external source (e.g. from economic dispatch software), this algorithm step is simply reduced to the downloading of  $P_{G_0}$  from an external data file.

### 3.2.4. Final load power demand shedding and/or generation power re-dispatching

When the cascade phenomena phase ends it is necessary to compute the network's final power balance, i.e. the final load power demand shed and/or generation power re-dispatch, taking into account the tripped lines. Then, depending on if one or several lines tripped, it could be necessary to re-dispatch power generation and potentially to shed load power demand to assure network stability, i.e. to assure power balance as well as respect of network physical constraints. In DC SPFM, both generation power re-

dispatching and potential power demand load shedding result from an Optimal Power Flow (OPF final) calculation aiming to minimize a given objective function (Equation 3-15), while respecting network physical constraints (Equation 3-16 and Equation 3-17).

The aim of objective function  $J(X)$  is to determine a final balance set point aiming to be as close as possible to initial load power demand  $P_{D_0}$  as well as to initial generation power dispatch  $P_{G_0}$ . If such an objective cannot be fulfilled the proposed strategy is, in a first step, to re-dispatch the generation, then if necessary, to shed power demand load. Priority to generation, re-dispatch are introduced through weighting coefficients  $\omega_{G_i}$  and  $\omega_{D_j}$  in criteria  $J(X)$ .

$$J(X) = \sum_{j=1}^{N_L} \omega_{D_j} (P_{D_{0j}} - P_{D_j})^2 + \sum_{i=1}^{N_G} \omega_{G_i} (P_{G_{0i}} - P_{G_i})^2 \quad \text{Equation 3-15}$$

$$\begin{cases} P(\theta) - P_G + P_D = 0 \\ T_L(\theta) - T_{L_{max}} \leq 0 \end{cases} \quad \text{Equation 3-16}$$

$$\begin{cases} \theta_{min} \leq \theta \leq \theta_{max} \\ P_{G_{min}} \leq P_G \leq P_{G_{max}} \\ 0 \leq P_D \leq P_{D_0} \end{cases} \quad \text{Equation 3-17}$$

with the associated optimization variable vector given by

$$X = [\theta, P_G, P_D]^T \quad \text{Equation 3-18}$$

The maximal generation power limit  $P_{G_{max}}$  is set depending on network operation conditions. On the one hand, if generation power margins can be considered (e.g. AGC generation reserve), the limit  $P_{G_{max}}$  is set to take into account such generation margins. However, if generation re-dispatching is not allowed, the maximum generation power limit  $P_{G_{max}}$  is set equal to the initial generation dispatch  $P_{G_0}$ , i.e.  $P_{G_{max}} = P_{G_0}$ . In any case, the minimum generation power limit  $P_{G_{min}}$  must be kept free to allow network power balance when power demand load shedding is required.



### 3.2.5. Identification of “power demand shedding” event

Power demand load shedding events are identified when the amount of shed power demand  $\Delta P_D$  is greater than a defined shed power demand threshold  $\Delta P_D^{min}$ , i.e. when

$$\Delta P_D = \sum_{j=1}^{N_L} (P_{D_{0j}} - P_{D_j}) \geq \Delta P_D^{min} \quad \text{Equation 3-19}$$

## 3.3 Fast dynamics: Cascade phenomena

In a SOC mechanism, fast dynamics is linked to avalanche or cascade phenomena (e.g. sand avalanche in sand-pile case). In DC SPFM cascade phenomena are related to line failures. Each line has a given probability to trip, probability which could be dependent on the line loading state (i.e. more loaded is the line, greater is its probability to trip). So, through a “game” of load report when line initial fault occurs, line trip cascades could appear with potential load power demand shedding as consequence.

### 3.3.1. Line trip initial occurrence

Cascade phenomena are generally the consequence of initial tripping events occurring in the network. In DC SPFM such initial tripping events are only related to line tripping occurrences. Such line tripping events could be associated with weather conditions (e.g. storms), bad network maintenance (e.g. line contacting trees, aged components), human errors, or network attacks (e.g. terrorism actions). In DC SPFM, these initial line tripping events are depending on a given line failure probability introduced through a constant initial fault probability  $p_{fr}^0$  associated to each line  $r$ .

#### 3.3.1.1. Overloaded line condition

An overloaded line condition is related to the line-loading rate  $L_r$ , defined, for line  $r$ , as follows

$$L_r = \frac{|T_r|}{T_{max_r}} \quad \text{Equation 3-20}$$

Then, defining line  $r$  loading rate threshold  $L_r^{th}$ , line  $r$  is said to be overloaded if the following condition holds.

$$L_r \geq L_r^{th} \quad \text{Equation 3-21}$$

### 3.3.1.2. Overloaded line trip occurrence

When a line  $r$  is declared overloaded it has a given probability  $p_{f_r}^1$  to trip. In DC SPFM,  $p_{f_r}^1$  could be a constant probability function, generally higher than the initial line trip probability (i.e.  $p_{f_r}^1 > p_{f_r}^0$ ), or be dependent on line loading rate  $L_r$ , i.e.  $p_{f_r}^1 = f(L_r)$ . Figure 3-5 shows an example of a linearly dependent probability function  $f(L_r)$ .

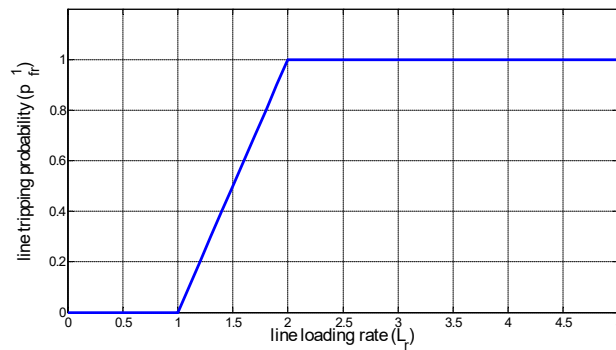


Figure 3-5. Example of a line loading rate dependent probability function  $p_{f_r}^1 = f(L_r)$

### 3.3.2. Power demand load shedding and/or generation power re-dispatching process

When at least one line is tripped (i.e. a new network topology is defined) it is necessary to compute a new network power balance. The associated process is computed by solving an optimal power flow problem similar to the one presented above and defined by the objective function Equation 3-15 to be minimized and the network physical constraints Equation 3-16 and Equation 3-17 to be respected. However, generally during cascade phenomena power flowing through lines cannot be controlled and might be

greater than maximum allowed power flow. Such a condition can easily be introduced by removing the second equation of system Equation 3-16 (relative to physical line power flow limitation constraint) in OPF problem solution computation, i.e. constraint Equation 3-16 is replaced by constraint Equation 3-22 in OPF problem to be solved.

$$P(\theta) - P_G + P_D = 0 \quad \text{Equation 3-22}$$

### 3.4 DC SPFM inputs and outputs summarize

The DC SPFM model has several input parameters and many output data. These inputs and outputs are related to both network slow dynamic and fast dynamic behaviours. General input parameters are related to the model description that was done. Some dedicated input parameters are associated with the SOC condition setting process. In both cases the model issues the same outputs.

#### 3.4.1. DC SPFM input parameters summarize

Slow dynamic input parameters are relative to network power evolution (both power demand and power generation) and to network line transportation capacity evolution. The modification of the relative balance between power characteristics and line capacities will bring the network into the so-called SOC condition. Table 3-1 summarizes slow dynamics related input parameters. Fast dynamics related input parameters concern cascading event dynamics, mainly associated with line tripping probabilities, and are presented in Table 3-2.

An additional input parameter is the total number of DC SPFM running iterations, here referred as  $N_{biter}$ .

#### 3.4.2. DC SPFM outputs summarize

The DC SPFM model has many outputs. These outputs are related to both network slow dynamic and fast dynamic behaviours. Table 3-3 summarizes slow dynamics related to outputs associated with network state at the beginning and the end of each iteration  $k$ .

From such information network general evolution can be represented. More particularly, load power demand shedding time series can be issued for further analysis

Load power demand	Generation power	Transportation lines
$\lambda$ : active mean load power demand constant increase rate	$\Delta P_G^{min}$ : minimal generation power margin	$\mu_i$ : constant improvement rate for increasing line maximal capacity in immediate strategy
$\alpha_k$ : iteration $k$ load power demand variation rate	$\kappa$ : constant generation power increase rate	$\mu_a$ : constant improvement rate for increasing line maximal capacity in delayed strategy
$\omega_{D_j}$ : relative weight associated to power demand shedding at load node $j$	$\beta$ : coefficient defining operational available generation power margin	$\tau_a$ : delay before increasing line maximal capacity in delayed strategy
$\Delta P_D^{min}$ : shed power demand minimal threshold	$\omega_{G_i}$ : relative weight associated to generation power re-dispatching at generator node $i$	$r_T$ : ratio between final and initial line maximal capacity in SOC condition setting process
$r_P$ : ratio between final and initial load power demand in SOC condition setting process	$H, C, D$ : cost constant matrices associated to economic dispatch OPF (OPF eco)	
	$r_P$ : ratio between final and initial generation power in SOC condition setting process	

Table 3-1 DC SPFM slow dynamics related input parameters

Transportation lines		
$p_{f_r}^0$ : initial tripping probability for line $r$	$p_{f_r}^1$ : tripping probability for overloaded line $r$	$L_r^{th}$ : loading rate threshold for declaring line $r$ overloaded

Table 3-2 DC SPFM fast dynamics related input parameters

Moreover, the evolution of characteristics and properties associated with physical SOC behaviour of the network can be highlighted and analysed. Table 3-4 summarizes fast dynamics related outputs. For each iteration  $k$  outputs give information at each step of cascading events. From such information events dynamics can be represented and analysed.

Initial load power demand $P_{D_{0j}}$ and final load power demand $P_{D_j}$ at each load node $j$
Initial generation power dispatch $P_{G_{0i}}$ and final generation power dispatch $P_{G_i}$ at each generator node $i$
Maximal available generation power $P_{G_{max_i}}$ at each generation node $i$
Operational available generation power $P_{G_{max_i}}^{op}$ at each generation node $i$
Line physical characteristics: allowed maximal power flow $T_{max_r}$ , series impedance $Z_r$ and shunt susceptance $B_{sh_r}$ for each line $r$

*Table 3-3 DC SPFM slow dynamics related outputs*

Load power demand $P_{D_j}$ at each load node $j$
Generation power dispatch $P_{G_i}$ at each generator node $i$
Line loading rate $L_r$ for each line $r$
Line status (open or closed) for each line $r$
Line overloading status (overloaded or not) for each line $r$

*Table 3-4 DC SPFM fast dynamics related outputs*

### 3.5 DC SPFM inputs from Colombian system

The parameter was worked with the historic database and operation criteria for transmission, generation, demand and faults.

#### 3.5.1. Parameter for Transmission DC SPFM Model:

The evolution of the transmission network is determined by four parameters, mainly  $\mu_b$  (short-term) and  $N_{over}$ ,  $\mu$  and  $T_d$  (long term). Network parameters associated with the evolution of the transmission are shown in Figure 3-6.

