**Special Workshop on Risk Acceptance and Risk Communication**
March 26-27, 2007, Stanford University

# Risk Assessment of Complex Infrastructures

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## Abstract

This paper studies the effect of cascading failures in the risk and reliability assessment of complex infrastructure systems. Conventional reliability assessment is limited to connectivity analysis and does not include the effect of increased flow demand or flow capacity of existing network components. Network flows are associated with congestion-based disruptions which can worsen connectivity-based predictions of performance. Susceptibility to cascading overloads is modeled with a tolerance parameter that measures current flow against flow capacity. In this study, natural hazards and targeted disruptions constitute the triggering events for cascading failures. It is observed that improvements in component tolerance alone do not ensure robustness to cascading failures. Topological changes are also needed to improve cascading robustness at practical tolerance levels. Interestingly, targeted disruptions of single components can affect network performance more severely than earthquake or lightning episodes. In the event of infrequent natural hazard disruptions, cascading failures do not develop due to significant damage during the triggering event phase.

## 1. Introduction

This study quantifies the effects of natural hazards and targeted disruptions on the risk and reliability of complex infrastructures. A key feature of the risk assessment approach implemented in this work is the inclusion of *cascading* failures in addition to the traditional connectivity-based aspect of networked system evaluation.

Infrastructure systems and the demand for the commodities that they carry are growing at a rate that is outpacing the efforts to upgrade flow capacity and maintain safety margins. In addition, infrastructure systems are becoming more interdependent and failures at a given system are more likely to reduce the performance of other systems (Chen et al., 1996; Haimes et al, 2005; Adachi and Ellingwood, 2007; Duenas-Osorio et al., 2007). These reduced safety margins and increased interdependencies make performance evaluation of infrastructure systems less tractable. Additionally, the interactions among constituent components operating at different regimens make infrastructure systems more complex. In fact, modern infrastructure systems exhibit the hallmark properties of so-called complex systems: large number of interacting components, emergent properties difficult to anticipate from the knowledge of individual components, and adaptability to absorb disruptions (Boccara, 2004; Ottino, 2004).

Power transmission grids are used in this research as an example of an engineered complex system (Watts, 1999; Newman, 2003). Transmission grids have high voltage power lines in a mesh-like configuration, while distribution grids have radial topologies with low-voltage power lines. Power system reliability evaluation in transmission or distribution systems is typically performed at the *adequacy* assessment level, where adequacy relates to the existence of sufficient facilities to ensure power supply and demand balance. This adequacy approach is associated with the static conditions of the power system that ensure the existence of paths between power generation points and power consumption points or loads. Hence, adequacy does not account for the dynamic effects within the networks triggered by disruptive events (Billinton and Li, 2006). In addition, reliability assessment of power systems subjected to infrequent natural hazards is not widespread within the power industry. In the case of power distribution systems, utilities are allowed to report to regulatory agencies their reliability data without including major system disruptions. The argument is that reliability should be ensured for a wide range of operating conditions, but excluding low-frequency triggering events that are impractical and uneconomical to handle (Balijepalli et al., 2004; Li, 2005; Warren and Saint, 2005).

The limitations of adequacy-based reliability assessment become evident when trying to capture time-dependent features of the power systems. For instance, the increasing congestion of power flow in transmission and distribution lines has a direct impact in the ability of the system to absorb unforeseen disruptions (Bush, 2003). This increased congestion, or decreased tolerance, implies not only that low-frequency hazards can significantly impact the performance of power systems, but also that common disruption causes can trigger large-scale performance losses–due to cascading failures. As an example, the North American blackout of August 2003 was initiated by an untrimmed tree too close to high voltage transmission lines in Ohio (U.S.–Canada PSOTF, 2004).

This study uses numerical simulation methods to capture the effect of cascading failures on power transmission systems subjected natural and intentional hazards. A "cascading effect" metric is used to quantify the additional disruption on power system as compared to conventional connectivity-based reliability assessments. The evaluation of transmission system performance is implemented for natural hazards, such as seismic and lightning, and for random hazards that capture common cause failures (e.g., aging, animals, vandalism, etc.) Disruptions targeting the most connected and loaded nodes are also monitored to evaluate power system robustness to intentional attacks. Since each disruptive event triggers flow redistribution within the network, a tolerance parameter $\alpha$ is introduced to establish the critical flow to capacity ratio levels that fuel cascading failures. The power transmission systems used in this study correspond to a test network of the Institute of Electrical and Electronics Engineers (IEEE) on $n_{IEEE}$ = 118 nodes (Christie, 1999), and a transmission and distribution (TD) model for geographically distributed infrastructures on $n_{TD}$ = 100 nodes (Duenas-Osorio, 2005). The TD model reproduces statistical properties of power transmission systems and is used to explore system performance for a variable number of nodes $n$.

