Chapter 8
Power Grids, Smart Grids and Complex Networks

Antonio Scala, Guido Caldarelli, Alessandro Chessa, Alfonso Damiano, Mario Mureddu, Sakshi Pahwa, Caterina Scoglio, and Walter Quattrociocchi

Abstract We present some possible Complex Networks approaches to study and understand Power Grids and to improve them into Smart Grids. We first sketch the general properties of the Electric System with an attention to the effects of Distributed Generation. We then analyse the effects of renewable power sources on Voltage Controllability. Afterwords, we study the impact of electric line overloads on the nature of Blackouts. Finally, we discuss the possibility of implementing Self Healing capabilities into Power Grids through the use of Routing Protocols.

A. Scala (✉)
ISC-CNR Physics Department, Univ. La Sapienza, Piazzale Moro 5, 00185 Roma, Italy
e-mail: antonio.scala@cnr.it

G. Caldarelli • A. Chessa
IMT Alti Studi Lucca, piazza S. Ponziano 6, 55100 Lucca, Italy
e-mail: guido.caldarelli@imt.it; alessandro.chessa@imt.it

A. Damiano
Dipartimento di Ingegneria Elettrica ed Elettronica, Univ. di Cagliari, Cagliari, Italy
e-mail: alfio@diee.unica.it

M. Mureddu
Linkalab, Complex Systems Computational Laboratory, 09129 Cagliari, Italy
e-mail: mario.mureddu@linkalab.it

S. Pahwa • C. Scoglio
Department of Electrical and Computer Engineering, College of Engineering, Kansas State University, Manhattan, KS, USA
e-mail: sakship@ksu.edu; caterina@ksu.edu

W. Quattrociocchi
London Institute of Mathematical Sciences, 22 South Audley St, Mayfair, W1K 2NY London, UK
e-mail: walter@londoninstitute.org

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8.1 Introduction

Nowadays, one of the most pressing and interesting scientific challenges deals with the analysis and the understanding of processes occurring on complex networks [1–9]; one of the most important target for applying the results of such a field are real infrastructural networks. Our society critically depends on the continuity of functioning of Network Infrastructures like power, gas or water distribution; securing such critical infrastructures against accidental or intentional malfunctioning is a key issue both in Europe and in the US [10, 11]. Among those infrastructures, the electrical power grid is perhaps the most crucial one as many other facilities like telecommunications, banking systems, oil and gas pumping, and even water depend on the electric power system [12].

In Sect. 8.2 we give an overview of the electric power systems and of the effects of the recent introduction of distributed renewable sources.

In Sect. 8.3 we study the effects of the allocation of distributed renewable generation on the resilience of power grids.

In Sect. 8.4 we investigate the phenomenon of abrupt breakdown of an electric power-system under two scenarios: load growth (mimicking the ever-increasing customer demand) and power fluctuations (mimicking the effects of renewable sources).

In Sect. 8.5 we introduce the concept of resilience by exploitation of redundant links to recover the connectivity of the system. The introduced self-healing capabilities through the application of distributed communication protocols grants the "smartness" of the system.

Finally, we summarise our results in Sect. 8.6.

8.2 Power Networks and Distributed Generation

Historically, electric power systems have developed bottom-up by the integration of local networks into regional and national ones. Such a trend is nowadays still continuing via an integration on an international scale.

The three primary functions of the electric utility are Generation, Transmission, and Distribution (Fig. 8.1). The Distribution system is the most readily perceived part of the electric power system since it contributes most directly to providing electric power to the customers. It can be distinguished in Primary distribution operating at Medium voltage ($\sim 10^3$ V) and in secondary distribution operating at Low voltage ($\sim 10^2$ V). Industries are generally served by Medium voltage; residential customers by Low voltage. Distribution networks are local networks and have mostly a radial (tree-like) structure in order to optimize the economic costs and to calculate the power consumption of each user on an simple basis. The Transmission system dispatches large flows of electric power at long distances; in order to minimise dissipation, it operates at High voltages ($\sim 10^4$–10^5 V). As a network, it has a