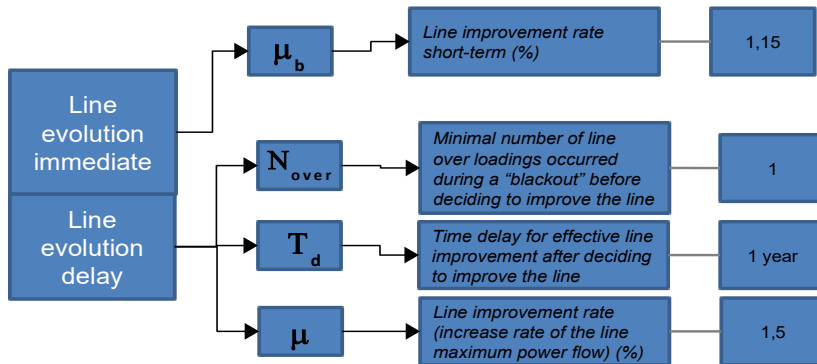
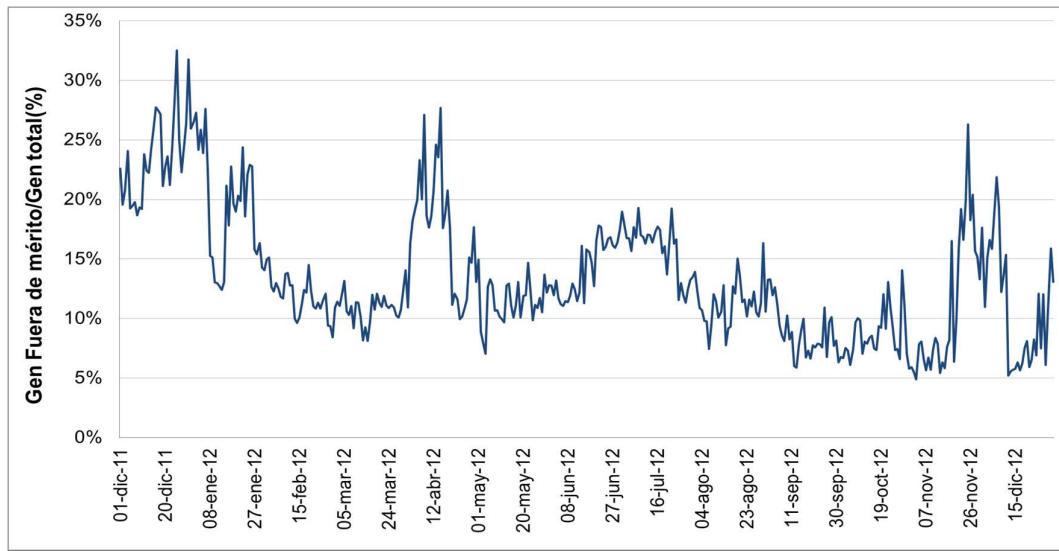


Figure 3-6. Parameters associated with transmission evolution

The  $\mu_b$  is short-term line improvement rate corresponding to the electric system operational actions seen in the real system. This can be assumed to be the restrictions applied to electrical transmission network. Calculated on all electrical systems as limitations that are imposed on the operation of systems for the generation dispatch, that has a feasible solution.

The parameter associated value in the Colombian network is initially estimated at 15% (average) in the Figure 3-7 shows that this value can vary from 5% to 32%. It is calculated as a percentage of generation out of merit, that is to say it is the forced generation required to supply the constraints of the national grid, whose bid price is higher than the pool price (CREG, 2012).

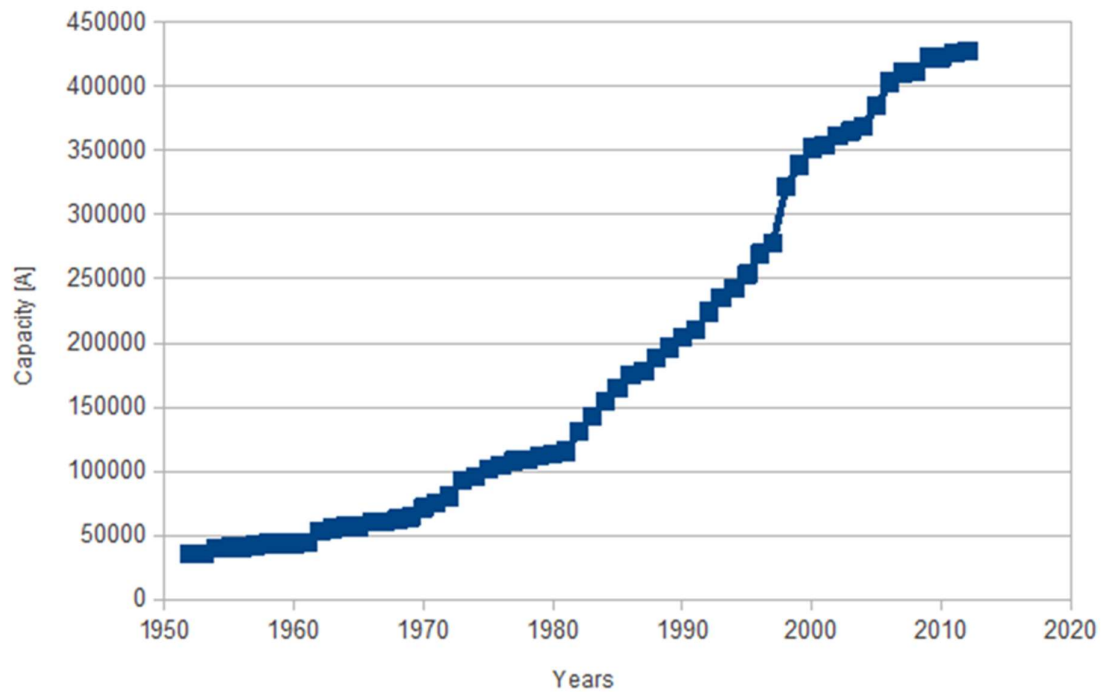


*Figure 3-7 Evolution of the generation associated with system constraints against total*

In the analysis of long-term evolution of the transmission network there are three main parameters.

The  $N_{over}$  parameter is measured after many failures in the transmission line and is improved. Reviewing post-operative analysis, each line participating in an event of demand non supply, has recommendations for improvement in almost 99% of cases. A case in which the transmission line participated in two events of demand non supply before improving occurs in the information analyzed. Therefore assuming this parameter value as 1 is consistent with what happens in the real system.

The  $\mu$  parameter evaluates the rate of improvement in the transmission network in the long term, using expansion studies an analysis of the evolution of the transmission network in time is made (XM, 2013). It is observed in Figure 3-8, that the calculated and the system data is around 1.05. This value confirms the results of simulations using the value of 1.5 as a growth strategy for the long term. Performing a similar plot for the simulated data is similar to the behavior of the real system.



*Figure 3-8. Transmission expansion evolution*

$T_d$  is the time between the identification of the need for improvement and the entry into operation of the transmission line. Taken as reference construction public calls of transmission lines and equipment input (UPME, 2004; UPME, 2007; UPME, 2008; UPME, 2008; UPME, 2009; UPME, 2009; UPME, 2009; UPME, 2009; UPME, 2010; UPME, 2010; UPME, 2010), the average time is 24 months. However a quarterly expansion plan revision against the constraints of the system is given. The time of analysis of events and the approval time of the public offering after the expansion plan must be added. This time is highly variable and will need to be considered on a case by case basis. The value taken in the simulation, one year, this could be underestimated.

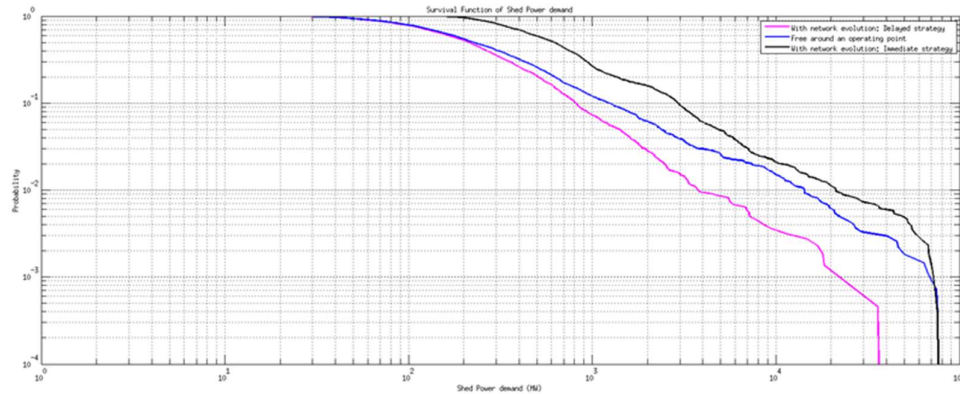
The scope of the thesis is the short term, given the day ahead market, the parameter  $\mu_b$  is of special relevance for this work.

Figure 3-9 shows three cases, the first curve (black) corresponds to the electric system response without consideration given to short-term improvement ( $\mu_b$ ) or long-term expansion ( $\mu$  and  $T_d$ ). The second curve (blue) corresponds to the electrical system



with short-term improvement only and the third curve (red) corresponds to short-term joint improvement and long-term expansion.

It can be seen from the graph that the joint effect of short term improvement and long-term expansion decreases both the probability and the severity of a blackout.



*Figure 3-9 combined effect of improve short-term and long-term network*

### 3.5.2. Parameter for Demand DC SPFM Model:

Demand parameters are illustrated in Figure 3-10.  $\lambda$  Daily increase rate of the mean electrical power of load buses. The growth rate of energy demand is strongly correlated with external variables such as gross domestic product, population growth, consumption habits, energetic policies, inflation, etc.

In order to estimate the growth rate, after analyzing the historical behavior of the data series, we need to consider; forecast energy sales (taking into account the projections of external variables), the energy losses in transmission and distribution, as a percentage of energy sales and special charges (which are significant), especially associated with the mining and petroleum industry.

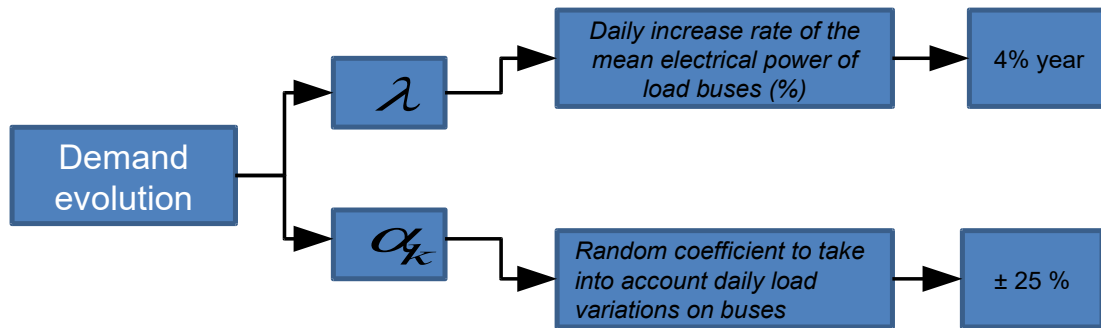


Figure 3-10. Parameters associated with demand evolution

Given the uncertainty in the predictions three scenarios are typically performed called low, medium, and high. Figure 3-11 shows these scenarios.

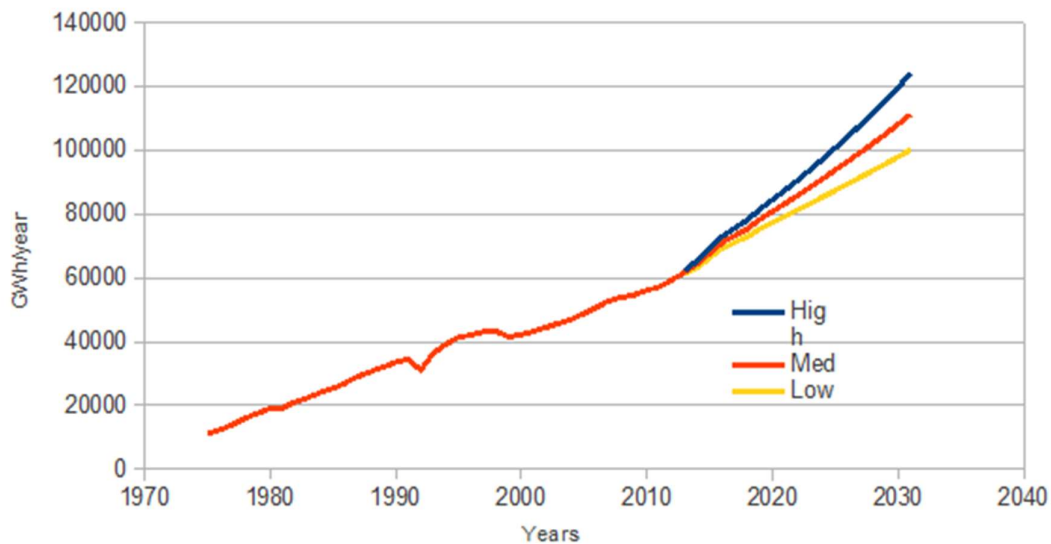


Figure 3-11. Evolution of demand and forecast

During the last decade the consumption grew at an average annual rate of 2.9%, partly affected by the economic downturn of 2009. A future scenario is estimated to average a growth in electricity demand between 3.9% and 4.4%, encouraged by the input value of new oil loads. An average annual growth demand of 3.9% for medium scenario, 3.4% for the low scenario and 4.5% for the high scenario (UPME, 2013) is projected for the period 2012-2020.