Results from this study indicate that the effects of cascading failures are significant when system tolerance low. For the systems under consideration, a common critical tolerance within the range of $\alpha$ = (0, 0.1) is found to dominate the size of cascading failures. Also, a reduced tolerance makes the systems more vulnerable to cascading failures triggered not only by infrequent hazards, but also by common disruption causes. More frequent cascading failures due to tolerance reduction manifest as a power law tail in the probability of observing power system blackouts. This algebraic decay contrasts the traditionally accepted exponential decay of the probability of observing rare events. Power law decays are significantly slower relative to exponential decays; hence, the risk from large blackouts quantified as the product of blackout size and its probability of occurrence is comparable to the risk from frequent but small cascades. Systems displaying the frequency of disruption severity as power laws operate near critical states and their dynamics are governed by the laws of complex systems. These laws imply long range autocorrelations and coupled failures modes, which warrant new methods for risk reduction. Preliminary evidence of this observation is provided by the historical sizes of blackouts in North America and simulation models of complex dynamics (NERC, 2003; Carreras et al., 2004). The results from the TD models imply that heightened risks are a property of geographically distributed infrastructures.

This paper is divided in six sections. Section 2 presents the benchmark power transmission systems for reliability assessment, which correspond to the IEEE 118 node network and the TD 100 node network. Section 3 introduces the disruptive actions from natural and targeted hazards, and describes the reliability metrics used to quantify system performance under cascading regimens. Section 4 compares the simulated response of the power systems with and without cascading failures after the triggering hazard takes place for different values of the tolerance parameter $\alpha$. The implications of accounting for cascading failures in risk estimations are discussed in Section 5. The conclusions of this research are presented in Section 6.

## 2. Benchmark power transmission systems

Two networks are used to represent the power transmission systems of this study. The first system is a modified version of the IEEE 118 node network which is used for reliability testing in the electric engineering community (Christie, 1999). The modification consists of assigning lengths to each of the transmission lines according to a lognormal distribution fit of transmission line lengths for test systems (Billinton and Li, 2006). The median length for transmission line test systems is $L_m$ = 35 kilometers and the lognormal standard deviation is $\xi_L$ = 1.22. Table 1 summarizes the topological properties of the IEEE 118 node network. The *order* refers to the number of nodes and the *size* to the number of transmission lines. The set of nodes is defined as the union of two different types of nodes: generation $n_G$, and transmission and distribution nodes $n_T \cup n_D$, which in a transmission system correspond to high, medium, and low voltage electric substations.

*Table 1: Topological properties of benchmark power transmission systems.*

| Network | Network Order $n$ | Network Size $m$ | Generation Subset Order $n_G$ | Transmission and Distribution Subset Order $n_T \cup n_D$ |
|---|---|---|---|---|
| Modified IEEE 118 node network | 118 | 358 | 54 | 64 |
| TD 100 node network | 100 | 158 | 29 | 71 |

The second system for analysis is a network model developed to capture the main properties of real transmission and distribution systems. The system is referred to as the TD model and is obtained from a template which corresponds to a two dimensional aperiodic lattice with nodes having 8 neighbours or direct lines to 8 other nodes except at the boundaries. This template resembles a square grid with additional lines connecting every other node (Duenas-Osorio, 2005). The TD model is constructed by retaining each transmission line of the template with probability $p_m$ (Figure 1). The probability $p_m$ is estimated as the ratio between the average number of transmission lines in real power systems of different orders and the number of transmission lines in original templates of similar order. Several IEEE network models of order ranging from 9 to 300 were used to estimate $p_m$, which as a function of $n$ results in:

$$p_m = 0.55 n^{-0.05} \quad (1)$$

The retention of edges is performed sequentially to ensure connectivity. The resulting TD model captures the two-dimensionality of real systems and the property that transmission lines have *short range*. The concept of range measures the distance between two nodes of a network in the absence of the line that is connecting them directly. Table 1 also summarizes the fundamental properties of the TD power model. The estimation of appropriate $p_m$'s for other infrastructure systems can lead to the development of generic TD infrastructure models.