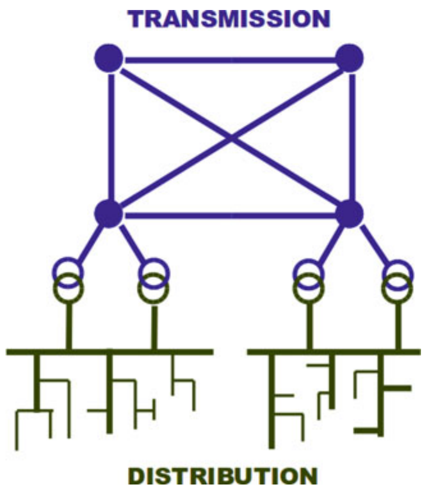

Fig. 8.1 The electric power system is separated in Transmission (High voltage lines, $\sim 10^4$–10^5 V) and Distribution (Medium voltage $\sim 10^3$ V and Low voltage $\sim 10^2$ V, also referred to as Primary and Secondary distribution). Transmission dispatches along long distances high quantities of power generated by large generators; for the sake of robustness, it is a meshed network. Distribution networks are local networks optimised for power dispatch and have mostly a radial (tree-like) structure in order to optimize the economic costs and to calculate the power consumption of each user on an simple basis. Industries are generally served by Medium voltage; residential customers by Low voltage

meshed configuration that allows to increase its robustness through redundancy. In the first years the electric power system was a collection of local, disconnected networks and Generation was distributed. Subsequently, due to economy of scale, Generation has concentrated in large facilities, requiring the creation of high-voltage lines for long-distance dispatch (Transmission). Nevertheless, Distributed Generation has never disappeared since it has an important ancillary role both in ensuring backup power in case of malfunctioning and in sustaining the variations in loads due to the customer demand dynamics. In fact, large facilities have long reaction times (it can take a day or even more to start up or shut down a large fossil-fuel power station) while smaller facilities can be as fast as fraction of hours.

Electric power systems are mostly designed to operate at a sinusoidal voltage of a given frequency (typically 50 or 60 Hz) and magnitude. Any significant deviation in the waveform magnitude (± 5 %) or frequency (± 1 %) is a potential problem for the quality of the dispatched power. To operate properly, a continuous and accurate balance between power demand and generation has to be maintained in the system; up to know, daily forecasts and the high-frequency electric power market have allowed to keep the system mostly in a stable state.

Nowadays we are experiencing an increase of Distributed generation due to the introduction of low cost green generators (mostly solar and wind). Such "green" generators, while very advisable for the sake of emission decrease and

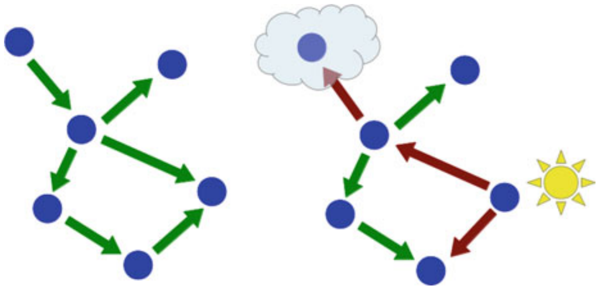

Fig. 8.2 The erratic nature of renewable sources introduces fluctuations in the power production that can push the power system away not only from its stable state, but even to the region of parameters where the system has been designed to work safely. As an example, we sketch the effects of the introduction of renewable generators on a isolated grid like the ones that can be found on isolated islands like Guadalupe. On the *left panel* we show an hypothetical power flow configuration along which the actual grid has been engineered: not only the possible amounts of power flowing along the lines have been considered, but also their directions. On the *right panel* we show the effect of the introduction of "*green*" generation: a weather instability can switch the direction of the power flows, eventually causing automatic protections to trip the lines

of environmental sustainability, introduces several problems in the electric power system. In fact, at difference with "classical" distributed generators that can be controlled to enhance system's stability, the erratic nature of renewable sources introduces fluctuations in the power production that can push the power system away not only from its stable state, but even to the region of parameters where the system has been designed to work safely. As an example, consider the effects of the introduction of renewable generators at the distribution level. Most distribution grids have been engineered considering not only the possible amount of power flowing along the lines, but also its direction. "Green" power can eventually switch the direction of the power flows, eventually causing automatic protections to trip the lines (Fig. 8.2).

The difficult task of integrating the stochastic and often volatile renewable sources into a the grid designed with a power-on-demand paradigm could perhaps solved leveraging on distributed storage [13]; nevertheless, massive and economic power storage is not yet readily available.

As a consequence of the introduction of renewable sources, many studies have concentrated on the dynamic behaviour of power grids to understand how to ensure stability and avoid loss of synchronization during typical events like the interconnection of distributed generation. The large number of elements present into real grids calls for simplifications like the mapping among the classic swing equations [14] and Kuramoto models [15–17] that allows to study numerically or analytically the synchronization and the transient stability of large power networks. Even simple models [18] akin to the DC power flow model [19] show that the network topology can dynamically induce a complex size probability distributions of blackouts (power-law distributed), both when the system is operated near its limits [20] or when the system is subject to erratic disturbances [21]. New realistic metrics to assess the robustness of the electric power grid with respect to the cascading failures [22] are therefore needed.