The next decade 2020 to 2030 shows a medium growth scenario of 2.9%, 2.4% for the low and 3.6% for the high scenario. The growth rate is considered lower, but given the

scope of the thesis and the day ahead market, the forecasts to keep in mind are the early years so a value of 4% is close to the estimated.

$\alpha_k$  Random coefficient to take into account daily load variations on buses. This parameter sets the variation of demand throughout the day and can be extracted from the daily curve of electrical system consumption. This parameter depends on the type of load (residential, commercial and industrial), the type of day (holiday or work) consumption habits, special events, weather etc; and therefore has high variability.

If we take the load type for a particular city values of 46%, 25% and 30% for the industrial, commercial and residential loads respectively can be inferred (Tabares & Hernández, 2008). Values of 62% for Sundays and holidays, 56% for Saturday and from 48% for working days can be estimated based on historical data.

Although the value originally taken from the 25% seems low compared to the experimental data in a specific city, it is important to mention that in the evolution of typical daily curves observed in a power system there is a decrease in the distance between the minimum demand and maximum demand.

### **3.5.3. Parameter for generation DC SPFM Model:**

The summary of generation parameters are shown in Figure 3-12.  $\Delta P_G^{min}$  is the whole generators minimum available power margin (%), This parameter depends on the reference used for example the maximum capacity, available capacity, or firm capacity. Some definitions are as follows:

Firm energy is the maximum power that a generation plant is able to deliver continuously under conditions of low hydrology over a period of one year.

Effective capacity, is the maximum amount of net power that a generating unit can supply in normal operating conditions.

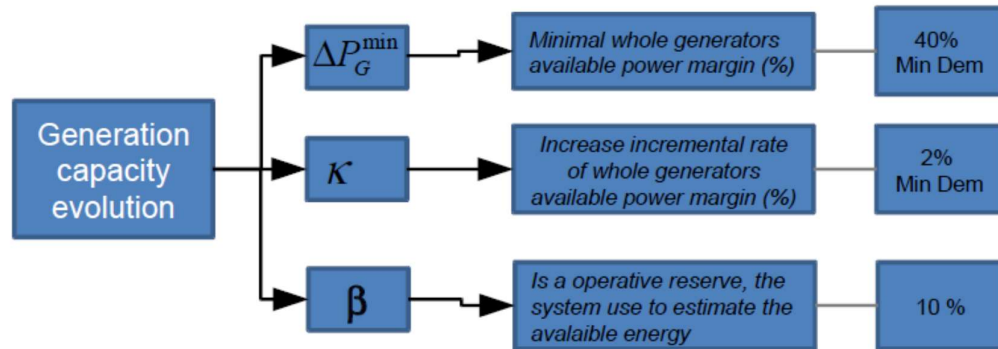


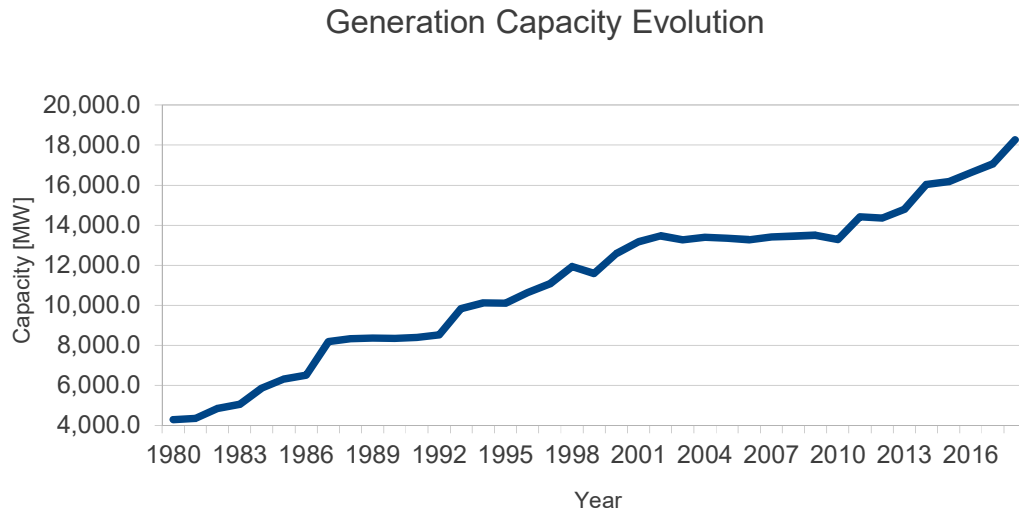
Figure 3-12 Parameters associated with generation evolution

Availability of generation: The real capacity of the generating station over a period of time. The difference to the installed capacity is that the second can be affected by conditions of maintenance, testing, use of alternative fuel, or decreases by reservoir levels, which all decrease the nominal capacity of the plant.

The evolution of marge generation was analyzed over 5 years. The  $\Delta P_G^{min}$  value for the maximum capacity is 49% on average and for available capacity is 27%. The value taken from the model is 40%.

**K** is the incremental rate of whole generators' available power margin. The incremental rate of generation capacity in front of the growth rate of demand for electricity can be used to estimate this value.

In this case, the growth rate of generation capacity is given in Figure 3-13, it agrees at 4% a year and the rate of growth of electricity demand in the last 20 years is on average 2.4%. It is reasonable then to use the value 2%.



*Figure 3-13 Generation capacity evolution*

With an operative reserve, the system used to estimate the available energy, this parameter can be estimated as the primary reserve and secondary energy that shows the electrical system in operation for the first value between 1% - 3%.

As for the secondary reserve AGC (automatic generation control), this value is variable per hour in each day and varies between 3% and 5%. The spinning reserve is given by the marginal generator market, this value is very variable both in the day and time and it is difficult to estimate. This value was estimated for the simulation as 10%.

#### **3.5.4. Parameter for line fault DC SPFM Model:**

The estimation of these values are performed using the data analysis from the events analyzed in the postoperative definitive reports analysis (XM, 2015), and from the expert's opinion of the events analysis, which are regulated in (CNO, 2012). The failure probability of a non-overloaded line was estimated at 0,0015, and the fault probability of an overloaded line at 0,20. Figure 3-14.

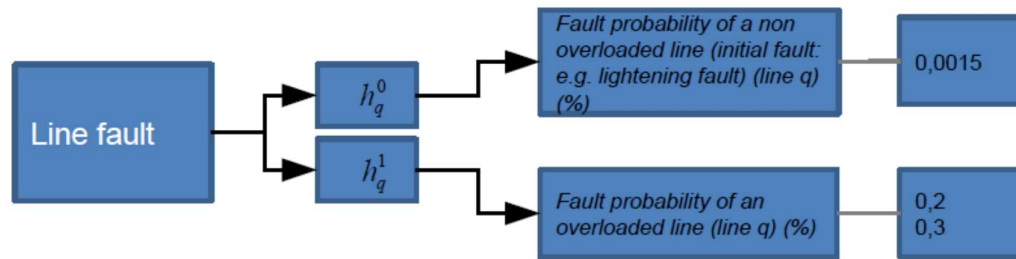


Figure 3-14. Parameters associated with line fault

### 3.6 SOC Conditions Settings

The Colombian electric power system has a SOC behavior when looking at the historic data, but when an economic dispatch is analyzed, it is not found in normal operation for a particular day. That is to say, the power system doesn't have a SOC condition behavior every time. The question now is how to be able to analyze the power system in SOC conditions for a particular point of operation?

Considering an electrical network under self-organized criticality regime is therefore needed when one takes into account the grid in its environment, i.e. consider the necessary reaction for its operation. It can be operational policy control, human intervention, maintenance operations, and planning policy and it can be quantified. The grid is then a dynamic system, managed by two opposing forces, in the critical regime. The power law behavior observed experimentally finds its origin in this competition.

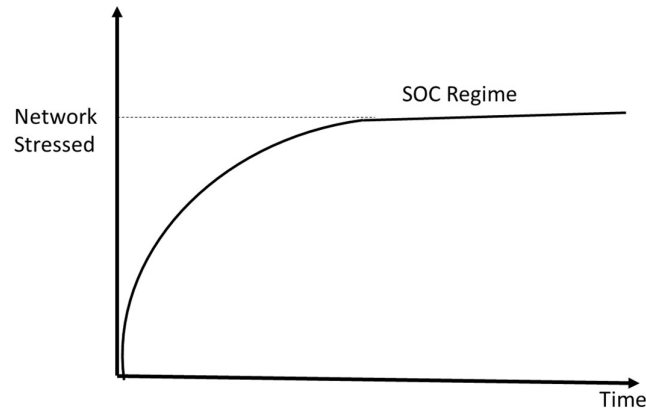
The model is based on a DC Power Flow resolution with, as variables of interest:

- Evolution of the load in the nodes,
- Improvement of the lines.

Failures or external events are randomly generated and two dynamics are represented, the slow dynamics representative of the evolution of the load and fast dynamic representative of the avalanche phenomenon on the lines. Temporal resolution  $\Delta t$  is 1 day and the time horizon for day-ahead markets.

The configuration of the power grid with its distribution of generation sources and demand, and the network topology with maximal power flow lines, in a DC power flow analysis where contingencies and security analysis is used is N-1. The SOC behaviour

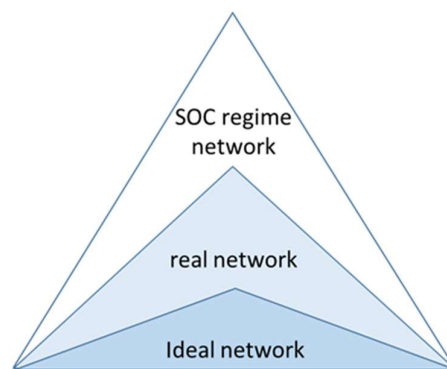
of electrical power systems (for long term) has been proved by the Dobson team using historical data but it is not necessary true for a particular point of operation, like day ahead dispatch. Figure 3-15.



*Figure 3-15 SOC regime of transition*

The network works in its environment (specifically one that allows it to run) and it is this set which can be self organized criticality. The very idea of the SOC model is to estimate not only one but all possible failures that can the network can have in a given configuration.

In the Equation 3-16, the ideal network means that there aren't constraints for the transmission of energy, no energy losses. In a real network there are some constraints, in part because the system could have a critical situation. In a SOC regime all the network has a critical stress.



*Figure 3-16 Sand pile evolution: from ideal network to SOC regime network*

This means that the SOC regime in a power grid is equivalent to putting the power grid under maximum stress where any random event can produce a minor failure or a major failure all over the network. This is the very significance of this new condition that

states that the SOC regime introduces new physical limitations; thermal, voltage, or stability limitations (Figure 3-16). In other terms, the SOC condition is a new regime where we are able to study the behaviour of a power grid under extreme conditions (as restriction, for instance). This regime has been validated experimentally where distribution of failure events showed specific power law regime. The SOC conditions then corresponds to the adaptation of the feedback process to the real distribution of events.

### 3.6.1. Cellular automata

Through the evolution of the load the SOC limitation are built using historical data or by using a renormalization technique we can put power grid under SOC stress through global variables,  $\tau_{SOC}$  and  $\gamma_{SOC}$ . In SOC conditions (with initial random events) these two variables will be roughly constant while local distributions of  $T_{ij}$  (power flow on line  $ij$ ) will be different.

Network improvement strategy refers to feedback actions done by an operator to improve the behavior of the network, i.e. feedback energy has to be provided to the network in order to keep it operating well. In DC SPFM, network improvement actions are relative to the increase of transmission line maximal capacities and are introduced as follows:

- An immediate feedback strategy, which characterizes the “sum” of all actions that are done, in a continuous way, to maintain a well operating network.
- A delayed feedback strategy, which could be better referred to as an expansion strategy.

#### 3.6.1.1. Local Phase

For the local phase line improvements are applied immediately.

An immediate strategy consists of increasing the maximal capacity of transmission lines that have been declared overloaded when a blackout occurs on iteration  $k$ . Maximal power transmission capacity of such identified lines is modified, the iteration after the blackout occurs (i.e. on iteration  $k + 1$ ), according with Equation 3-7 and Equation 3-8.



### 3.6.1.2. Accumulation phase

During the transient regime, for the accumulation phase, the delayed improvement of lines is applied.

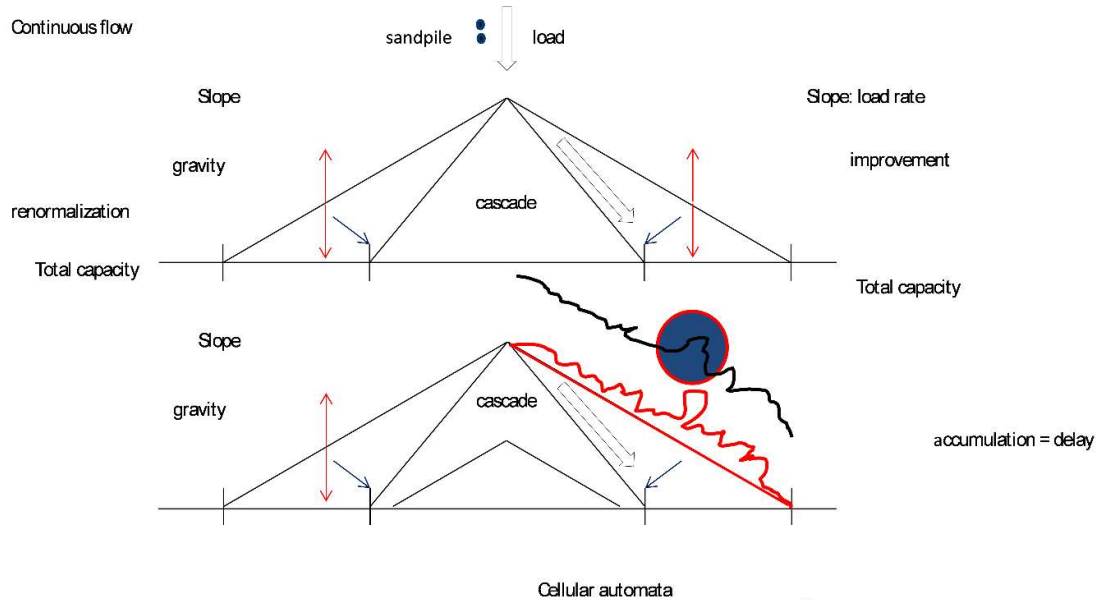


Figure 3-17 Accumulation phase

In a delayed strategy approach the above mentioned immediate strategy is associated with a delayed improvement of lines. Lines which have been declared overloaded when a blackout occurs, on iteration  $k$ , are also improved after a delay, referenced here as  $T_{delay}$ . Maximal power transmission capacity of such identified lines is then modified on iteration  $k + T_{delay}$  as proposed by Equation 3-9 and Equation 3-10.

### 3.6.1.3. Transmission evolution capacity

The demand evolution follows a linear evolution. As the transmission capacity evolves by multiplicative process (%), we shall find an exponential or power law evolution (

Figure 3-18).

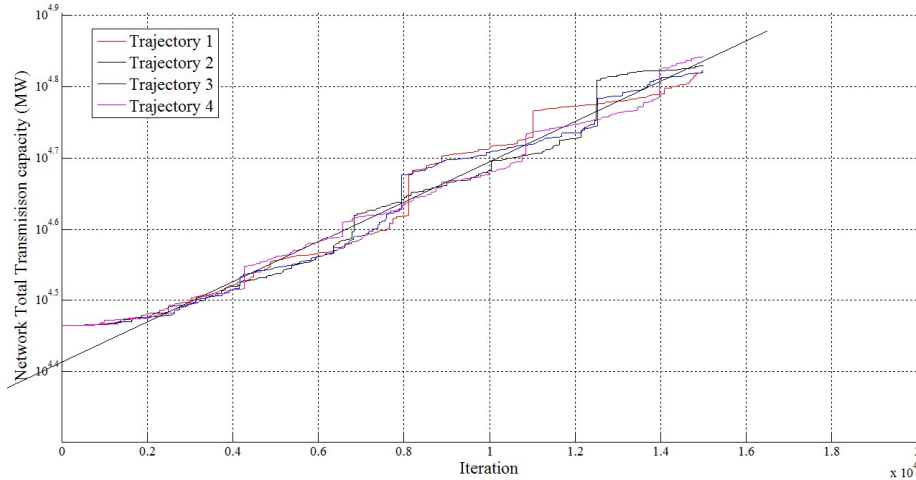


Figure 3-18 Transmission capacity evolution in semi log

### 3.6.1.4. Determination of coefficient (local phase and accumulation phase) with respect to the observable (historical data)

As shown in Figure 3-19, the middle part of the probability distribution function corresponds to the accumulation phase. It is required to invest in new infrastructure to change the associated slope. The local phase, corresponding to the immediate improvement, is found in the last part of the curve, this changes and depends on the decisions made during operation. You can increase or decrease the risk appreciably with operational measures in the system.

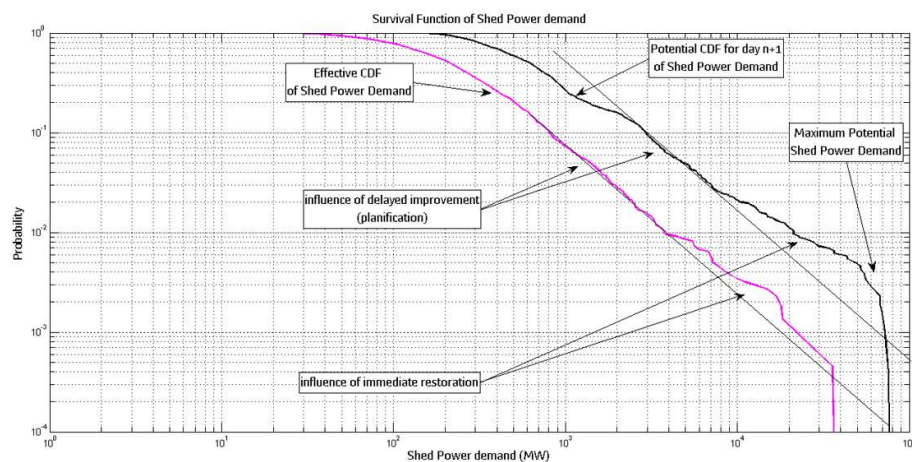


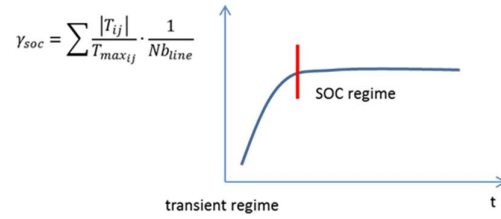
Figure 3-19 Local phase and accumulation phase respect to historical data

### 3.6.2. Parameter associated with SOC conditions setting

SOC behaviour is characterized by two global parameters associated with the loading level of a network:

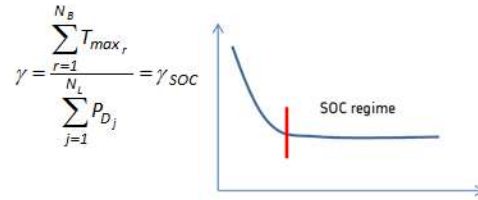
- A constant ratio between the sum of a line's maximum power flow capacity and the sum of the node load demands.

$$\gamma = \frac{\sum_{r=1}^{N_B} T_{max,r}}{\sum_{j=1}^{N_L} P_{D_j}} = \gamma_{SOC}$$



- A constant mean line loading level.

$$\tau = \frac{\sum_{r=1}^{N_B} \frac{|T_r|}{T_{max,r}}}{N_B} = \tau_{SOC}$$



with  $T_{max,r}$ , the maximal transmission capacity of line  $r$ ,  $P_{D_j}$ , the power demand at node  $j$ ,  $T_r$ , the line  $r$  power flow,  $N_B$ , the total number of lines.  $\gamma_{SOC}$  and  $\tau_{SOC}$  being constant coefficients characterize the SOC condition.

The SOC condition setting process is carried out using the DC SPFM model. The associated objective is to determine the distribution of a line's maximum transmission capacity (here referred as  $T_{max,ij}^{final}$  for line connecting node  $i$  to node  $j$ ) in order to set SOC condition for a given network topology and a given final mean demand power set point (here referred as  $\bar{P}_{DK}^{final}$  for node  $k$ ). The process is then described as follows:

### 3.6.2.1. Physical point of view of SOC for power grid

Using the analogy from a sand pile to explain power grid behaviour (with its surrounding) is a really efficient way to do integral analysis. The very physical meaning of self-organized criticality (SOC) for a power grid is:

- The DC SPFM (direct current statistical power flow model) model is based on a Power Flow resolution with variables of interest, the evolution of the load (nodes), and the improvement of the network (lines). Failures or external events are randomly generated and two dynamics are represented, the slow dynamics representative of the evolution of the load and the fast dynamic representative of the avalanche phenomenon on the lines. Temporal resolution  $\Delta t$  is 1 day and the time horizon may be years or even more. The indexing time can be reassessed because it is a sequence of events.
- The maximum stress condition of the entire power grid is a condition where any random event can produce any failure over the network. The SOC regime introduces new physical limitations to network.
- From historical data we can translate power grid information into SOC conditions. From global behaviour the local state of criticality can be deduced for each line and support deterministic (N-1) contingencies. As we consider a critical phase transition a very sensitive risk zone can be defined. The local restriction becomes a control variable.
- From SOC conditions and with no feedback reaction (free evolution) we are able to deduce, for a day-ahead configuration, the distribution of potential events on all over the power network (their intensity, their location and cascading propagation). This analysis supports (N-1) contingencies analysis as it reproduces a part of CDF of events. From historical data until the day concerned, with generation and load demand defined, DC SPFM allows for the evaluation of the probability of the maximum potential shed power demand for the next day for the entire power network.

### 3.6.2.2. Assumptions from the Colombian power system

The input data were provided by XM, the source is the database of technical parameters and operating data for a specific day (October 17, 2013), for a transmission network without electrical reliability. The unavailable items are taken into account from the day-ahead market analysis. However the validation was performed with two additional dispatches.

The Colombian transmission system is modeled on an optimal load DC flow, the high voltage (i.e. 110 kV, 220 kV and 500 kV) transport network is considered. Network main features are: 392 buses (or nodes), 94 “generator” nodes, 647 lines and demand is used for hour of maximal demand in the day.