8.3 Voltage Control

In this section we will concentrate on the stability of the system respect to voltage fluctuations. Deviations of the voltage amplitude on a power grid can cause system operation problems; although voltage constraints are not as restrictive as frequency constraints, it can be regulated or controlled by generation or other connected equipment as long as it is in the range of the $\pm 5\,\%$ allowed fluctuations around its nominal value.

8.3.1 AC Power Flow

To model power grids, we use the more computational intensive AC power flow algorithms since, although DC flows are on average wrong by a few percent [23,24], error outliers could distort our analysis.

The AC power flow is described by a system of non-linear equations that allow to obtain complete voltage angle and magnitude information for each bus in a power system for specified loads [25]. A bus of the system is either classified as Load Bus if there are no generators connected or as a Generator Bus if one or more generators are connected. It is assumed that the real power P_i and the reactive power Q_i at each Load Bus i are given, while for Generator Buses the real generated power P_i and the voltage magnitude $|V_i|$ are given. A particular Generator Bus, called the Slack Bus, is assumed as a reference and its voltage magnitude $|V|$ and voltage phase Θ are fixed. The branches of the electrical system are described by the bus admittance matrix Y with complex elements Y_{ij}s. Figure 8.3 sketches the complex network associated with the AC power flow description of a grid.

8.3.2 Model for the Erratic Renewables

To model distributed renewable sources, we will introduced a skewed probability distribution of load demands representing a crude model of reality that ignores the effects like the correlations (due for examples to weather conditions) between different consumers or distributed producers. Thus, the effects of "green generators" on a power grid are considered to be stochastic variations in the power requested

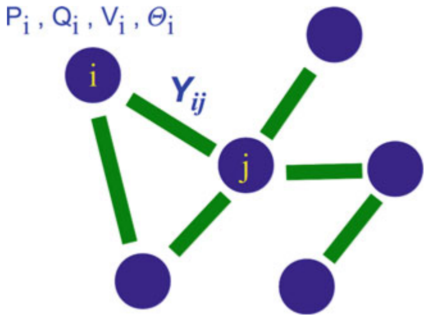

Fig. 8.3 Even in the simplified AC power flow description where the system is assumed to be stationary (the signal is a stationary sinusoidal), the network corresponding to a power grid is a weighted networks where both nodes (buses) and edges (lines) have multiple characteristics. In particular, P_i is the net real power and Q_i is the net reactive power injected at the ith bus, Y_{ij} is the complex impedance of the $i-j$ line, V_i is the voltage amplitude and θ_i is the voltage angle at the ith bus. Moreover, additional parameters like the maximum capacity of a line (i.e. the maximum amount of power that can flow) must be considered when analysing system failures

by load buses. Load buses with a green generator will henceforth called green buses. We will consider the location of green buses to be random; the fraction p of green buses will characterize the penetration of the distributed generation in a grid.

If the power dispatched by distributed generation is high enough, loads can eventually become negative: this effect can be related to the efficiency of green generators. We model such an effect by considering the load on green buses described by the skew-normal distribution [26], a pseudo-normal distribution with a non-zero skewness:

$$f\,(x,\alpha) = 2\phi\,(x)\,\Phi\,(\alpha x)$$

where α is a real parameter and

$$\phi\,(x) = \exp\left(-x^2/2\right)/\sqrt{2\pi} \qquad \Phi\,(\alpha x) = \int_{-\infty}^{\alpha x} \phi\,(t)\,dt$$

Thus, the parameter α will characterize the level of the distributed generation: to positive α correspond loads positive on average, while for negative α green nodes will tend to dispatch power.

8.3.3 Analysis

Our model grids will therefore consist of three kind of buses: N_G generators (fixed voltage), N_l pure loads (fixed power consumption) and N_g green buses (stochastic

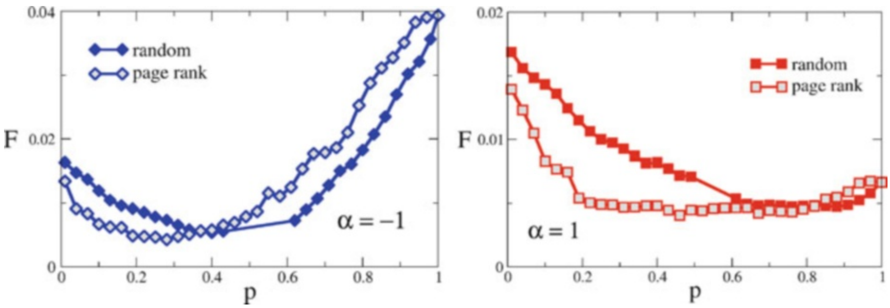

Fig. 8.4 Comparison between random placement (*filled symbols*) and page-rank placement (*empty symbols*) of green generators in the Polish grid, both for surplus production of renewable energy (*left panel*, $\alpha = -1$) and for levels of renewable energy production below the normal load request (*right panel*, $\alpha = 1$). The page-rank placement of renewable sources allows to attain lower values of the fraction F of buses operating near their nominal tension (and hence a higher resiliency) at lower values of the penetration p. The best case is realized for levels of renewable energy production below the normal load request, where a plateau to low values of F is quickly attained

power consumption) with $N_G + N_l + N_g = N$ the total number of buses and $N_g + N_l = N_L$ the number of load nodes. The fraction $p = N_g/N_L$ measures the penetration of renewable sources in the grid.

Hence, a steady state analysis has been carried out and the transient phenomena connected to the power flow control have been neglected. Under this hypothesis the frequency variation connected to power flow control has been considered stabilized and the system has been considered characterized by a constant steady state supply voltage frequency. Therefore, if all the nodes are near their nominal voltage, it is much easier to control the system and to avoid reaching infeasible levels of power flow. Consequently, to measure the effects of power quality of a power grid under distributed generation we measure the fraction F of load buses whose tension goes beyond $\pm 5\,\%$ of its nominal voltage. Notice that real networks are often operated with some of the buses beyond such parameters so that (especially for large networks) it is expected to be $F \neq 0$ under operating conditions. The maximum of the resilience for a power grid (intended as the capability of restoring full feasible flows) is expected to be for $F = 0$.

In Fig. 8.4 we show the effects on the voltage stability of the penetration of the renewables on the Polish Grid. We model the penetration both in the case where the locations of the renewables are chosen at random and in the case where the locations are chosen according to a policy. In particular, we analyse the case in which new renewables are introduced according to their Page-Rank metrics [27]. As already shown in [24], we find that the Page-Rank policy makes the system less unstable respect to voltage fluctuation both in the case of traditional distributed generation ($\alpha > 0$) and green distributed generation ($\alpha < 0$). Notice that Page Rank is strictly related to several invariants occurring in the study of random walks and electrical networks [28].

8.4 Cascading Failures

High standards for the reliability of interconnected Electric Power Systems (EPSs) are being developed both in Europe and the US by councils and associations of EPS operators [29, 30]. Nevertheless, not only do power outages occur, but also large outages are more likely than what would be naively expected; in fact, the analysis of historical data reveals that their occurrence is power-law distributed [31], implying a significant risk of system-wide failures. Given the disruption and economic damages caused by major outages, understanding the nature of such occurrences is a major problem to be addressed.

An important general question is whether EPSs are subject to emergent behaviour or not. In fact, EPSs are aggregations of large number of simple units; it therefore makes sense to ask if EPSs, as a whole, exhibit additional complexity beyond what is dictated by the simple sum of its parts. To this aim, we investigate if an abrupt breakdown transition could emerge in a simple yet realistic model of power grids.

In the context of power systems, a cascading outage is a sequence of failures and automatic disconnections consequent to an initiating event; a system-wide outage is also called “black-out”. The rapid succession of automatic reactions in an EPS happens in a time-scale that is typically too short to stop the process by human intervention. Reactions following an initiating event or events include sequential tripping (disconnection) of transmission lines and generators. Initiating events can be due to natural causes (like a line sagging into vegetation, or high wind or lightning shorting a line) but also to human actions (or inaction) or due to imbalances between load and generation.

While no two cascading outages are the same [32], we will study a class of possible outages and analyse their characteristics. In particular, we will consider the fragility of EPSs with respect to outages due to cascades of line overloads causing lines to trip. To this end, we will put under stress a realistic EPSs to understand the nature of systemic outages. The nature of the stress will be twofold: first, we will consider the case in which an increasing demand on a fixed infrastructure leads to line overloads and subsequent outages. This would correspond to the (hopefully) unrealistic case of EPS that are operated to the limit of their capacities in order to maximize profits. Second, we will consider the important case of fluctuations in demands and generation; this is a particularly relevant case as the steady penetrations of renewable sources is introducing in the grids new erratic sources whose effects and consequences on existing power grids have not yet been fully understood.