For operative analysis, in a day-ahead typical process, different steps are considered, each of them defining a specific generation power dispatch map, associated with different levels of constraints. Three generation dispatches are considered for the same day here:

- An “Ideal Dispatch”, which considers an economical cost objective, as well as area power balance constraints. It does not consider any network constraints.
- A “Network Dispatch”, which introduces network topology constraints, maintenance outputs, and some restriction analysis, but does not include the operative recommendations given for the electric analysis. All the analysis is done in this dispatch.
- A “Coordinated Dispatch”, which takes into account additional network requirements (e.g. voltage and stability constraints) while seeking be as close as to the operation in real time.

To exercise the criteria of reliability network evolution is not allowed, it is fixed at a point of operation. So for each path the initial shots for each line  $j$  is repeated 50 times, that is to say,  $K = p_0 = 1$ . Several paths to observe the dispersion of results between simulations are performed. In statistical terms it would have 200 times the N-1 criterion for each line.

A high level of power demand (stressed network):

$$\sum_{j=1}^{N_L} P_{D_j}^{final} = \sum_{i=1}^{N_G} P_{G_i}^{final}$$

Furthermore, the cascade phenomena, which could appear following an initial line trigger event is simulated with operating conditions as close as possible to real operating conditions:

- No generation power re-dispatch is considered (i.e. maximal generation power limit ( $P_{G_{max}}$ ) is set equal to the initial generation dispatch ( $P_{G_0}$ )). Generation dispatch is modified only if shed power demand is required in order to respect network power balance constraint (i.e. to allow DC SPFM model convergence).
- No line maximal transmission capacity constraints are considered. So line power flows could be greater than allowed maximum capacities during the cascade phenomena process, so potential line tripping on the basis of given line tripping probabilities occur.

A balance between two antagonist forces governs the behavior of a SOC system. In the DC SPFM, these two forces are represented by the level of power demand load and the total network transportation capacity (line capacities).

Setting a SOC condition will then require finding out the appropriate balance between these two forces. In DC SPFM SOC condition setting process, evolution of power demand and power generation are linear (see *Equation 3-1* *Equation 3-2* *Equation 3-3* *Equation 3-4*), and mainly governed by two model input parameters ( $r_p$  and  $Nb_{iter}$ ).

Total network capacity evolution is mainly driven by the following input parameters ( $\mu_i$ ,  $\mu_a$  and  $\tau_a$ ). Setting the DC SPFM input parameters was estimated from real data. More specifically, it is possible to extract the distribution of power demand shed from the Colombian database. This distribution can be seen as a signature of the Colombian network operating in SOC condition.

So, the aim is to find out the appropriate set of parameters that simulates power shed distribution as close as possible to the one issued from historical real data. The setting of input parameters is done and the resulting input parameter values are presented in Table 3-5.

$\lambda$ : not used (linear variations of power demand)	$\alpha_k = 1$	$\beta = 100$
$\Delta P_D^{\min} = 0.01\% \text{ of } \sum_{j=1}^{N_L} P_{D_j}$	$\Delta P_G^{\min} = 0$ (no generation power re-dispatch is allowed)	$\kappa = 2\%$ (not be used in day-ahead analysis)
$\mu_i = 1.05$	$\mu_a = 1.50$	$\tau_a = 150 \text{ iterations}$
$h_q^0 = 0.0015$ initial tripping probability for line r	$h_q^1 = 0.2$ tripping probability for overloaded line r	$L_r^{\text{th}} = 0.99$ loading rate threshold for declaring line r overloaded
$r_p = 5$	$r_T = 5$	$Nb_{\text{iter}} = 15000$

Table 3-5 DC SPFM main input parameters

Figure 3-20 presents the linear evolution of total power demand load and total available power generation towards the final set point during the whole SOC condition setting process, and the feedback response of the system to power demand linear increases during the SOC condition setting where the evolution of network total transmission capacity is reported. Associated cumulative distribution function (CDF) is presented in Figure 3-21 in log-log plot. As it can be observed, DC SPFM model parameters have been tuned in order to obtain a power demand shed CDF close to the CDF of power demand shed issued from the historical database. More specifically, both real historical data, and simulation CDF exhibits a power law behavior characterized by a linear distribution tail.

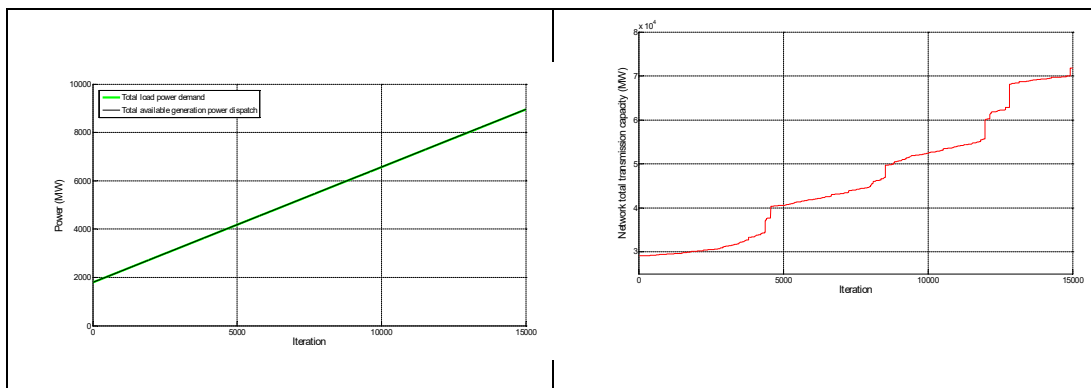


Figure 3-20: Evolution of total load power demand, total available generation and total transmission capacity power for day 1

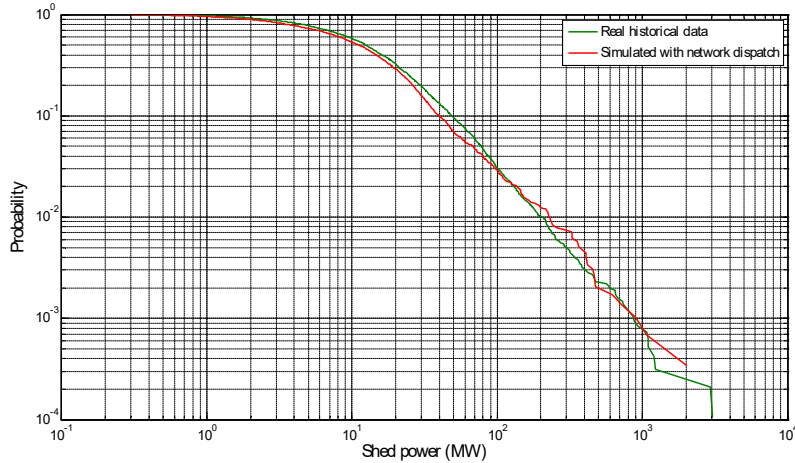
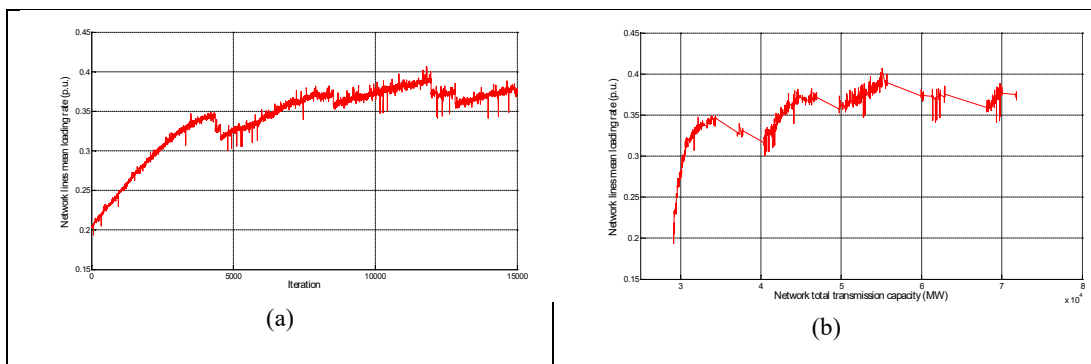


Figure 3-21 CDF of shed power demand Network Dispatch and for historical data

The evolution of parameter  $\tau$  and  $\gamma$  is showed in the Figure 3-22. Associated mean line loading rate  $\tau$  evolution has a convergence towards a constant value, here referred as  $\tau_{SOC}$ . And the evolution of  $\gamma$ , the ratio total transmission capacity over total power demand. It can be observed that the ratio tends towards a constant value, here referred as  $\gamma_{SOC}$ . Such tendency towards constant parameters is characteristics of SOC regime operation.

This behavior is also illustrated in Figure 3-22 (b) and (d) which respectively report the evolution of rate  $\tau$  and ratio  $\gamma$  versus total network transmission capacity. It can be noted that the system evolves with constant rate  $\tau_{SOC}$  and ratio  $\gamma_{SOC}$  in SOC regime operation regardless of network transmission capacity (as well as power demand level). It can be seen as normalized evolutions of these two parameters and could be advantageously used for comparison of simulated scenarios carried out in different simulation conditions (e.g. different numbers of iterations).





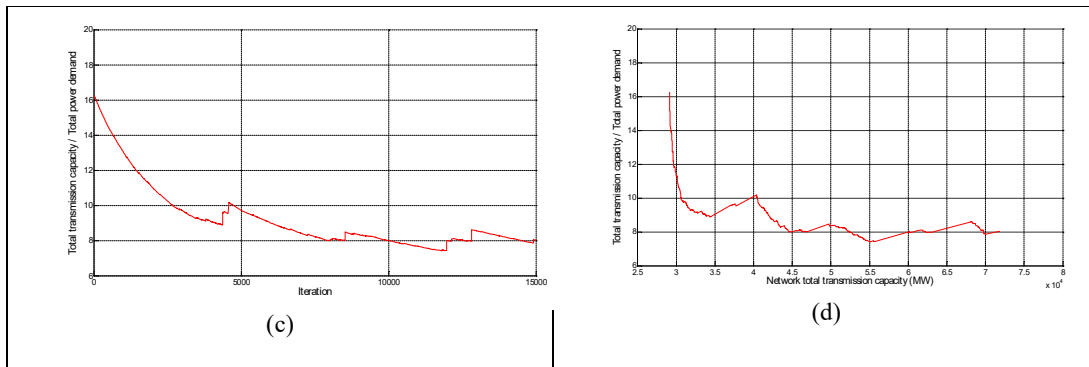


Figure 3-22 Evolution SOC parameter,  $\tau$  and  $\gamma$ . (a) Network lines mean loading rate and (b) its normalization with network total transmission capacity. (c) Ratio total transmission capacity over total power demand and (d) its normalization with network total transmission capacity.

Until this point, the DC SPFM model has been implemented with the Colombian electric system data and it has evolved to the SOC conditions for a particular day simulation. The following is to simulate reliability criteria according to the assumption made. The results and conclusions relative to the network behavior main features obtained for configuration Network Dispatch,  $N - k$  contingency is going to be shown in the next section. More specifically, the simulation gives a complete distribution of potential power demand shed for this particular network configuration, which is helpful for further risk assessment purpose.

## In conclusion

The DC SPFM was modeled using the Colombian data parameter from the electrical power system and operational criteria, associated with the evolution of transmission improvement and capacity, capacity generation associated with system constraints, transmission expansion, demand growing and forecast, and line failures.

The simulation was done and each parameter was validated using historical behavior or operational criteria by XM.

The historic data demonstrates that the Colombian electric power system exhibits SOC behavior. In normal operations of a power system for a particular day, it is necessary to ensure compliance of SOC conditions, thus we propose a setting process, and the use of

two global parameters associated with the loading level. A contribution of this thesis is the application in the short term for the operational situation. The literature in general is associated with applications for the expansion of transmission in the long-term.