We consider the model introduced by Pahwa et al. [33]. In such a model, the initial distribution of loads and sources represents the stress imposed to the power grid. The initial power flows on lines are calculated using the DC power flow model (see Materials). If the load on a line goes beyond its capacity, the line trips (disconnects) and power flows are recalculated on the new topology (i.e. the grid *minus* the tripped lines). Such procedure is repeated until convergence; we will refer to such a model as the Overload Cascade Model (*OCM*).

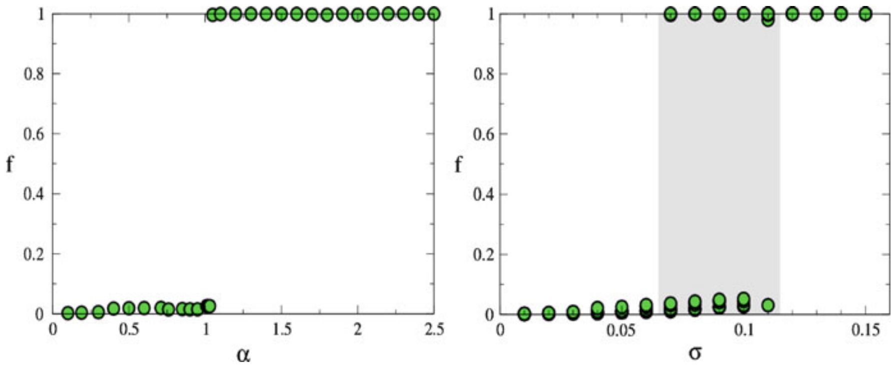

Fig. 8.5 *Left panel*: Effects of a constant increase in loads. Notice the abruptness of the transition. *Right panel*: Effects of fluctuations in loads. The points corresponds to 10 different realizations of the noise. The transition is abrupt (the fraction of tripped lines is either ∼0 or ∼1), but whether a cascading failure happens depends on the actual realization of the noise. Therefore, the transition does not happen at a particular critical value of σ but can occur in a region where fluctuations range between 6 and 12 % of the nominal loads (*shaded area*)

Our model does not account for the whole complexity of an EPS; in particular, it disregards both transients and the dynamics of phase angles. Nevertheless, it allows to sort out the role of a class of events always present in any blackout, i.e. line overloads. Another important property of the *OCM* is that, due to the long-range nature of the interaction, it is amenable to analytic approximations that lead to predict the universal behaviour of the system [34].

For our scopes, we consider a network of 2,746 nodes, consisting of a snapshot of the national high-voltage Polish power grid obtained from the data collected and used by Polish transmission system operators.

We first stress the Polish network by considering a growth in the power demand while keeping the network fixed. Such mechanism is not so far from reality, as in recent years, the economic competition and deregulation has led the power systems to be operating fairly close to their limits. We model such growth of the demand as a simultaneous increase of all the loads by a factor α and record the fraction f of branches that fail at the end of a cascade.

We then stress the Polish network via are flow fluctuations mimicking both the stochastic components in customers' behaviour and the effects of erratic renewable energy sources. We parametrize the size of fluctuation by allowing the initial loads to fluctuate uniformly by a fraction σ.

The left panel of Fig. 8.5 shows that by increasing all the loads the breakdown is abrupt as in a first order transition. The situation is more complicated in the case of random loads. The right panel of Fig. 8.5 shows the results for different realization of the noise (fluctuations). We find that, for a given realization of the noise, the system is either in a safe state (the fraction of tripped links is ∼0) or in a systemic failure state (the fraction of tripped links is ∼1). At difference with the case of uniform load increase, the transition does not happens at a given σ, but can happen in a whole range of values. In particular, for the Polish grid we find that the grid stays essentially intact when the loads are allowed to fluctuate less than $\sim$6 % and that the system comes in a blackout state when loads are allowed to fluctuate more than 12 % of their nominal values. For intermediate values, the system can either be in a safe state or in a black-out state depending on the realization of the disorder. Such results are in accordance with mean field arguments indicating that black-outs in the *OCM* should be a first order phenomenon.

8.5 Distributed Algorithms for Smart Grids

The continuous growth and development of technological networks has introduced complex connectivity (as well as dependence) patterns within their constitutive components that can often trigger systematic side effects like system-wide cascades of failures. Hence, our current and future networks need healing mechanisms that are able to cope with systemic effects and multiple failures in an automatic and possibly distributed way. Such mechanisms are at the core of the process of building up Smart Grids, i.e. networks that are able to self-sustain and optimise in a distributed way to customers' needs.

At the Transmission level, electric power networks are already "smart", but in a centralised way: Supervisory Control and Data Acquisition (SCADA) systems allow operators to monitor, control, and dispatch generation. A failure either of the SCADA or of the supporting telecommunications can cause control operators to make incorrect system adjustments.

We consider instead the power system at the Distribution level, where the structure is mostly tree-like. We introduce a healing strategy based on the activation of fixed redundant resources (backup links) and study the resilience of the networks to multiple failures. Since the presence of backup links is customary in technological networks and our strategy can be implemented via routing protocols, our self-healing procedure is within the reach of current technology. For sake of simplicity, we will consider a single node to be the source of the quantity to be distributed on the network. Moreover, at each instant of time, the topology of the links in the network distributing the power is assumed to be a tree (the *active tree*). As a further simplification we will not take into account the magnitudes of flows – i.e., all links and sources are assumed to have infinite capacity – but we will focus on maximizing the connectedness of the system in order to serve as many nodes as possible.

In order to implement our strategy and its self-healing capabilities, we consider the presence of *dormant* backup links – i.e., a set of links that can be switched on. Nodes are assumed to be able to communicate with their neighbours by means of a suitable distributed interaction protocol with a limited amount of knowledge: the set of neighbouring nodes connected either via active or via dormant links. Then, when either a node or a link failure occurs, all the nodes below the failure will disconnect from the active tree and become unserved. Such unserved nodes can now try to

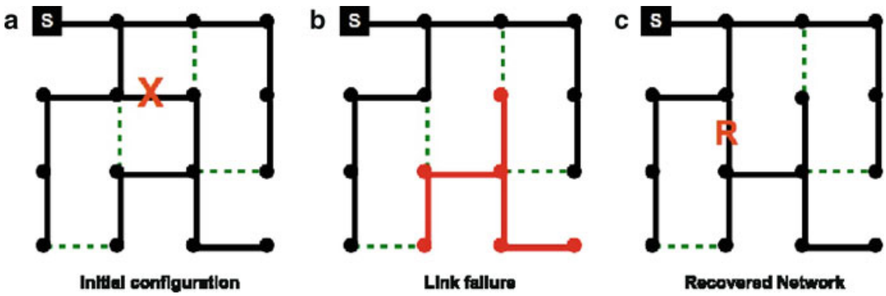

Fig. 8.6 Example of healing after single link failure. Notice that failure of a single node can be modelled as the failure of all its links; hence, multiple links failure are the more general event to be considered. (*Left panel*) In the initial state, the source node (*filled square*, *upper left corner*) is able to serve all 16 nodes through the links of the active tree. The *four dashed lines* (*green online*) represent dormant backup links that can be activated upon failure. The redundancy of the system is $p = 4/9$ as only 4 of the 9 possible backup links are present. The link marked with an **X** is the one that is going to fail. (*Central panel*) A single link failure disconnects all the nodes of a sub-tree; in the example, a sub-tree of 6 nodes (*red online*) is left isolated from the source – i.e., the system has a damage $\Delta = 6$. (*Right panel*) By activating a single dormant backup link, the self-healing protocol has been able to recover connectivity for the whole system, in this case bringing back the number of served nodes at its maximum value 16. The link that has recovered the connectivity is marked with an **R**

reconnect the active tree by waking up through the protocol some dormant backup links. Such a process will reconstruct a new active-tree that can restore totally or partially the flow, i.e. heal the system (Fig. 8.6).

By measuring the fraction *FoS* of served nodes after multiple random failures of k links, we study the effects of the redundancy r (the fraction of backup links added to the initial spanning tree). We investigate both the case which best resembles the actual situation – i.e. nodes disposed over a grid – and the role of the networks' connectivity patterns by generating different underlying topologies. In particular, we generate small-world and scale free networks [35].

We use square grids as an example of planar grids topologies. Small-world networks [36] are generated starting from planar square grids and rewiring with a probability p a link with a randomly selected node. Scale-free networks are generated through the Barabasi-Albert model [37]. In the case of technological networks, small world networks are important as they can show the effects of introducing long-range links in a planar topology.

To produce suitable initial configurations of our model distribution networks, we generate random spanning trees [38] associated to each kind of network structures. The links not belonging to the spanning trees form the set of the possible backup links of our system; among such links, we choose a random fraction r of *dormant* links that can be used to heal the system. We then simulate the occurrence of uncorrelated multiple failures by deleting at random k links of the initial active tree. Subsequently, we activate dormant links according to our self-healing procedure and calculate the *FoS*.