## **4. Applications in day-ahead market in real power system. N-1 criteria.**

The reliability criteria N-1 is used in power system traditionally. The complex systems are systems that constantly evolve and develop over time (Ren, et al., 2008). Transmission lines with different maximum limits permit different patterns of energy flow and experience cascading overload. As the network updates slowly in response to these patterns and causes maximum line flows to evolve (Arthur, 1999). Complex systems have a certain regularity that may arise from all interactions. A complex system in steady state (self-organizing) is in constant evolution, no half trends and reliability statistics are stationary in time. The reliability criteria deterministic, is short for the cascading failures in the power system.

The electrical system experiences slow growth and the load evolves over time to meet the increased demand with reliability and economy. The load growth by itself tends to reduce the reliability of the transmission, but the transmission network is also improving to maintain the reliability according to the criteria set for it. If the network is fixed and the load is fixed, the analysis can be performed using different criteria for loads or reliability. This analysis is short term as it analyzes the reliability of the network for a period of time short enough that the network does not evolve. The traditional estimation of reliability of power system is typically short-term. Consider instead a network whose demand grows slowly: Loading and system reliability will interact over time under the criteria of reliability, this analysis could be called long-term reliability, it describes the long-term reliability of a transmission network taking into account the interactions of the evolution of the load and reliability (Ren, et al., 2008).

The SOC condition in a power network is characterized by a specific distribution of maximum line capacities that put the network operating conditions under maximum stress, corresponding to the natural SOC behavior observed from the real historical data analysis.

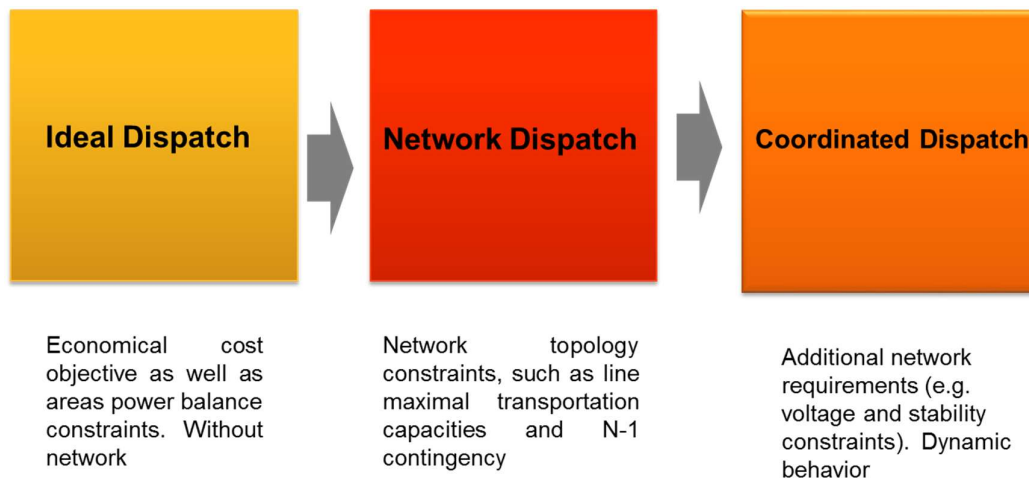
Regarding day-ahead markets, the main assumption here made is that most of information about system behavior can be deduced from the SOC condition setting process, computed for a given power demand set point, given a generation dispatch set

point and given a network topology, corresponding to the studied day-ahead network operating conditions. In this chapter, the result will be presented for the power system in general, for reliability, and some additional results.

More particularly, identification of components (e.g. lines) or/and areas, which could be considered as critical during operation and would require a particular attention from TSO (transmission system operator) engineers, can be carried out from such SOC condition setting processes. Furthermore, from DC SPFM output data line cascading event dynamics can be represented and analyzed.

## 4.1 General results

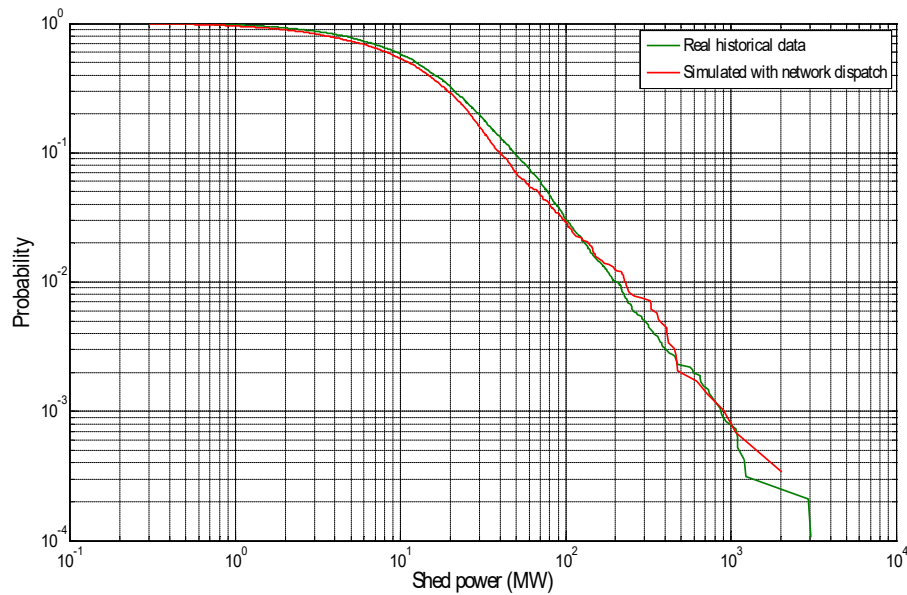
The day-ahead dispatch for the Colombian system has been assessed and the results of the analysis show that the constraints of the network are: unavailability of equipment, the analysis of constraints, reliability and stability of the power system and energy exchange with neighboring countries. Three dispatches are analyzed in this work (ideal, network and coordinated) see Figure 4-1, in principle this gives us an idea of cost of risk mitigation; the more restrictions it puts on the system the more it can reduce the risk, for example in the coordinated dispatch, however this has a cost to the market.



*Figure 4-1 Sequence for economic dispatch day  $k+1$*

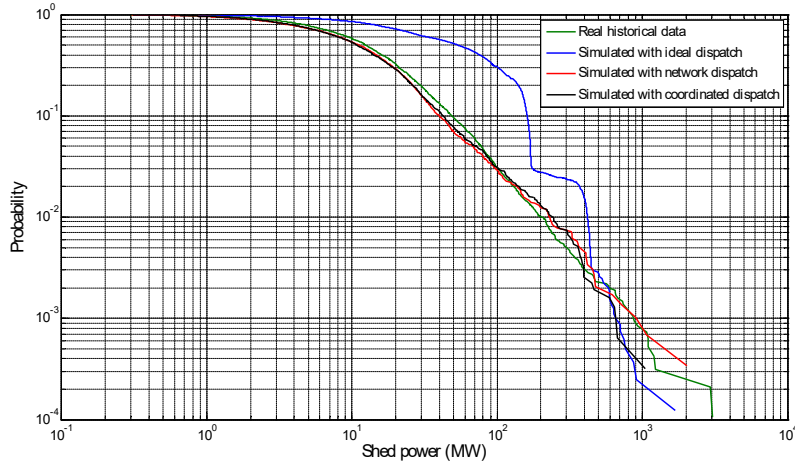
In Figure 4-2, the adjustment between historical data of the power system and a particular day can be observed. This result is the initial evidence that the concept can be applied in the short term, in the operation of electric power systems. It is verified with

historical data that SOC conditions are met for a dispatch of generation of a particular day.



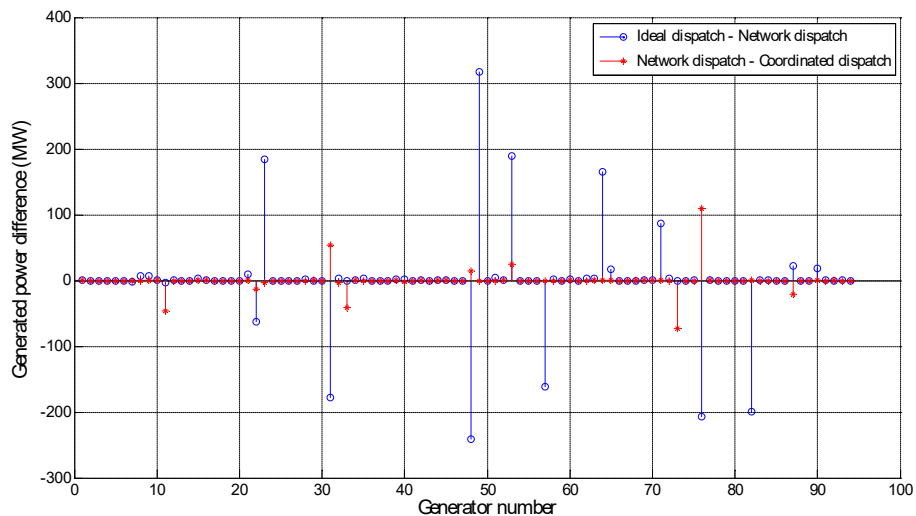
*Figure 4-2 Network Dispatch”: Fast dynamics cascade analysis*

It is not in the scope of this report to estimate such costs associated with risk assessment. However, some basic comparisons between distributions provided no demand for the three dispatches. See Figure 4-3. In the ideal dispatch the risk of events less than 500 MW is higher due to the ideal dispatch not modelling the network constraint, just constraints of areas of the system. More interesting is the comparison between network dispatch and coordinated dispatch. The coordinated dispatch has included additional (to criteria N-k) analysis of system security for voltage collapse, stability of angle, and voltage and dynamic simulations. However the PDF curve are similar for events less than 700 MW and has some differences with the others value. The question is, can the power system optimize risk in terms of the cascading failures?



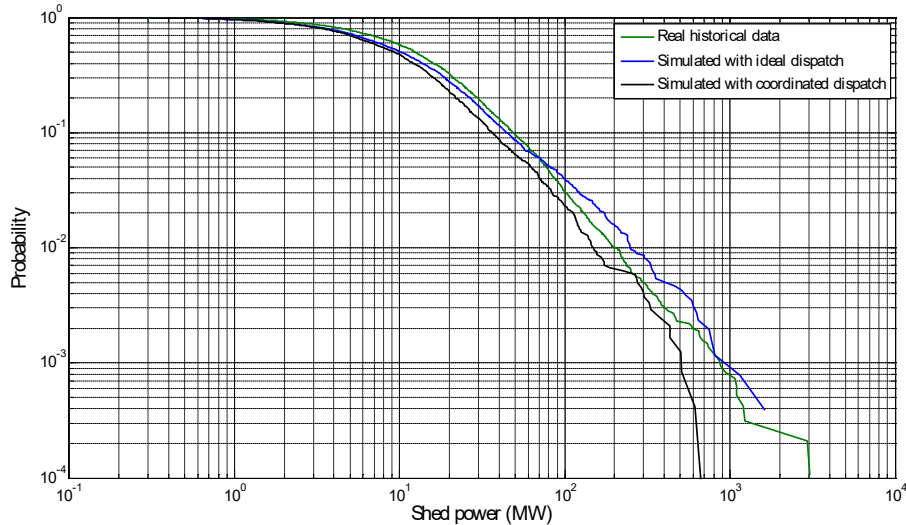
*Figure 4-3 CDF of shed power demand for N-k contingency, three dispatches and for historical data*

The three simulated economic dispatches are compared against the energy generation variable. There is a modification of 11.9% of the generation of the ideal office with respect to the network dispatch. That is, the ideal dispatch changes the energy generation by 11.9% because it includes the transmission network. The change in the power generated from the network dispatch to the coordinated dispatch is 2.3%. The coordinate dispatch has additional network requirements (e.g. voltage and stability constraints). Figure 4-4