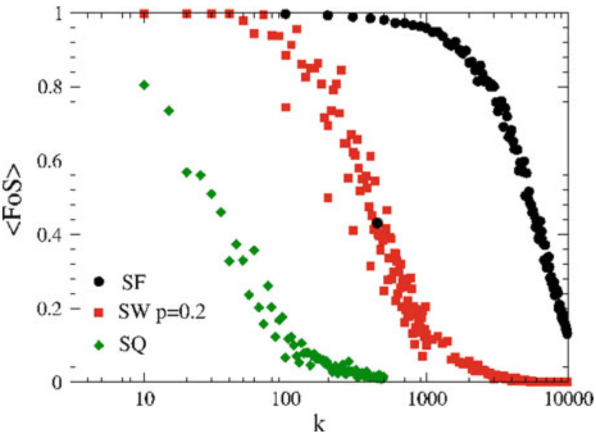

Fig. 8.7 (Color online) Comparison among different network structures. Here we show the performances of our self-healing algorithm with respect to the quality of service for increasing number of removed links with the redundancy r fixed to 0.3; for SW networks, the rewiring probability is $p = 0.2$. The average fraction of nodes$\langle FoS \rangle$ of served nodes is plotted against the number of failures k

Figure 8.7 shows that distribution grids based on the scale free topologies are the more robust. Nevertheless, they should be disregarded when considering the case of technological networks since economic and geometric constraints make scale free networks unfeasible on planar topologies. Therefore, the most relevant results are the ones on small-world networks, showing that introducing a small fraction of long-range links can enhance robustness by orders of magnitudes respect to planar grids with the same redundancies.

8.6 Conclusions

An unconstrained allocation and growth of the distributed generation can drive a power grid beyond its design parameters. In order to overcome such a problem, we propose in Sect. 8.3 a topological algorithm derived from the field of Complex Networks to allocate distributed generation sources in an existing power grid.

Several trans-national projects aim to integrate national power-grids into “super-grids”. The results of Sect. 8.4 indicate that increasing the system size causes breakdowns to become more abrupt. Thus, the possible enhancement of the systemic risk failures (blackouts) with increasing network size is an effect that should be considered in the planning of “super-grids”.

While transmission systems can already be considered “smart” (although in a centralised way), much less has been done at the level of distribution, especially at the low voltage (residential customer) level. In Sect. 8.5 we have introduced a simple distributed algorithm to keep the systems connected in the case of failures. By studying various network topologies, we have found that the introduction of some long-range connections in planar grids greatly enhances the resilience of local distribution networks to multiple failures.

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References

1. Arenas A, Diaz-Guilera A, Kurths J, Moreno Y, Zhou C (2008) Synchronization in complex networks. Phys Rep 469:93–153
2. Buldyrev SV, Parshani R, Paul G, Stanley HE, Havlin S (2010) Catastrophic cascade of failures in interdependent networks. Nature 464:1025–1028
3. Liu Y-Y, Slotine J-J, Barabasi A-L (2011) Controllability of complex networks. Nature 473:167–173. http://dx.doi.org/10.1038/nature10011
4. Dorogovtsev SN, Goltsev AV, Mendes JFF (2008) Critical phenomena in complex networks. Rev Mod Phys 80:1275–1335
5. Costa LF et al (2011) Analyzing and modeling real-world phenomena with complex networks: a survey of applications. Adv Phys 60:329–412
6. Perra N, Gonçalves B, Pastor-Satorras R, Vespignani A (2012) Activity driven modeling of time varying networks. Sci Rep 2. http://dx.doi.org/10.1038/srep00469
7. Barrat A, Barthelemy M, Vespignani A (2008) Dynamical processes on complex networks Cambridge University Press, Cambridge/New York
8. Alvarez-Hamelin JI, Fleury E, Vespignani A, Ziviani A (2012) Complex dynamic networks: tools and methods. Comput Netw 56:967–969
9. Casteigts A, Flocchini P, Quattrociocchi W, Santoro N (2012) Time-varying graphs and dynamic networks. Int J Parallel Emergent Distrib Syst IJPEDS 27:387–408
10. 2003 Homeland Security Presidential Directive HSPD-7 (2003). http://georgewbush-whitehouse.archives.gov/news/releases/2003/12/20031217-5.html
11. EU COM (2006) 786 EU directive on European Programme for Critical Infrastructure Protection, Brussels, 12.12.2006. http://eur-lex.europa.eu/LexUriServ/site/en/com/2006/com2006_0786en01.pdf
12. Rinaldi SM, Peerenboom JP, Kelly TK (2001) Identifying, understanding and analyzing critical infrastructure interdependencies. IEEE Control Syst Mag 21:11–25
13. Baghaie M, Moeller S, Krishnamachari B (2010) Energy routing on the future grid: a stochastic network optimization approach. In: International conference on power system technology (POWERCON), Hangzhou, 2010, pp 1–8
14. Stagg G, El-Abiad A (1968) Computer methods in power system analysis. McGraw-Hill Education, New York
15. Filatrella G, Nielsen AH, Pedersen NF (2008) Analysis of a power grid using a Kuramoto-like model. Eur Phys J B – Condens Matter Complex Syst 61:485–491
16. Fioriti V, Ruzzante S, Castorini E, Marchei E, Rosato V (2009) Stability of a distributed generation network using the Kuramoto models. In: Setola R, Geretshuber S (eds) Critical information infrastructure security. Springer, Berlin/Heidelberg, pp 14–23
17. Dörfler F, Bullo F (2012) Synchronization and transient stability in power networks and nonuniform Kuramoto oscillators. SIAM J Control Optim 50(3):1616–1642. doi:10.1137/110851584, http://epubs.siam.org/doi/abs/10.1137/110851584
18. Dobson I, Carreras BA, Lynch VE, Newman DE (2001) System sciences, 2001. In: Proceedings of the 34th annual Hawaii international conference on an initial model fo complex dynamics in electric power system blackouts, pp 710–718. doi:10.1109/HICSS.2001.926274
19. Wood AJ, Wollenberg BF (1984) Power generation, operation and control. Wiley, New York

20. Carreras BA, Lynch VE, Dobson I, Newman DE (2002) Critical points and transitions in an electric power transmission model for cascading failure blackouts. Chaos: Interdiscip J Nonlinear Sci 12:985–994
21. Sachtjen ML, Carreras BA, Lynch VE (2000) Disturbances in a power transmission system. Phys Rev E 61:4877–4882
22. Youssef M, Scoglio C, Pahwa S (2011) Robustness measure for power grids with respect to cascading failures. In: Proceedings of the 2011 international workshop on modeling, analysis, and control of complex networks, CNET '11, San Francisco. ITCP, pp 45–49
23. Stott B, Jardim J, Alsac O (2009) Dc power flow revisited. IEEE Trans Power Syst 24:1290–1300
24. Scala A, Mureddu M, Chessa A, Caldarelli G, Damiano A (2013) Distributed generation and resilience in power grids. In: Hammerli BM, Kalstad Svendsen N, Lopez J (eds) Critical information infrastructures security. Lecture notes in computer science, vol 7722. Springer, Berlin/Heidelberg, pp 71–79. doi:10.1007/978-3-642-41485-5_7, ISBN:978-3-642-41484-8, http://dx.doi.org/10.1007/978-3-642-41485-5_7
25. Grainger J, Stevenson W (1994) Power system analysis. McGraw-Hill, New York
26. Azzalini A (2005) The skew-normal distribution and related multivariate families. Scand J Stat 32:159–188
27. Brin S, Page L (1998) The anatomy of a large-scale hypertextual web search engine. Comput Netw ISDN Syst 30:107–117
28. Chung F, Zhao W Pagerank and random walks on graphs. http://www.math.ucsd.edu/~fan/wp/lov.pdf
29. NERC North America Electric Reability Corporation (2006). http://www.nerc.com/
30. ENTSO-E European Network of Transmission System Operators for Electricity (2008). https://www.entsoe.eu/
31. Report 1010701 (2005) Mitigating cascading outages on power systems: recent research approaches and emerging methods. Technical report, EPRI
32. Blackout in the United States and Canada, April 2004 (2004). https://reports.energy.gov/
33. Pahwa S, Hodges A, Scoglio CM, Wood S (2010) Topological analysis of the power grid and mitigation strategies against cascading failures. In: Proceedings of the 4th international IEEE systems conference, San Diego, pp 272–276
34. Quattrociocchi W, Caldarelli G, Scala A (2014) Self-healing networks: redundancy and structure. PLoS ONE 9(2):e87986. doi:10.1371/journal.pone.0087986. Public Library of Science. http://dx.doi.org/10.1371%2Fjournal.pone.0087986
35. Caldarelli G (2007) Scale-free networks Oxford University Press, Oxford
36. Watts DJ, Strogatz SH (1998) Collective dynamics of /'small-world/' networks. Nature 393:440–442. http://dx.doi.org/10.1038/30918
37. Barabási A-L, Albert R (1999) Emergence of scaling in random networks. Science 286:509–512
38. Wilson DB (1996) Generating random spanning trees more quickly than the cover time. In: Proceedings of the 28th annual ACM symposium on the theory of computing, Philadephia. ACM, pp 296–303