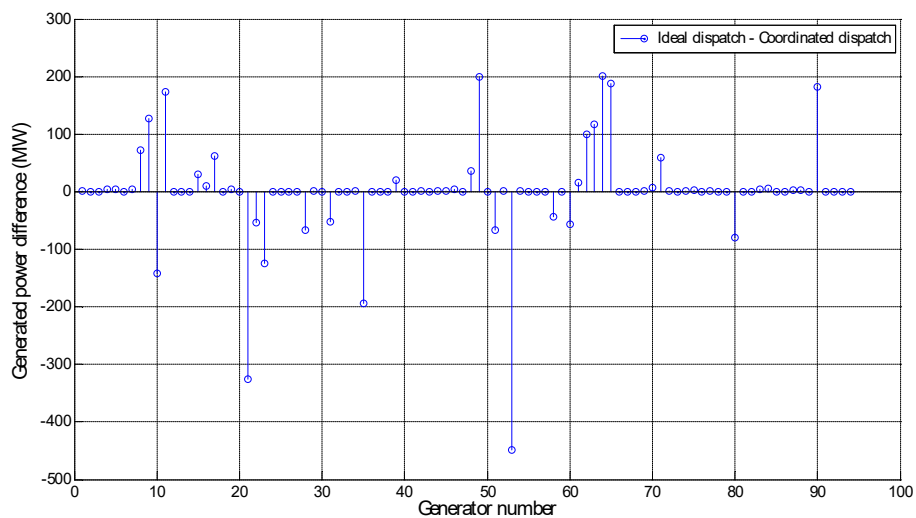
*Figure 4-4 Comparison of the three dispatches*

A sensitization is performed for another day of operation and the results are shown in Figure 4-5. The ideal dispatch is closer to the curve of historical data than in Figure 4-3. Also the curve associated with coordinated dispatch is less risk than the historical data



*Figure 4-5 CDF of shed power demand for N-k contingency, two dispatches and for historical data for other different day*

The economic dispatch of a different day is more hydraulic than the first economic dispatch analysed. Figure 4-6 shows the difference in power generated between ideal dispatch and coordinated dispatch is 21.8%. This value is much greater than that obtained for Figure 4-4



*Figure 4-6 Comparison of the two dispatches for other different day*

Another important result for the electrical system that can be derived from Figure 4-3 is for the analysis of maintenance, for example the possibility of modelling the output of machine maintenance. Using this one can know whether the risk of a system increases with a blackout, one can choose the best time of day for maintenance without causing more risk to the network, or one can introduce measures required to keep the risk at appropriate levels. This would be very useful information for system operation.

The analysis is not just for system operation, it can also be used to conduct sensitivity analyses on the expansion of the network with the construction of a line, or to determine the possible decreased risk for various scenarios and when is the best time to invest in improving the long-term network.

This analysis may also be useful in asset management because it determines which the critical lines are, and although they have a low probability they have high participation in major network events. You can focus the analysis on machines and improve the health of the equipment and the inventory management

## 4.2 Reliability criteria model

Now the power system is simulated under SOC conditions. So reliability criteria is modeled in Figure 4-7, for deterministic modeling criteria (N-1), widely used in the electrical industry,  $k = 1$  and  $p_o = 1$ . For comparison, probabilistic reliability criteria takes the same values for the first iteration and  $p1 = 0$ , on subsequent iterations.

N-1 contingency studies have been done using the DC SPFM model for the set point defined by power demand, generation dispatch, and network topology as of 17 October 2013 at 19h00, i.e. for the final set point of SOC condition setting process. Furthermore, maximum transmission line capacities are those defined by the SOC condition setting process.

As risk analysis associated with N-1 contingency study is a probabilistic approach, it is necessary to address a given N-1 contingency several times during the simulation process. So each N-1 line contingency is simulated 50 times. The total number of iterations for the whole simulation process is then equal to  $50 \times 647 = 32,350$ .



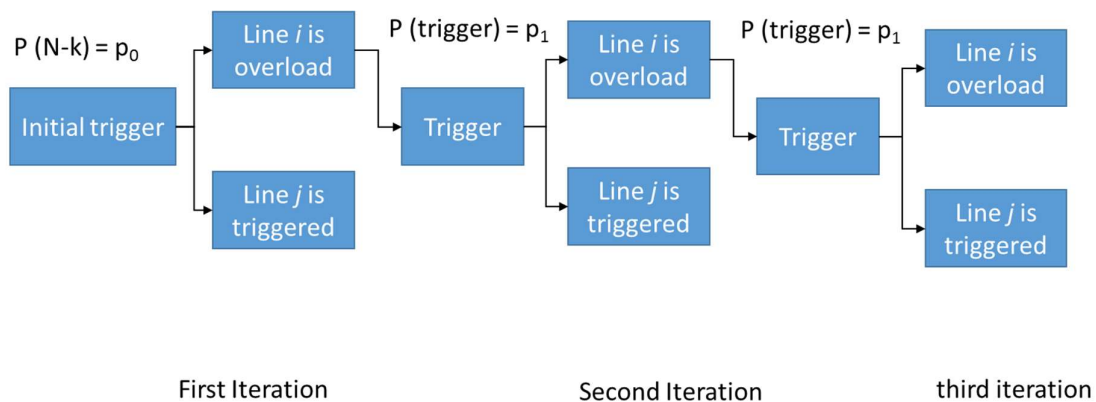


Figure 4-7 Model reliability criteria for electric power system

Four trajectories are simulated respectively associated with each of the 4 SOC condition trajectory settings. Figure 4-8 reports the CDF of power demand shed during the 4 trajectories N-1 contingency simulation. One can see that the paths have a similar behavior in the middle of the graph while the tails are quite different. However, taking into account the statistical character of the proposed risk assessment approach a rigorous comparison should imply to define mean value and confidence intervals for each CDF trajectory. The slope of the power law curve is retained. This confirms what was being sought, that the simulation had a similar historical behavior. A distance is observed in the curves left by the number of data for each curve. Towards the biggest events slope loses tune. They found some dispersion at the end of the curves closely related to the lines triggered and the immediate response of the system, where you have to explore the latter in terms of restrictions.

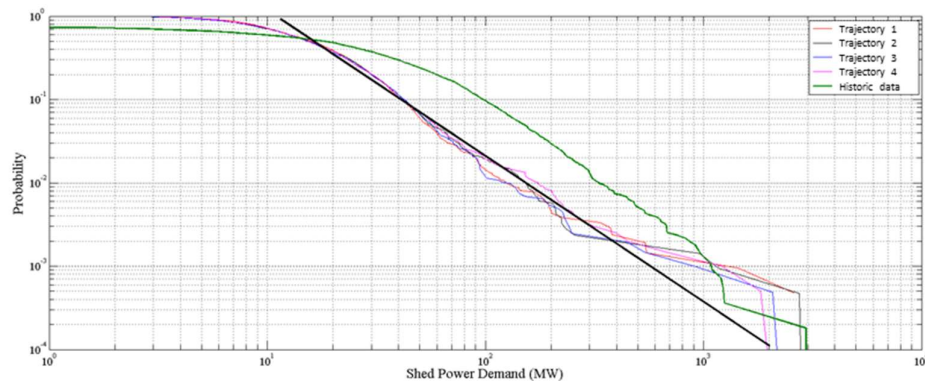


Figure 4-8 CDF of shed power demand during the 4 trajectories N-1 contingency simulation

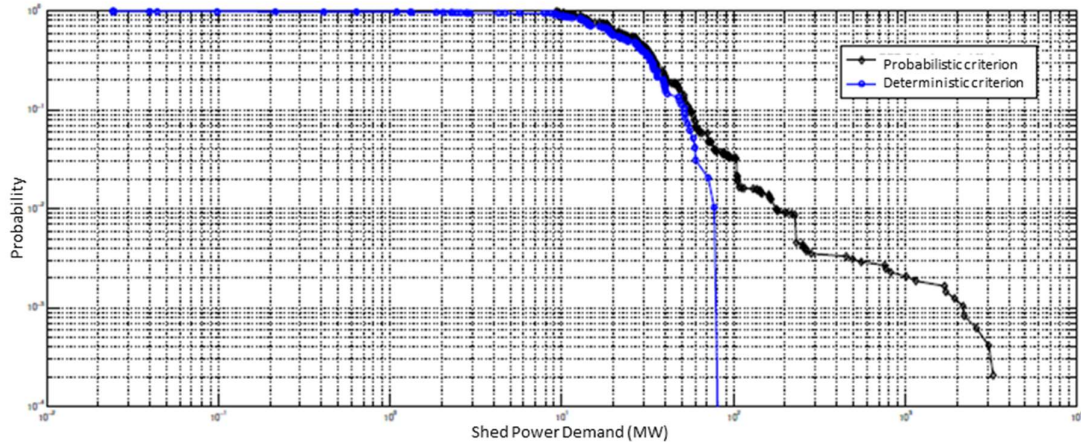
Deterministic criteria  $N - 1$ , used widely, assumes that the system has a failure probability  $p_1 = 0$ , ie, the system is ready for operation without an element of the network but as is known with great demand non supply events the system has more than one failure.

Figure 4-9 shows the comparison between the first iteration, assuming that the system has a probability of zero failure for an overloaded line and the probabilistic approach, which allows us to consider the cascading failures.

From the four paths analysed the lines involved in cascading failure are more than 5% of non-supplied demand (right end of the curve distribution probability). In general terms it is observed that the probability of major events are found in the East (the last blackout 2007, starts in this area). The Atlantic area, where the operators have some constraints, does not have a high probability for such events, possibly due to the size of the supply (over 1,400 MW).

Compared with the results of the tool used in day ahead market to assess the reliability for the day analysed, similarities are found in the area considered most likely to cascading failure, but not necessarily with the same lines. Failures in transformers are not modelled in DC SPFM in the scope of this work and they have the predominant operating results in the reliability analysis performed by the system operator.

It should be emphasized that the lines most likely to cause cascading failure events are associated with the eastern area and the southwest. For the day-ahead dispatch network the deterministic N-1 criterion is used, these kinds of results are not taken into account to obtain the probability of a cascading network failure. This can be seen in Figure 4-9, where the right end of the black curve corresponding to the probabilistic approach is compared with the deterministic approach (blue curve). There is an open area for which the system operator has no information.



*Figure 4-9 Comparison between deterministic assumption and probabilistic criterion*

The system with deterministic modelling criterion for this day (October 17) can cover events with a probability greater than 0.01 and its impact is less than 80 MW, for the other events (major ones) the system is at risk.

This situation may lead to underestimating the risk to system operation. Considering that these events have low probabilities underestimation of risks could be the best in terms of operational costs. Management of network restrictions or changes in generation can be very costly for the operation. However, this risk analysis should be considered in planning for expansion and considering the priority of line improvement. In order to manage the risk of a blackout better the possibility of implementing additional protection schemes should be considered and the lines involved should not come close to the operational limits of transport capacity.

### **4.3 Other interesting results**

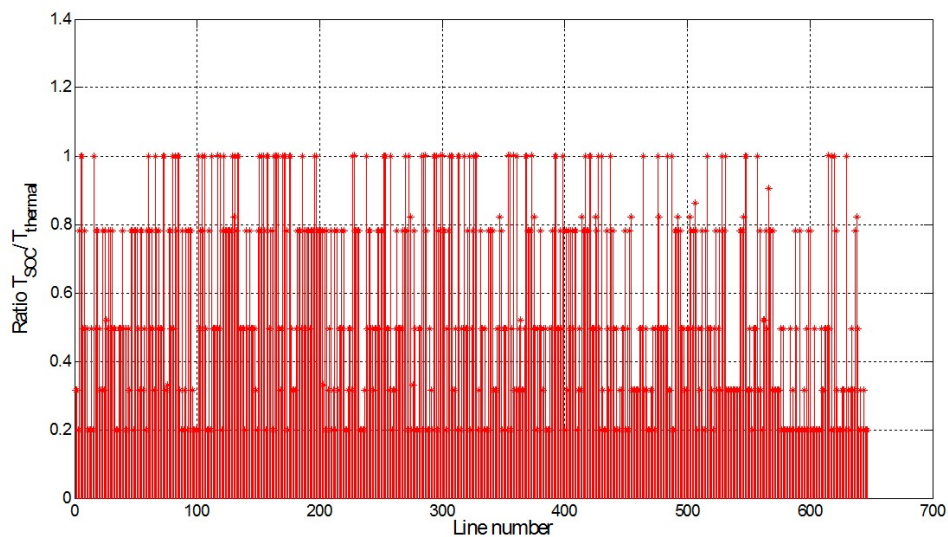
You can get valuable information of system status, such as critical lines, from the data associated with the simulation that may be involved in major cascading failure events. If events associated with heavy tail distribution of cumulative frequency is analysed, one can obtain interesting information on the statistics of failures, for example the frequency of failure of a particular line in the simulated data and even sequences of more frequent events. This can be a great application in analysing security schemes of both the system and the relays involved and the defence plans to establish the most probable sequence trigger.

### 4.3.1 Critical lines

Other interesting results are in areas not covered by the reliability deterministic analysis, where lines (or areas) are critical. The main assumption made here is that most of the information about such critical lines can be deduced from the SOC condition setting process. The selection of critical lines can start with making a list of the lines which are involved in the first steps of major events: identification of lines which are at the origin or are involved in first iterations (3 first iterations) of tripping cascade phenomena leading to major non supply demand events (2% of total number of events).

If several paths are simulated it is possible to establish the presence of such lines in each of the paths and estimate a better likelihood of critical lines.

To make a list of lines which often have been involved in cascading phenomena leading to power demand shed during SOC condition setting process: identification of lines whose the ratio  $T_{\max}^{final} / T_{\max}^{AC}$  is high (here chosen close to 1), see Figure 4-10. The list of critical lines is achieved using the intersection of the lines found with the index and the lines found participating in more than one power failure event in the tail of CDF of demand not supplied.



*Figure 4-10 Ratio between line capacity SOC limitation and line capacity thermal limitation: high ratio relative to line more often involved in power demand shed cascading phenomena during SOC condition setting process*

Application of such identification process has been carried out in case studies. A resulting list of 36 critical lines is given. Main critical areas can be identified from this list. The Colombian system operator has previously identified 9 lines using a list of 16 restricted lines. It could indicate that the operator is missing scene analysis information that can lead to a big event.

Additional initial evidence shows that these critical lines relax the critical condition and the value of risk decreases in PDF. In the Figure 4-11 (the black line is the historic data, the blue one is the N-1 simulation taken just the first iteration) observe the red line, this is the result from improving or relaxing the critical lines in the system, for an element present in the cascading failures of the tail of the distribution, it shows that the risk decreases. This is important evidence for future work regarding feedback response from the system, and for planner of expansion and operator of the system.

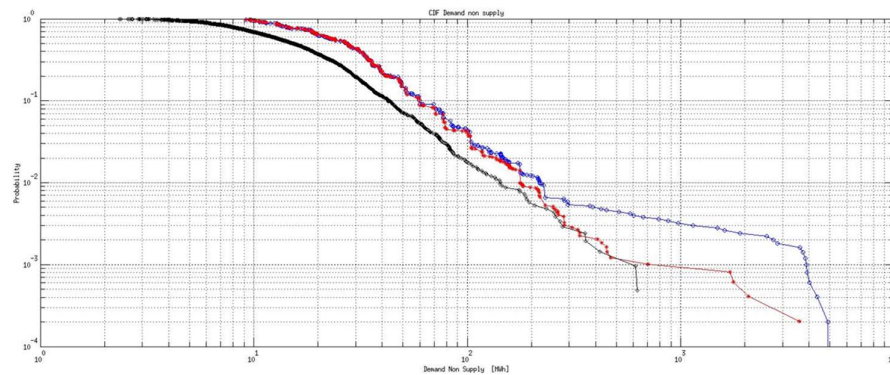


Figure 4-11. Initial evidence of system reaction for improvements on critical lines

### 4.3.2 Probability of fault on particular line

For estimating the probability of failure of a particular line, in the four trajectories four line failures are repeated. For example, the lines involved are: three circuits located in the eastern area; (lines 165, 166, and 308), and a circuit in the southwestern area; (line 370). Each of the trajectories has 50 times the simulation of the trigger on each line, if the model has 647 lines modeled, then the number of simulations in each trajectory is 32,350. And four trajectories are taken, thus the total number of simulations is then 129,400 in total.

So each line has 200 simulations of the initial trigger. For example, for line 166 of the Eastern area, after analyzing 200 initial trigger cases, there are 4 major events, with 34, 19, 31, and 9 sequences each.

This exercise establishes the probability of failure of an element using a sample failure, and although the probability for the sample is low it is significant that in four major blackouts simulated line 166 is present.

### 4.3.3 Sequence of events

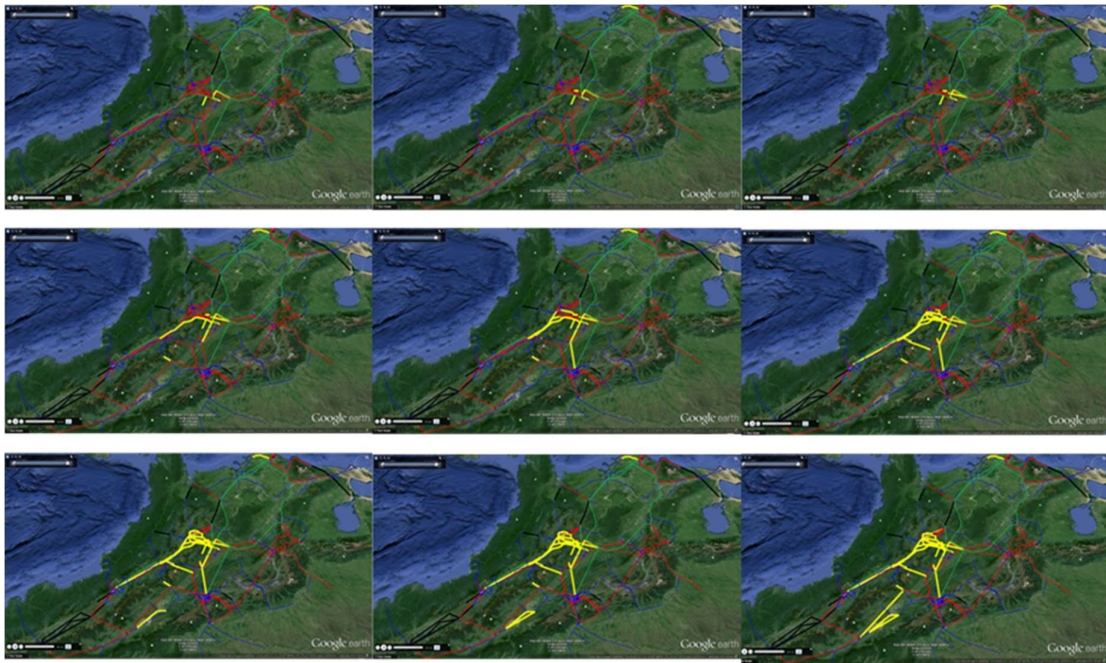
Table 4-1 shows the one of the sequence of 9 steps of line 166 with the associated demand not supplied event (DNS) at each step, the sequence of one of the major events for the initial trigger from the 166 detailed line. An interesting question at this point is whether it is possible to stop the cascading failure, for example, at the second step when the loss of demand is not very large (13, 6 MW) or in the worst case with a greater loss (100.6 MW). While a person is not able to do this, because the time between triggers is usually milliseconds, it is possible to use automatic devices that can limit the loss of a cascading event. This can be achieved by adjusting the electrical system protection or supplementary protection scheme.

Step	Lines	DNS [MW]
0	166	4,6
1	165	13,6
2	308	100,6
3	152; 415; 513	195,6
4	133; 157; 186; 394	294,7
5	134; 208; 370; 513	523,5
6	129;167; 369; 431; 476	694,7
7	152; 592	910,4
8	130; 140; 185; 484	1051,5
9	183; 191; 192; 121;493	1164,9

*Table 4-1 One sequence of cascading failure for line 166 Colombian power system*

It should be emphasized that several of these lines (165,166 and 308) participated in the early stages of the cascading failure causing a blackout event in Colombia on April 26, 2007, with total loss of the system (XM S.A.E.S.P., 2007).

Another graphical way to see the cascading failure sequence is shown in Figure 4-12, where you can see the growth of a cascading failure using nine slices in time as displayed in yellow on the map of the Colombian electric system.



*Figure 4-12 Sequence of cascading failure for Colombian power system*

## In conclusion

The model of the Colombian electric power system was validated with historical real data of DNS, and the simulation had the same behavior as the real system.

Then the reliability criterion N-1 is modeled using several paths. Verification of deterministic criterion in opposition to the probabilistic simulation, concluding with the use of the deterministic approach results in the electrical system being partially protected against blackout risk.

Other interesting results were the estimation of critical lines with sequence of cascading failure events, several of the analyzed lines participated in the early stages of the blackout event in Colombia on April 26, 2007, with total loss of the load of the power system.



## 5. Conclusions

Blackouts are a complex problem and to have a better understanding of the system it is necessary to explore different approaches from the classical ones, and use new tools and analysis from other perspectives in order to complement the current understanding we have of systems. By quantifying and analyzing the internal correlations of the system response to critical events we can make better decisions regarding the operation of electrical systems for the benefit of service continuity. That is to say, we can provide more information about network vulnerability in the operation of electrical systems.

In the operation of electrical systems information about the vulnerability of the system becomes invaluable in decision-making. The possible applications of this information can transcend the operation itself, and may be used for asset management, scheduling maintenance, expansion planning, insurance, etc.

The main conclusions are:

1. It has been shown the complex behavior of the Colombian system demonstrates power law behavior and also that it has a Hurst index greater than 0.5 this is consistent with that reported in the literature on the behavior of electric power systems in the world. In the statistical analysis, the CDF of Demand Not Supplied (DNS) from the Colombian power system, the real data were matched to  $\alpha$ -stable distribution, this characterizes complex phenomenon.
2. In the VaR estimation of demand not supplied data, the growth rate VaR in time is greater than the root 0.5, this implies that the risk is growing at a higher rate than the data with Gaussian behavior. The growth rate measured by VaR and Hurst index are related.
3. This approach has modeled the electrical system using a direct current statistical load flow model (DC SPFM) and is adjusted so that the simulations in the model are of the same nature as the behavior of the real system.
4. The SOC conditions have been established for the day ahead market through a reverse simulation setting the endpoint as the current situation of the system. This methodology allows the system to meet the requirements of a self-

organized criticality at a point of real operation and allows its use for the day ahead market.

5. After simulating, the reliability criterion can be used in the operation of the electrical system for better manage cascading failures. These results are of high value to electricity market due to the fact that they were made with real data from electrical systems and they were validated by historical failures obtained from electrical system. These results can establish the lines most likely to fail, the sequence of events associated with the failure, and which actions simulations expansion operation or reduce the risk of failure of the transmission network.

The possible benefits of using this methodology for real power system are the use of qualitative and quantitative analysis of operational information to improve decision-making based on refined and updated information. The expected benefits for the power system are appropriate estimation of network risk, increased system reliability, and an improvement of the day-ahead contingency planning (holistic analysis) and situational awareness.

Future work should be focused at better modeling and evaluating cascading outages from the steady-state and transient stability perspectives and improvement of data collection of cascading failure events in interconnected power systems. In general the existing tools are dealing with cascading events in steady-state domain while very limited use has been seen in dynamic domain. It should also be emphasized that the work presented will be useful to those developing new tools for risk prediction and prevention of cascading failure events.

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