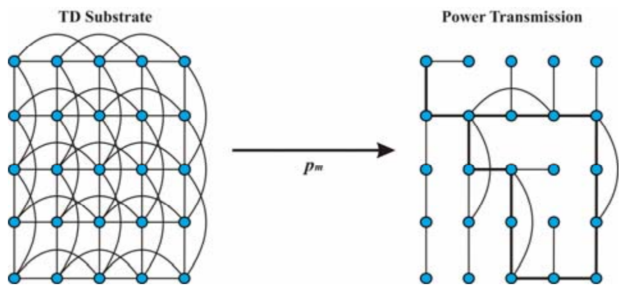


*Figure 1: Realization of connected TD power model with probability $p_m$.*

## 3. Disruptive events, cascading failures, and network performance

Disruptions of different nature are imposed to the power transmission systems. Two main categories describe the type of hazard: disruptions based on historical natural hazard rates, and disruptions targeting specific network components. In the first category seismic and lighting hazards are defined according to their rate of occurrence at different intensity levels in the western part of the United States (WUS). The occurrence of seismic events is estimated from the hazard rates reported by the United States Geological Survey (USGS, 2007). These rates are used to characterize the annual probability of peak ground acceleration (PGA) as modeled by a lognormal distribution with median $PGA_m$ = 0.15g and coefficient of variation $COV_{PGA}$ = 0.42. The probabilities of failure of power transmission system elements (e.g. electric substations of different voltage levels) are defined by their structural fragilities as a function of PGA. These fragilities have been estimated by the Federal Emergency Management Agency for use with its multi-hazard loss estimation methodology HAZUS-MH (FEMA, 2006). For high-voltage electrical substations the probability of exceeding a "slight" level of damage is described by a lognormal distribution with median $PGA_{ESS5\text{-}m}$ = 0.11g and coefficient of variation $COV_{ESS5}$ = 0.50. The "slight" damage state is defined as failure in 5% of the substation equipment and with restoration time of less than day. This "slight" damage is the only level considered in this study because of its increased probability of being exceeded and higher likelihood of triggering cascading failures. More critical limit states will initially damage the network so severely that no cascade can occur. Table 2 summarizes the seismic hazard and associated vulnerability of the power system components.

Lightning hazards are estimated from recorded ground flash densities in the continental United States. Typical mean annual flash densities $N_g$ for WUS range uniformly between 0 – 1 flashes/km$^2$/year with a standard deviation $\sigma_{Ng}$ = 0.3 flashes/km$^2$/year (Huffines and Orville, 1999). The effect of lightning hazards on network transmission lines is estimated from the rate $\lambda_L(N_g)$ at which lightning directly or indirectly strikes the lines (IEEE, 1997). The total flashover rate is used to calculate the probability of voltage overload from a spatially distributed Poisson process. Line failure occurs if at least one flash overloads the line. Hence, defining $L_{ij}$ as the length in km of line *ij*, the probability of failure of a link from the Poison process is:

$$P_{ij}(Failure) = 1 - e^{-\lambda_L L_{ij}} \quad (2)$$

Disruptive events that systematically target particular network components are based on the most connected and most loaded nodes. The connectivity of a node is measured by the vertex degree $d(v)$, which counts the number of lines that arrive and leave node $v$. The node with the largest degree $d(v)_{max}$ is chosen for vertex degree attacks. The maximum load or amount of flow passing through a node is measured by the vertex betweenness $B(v)$, which is calculated as the number of shortest paths that pass trough a vertex $v$ when trying to send flow from every generation node to every distribution node. The node with the highest vertex betweenness $B(v)_{max}$ is the node trough which most power flows within the system, and is chosen for load-based attacks.

*Table 2: Lognormal models for seismic hazard and component fragility at "slight" damage levels.*

| Hazard or Vulnerability | Median (g) | COV |
|---|---|---|
| Annual Seismic Hazard in PGA | 0.15 | 0.42 |
| Low-Voltage Substation (ESS1) | 0.15 | 0.70 |
| Medium-Voltage Substation (ESS3) | 0.15 | 0.60 |
| High-Voltage Substation (ESS5) | 0.11 | 0.50 |

Cascading failures are enabled by assigning capacities to each of the nodes of the system. The vertex betweenness $B(v)$ is used as an approximation of the load $L(v)$ that flows through each vertex $v$. Since engineered systems are optimized for maximum capacity and minimum cost, it is assumed that the capacity of the nodes $C(v)$ is proportional to the initial load $L(v)$ (Motter and Lai, 2002; Zhao et al., 2004):

$$C(v) = (1 + \alpha)L(v) \quad (3)$$

where $\alpha \geq 0$ is the *tolerance* parameter and $v = 1, 2, \ldots, n$. When a disruption to the network occurs, the distribution of loads or flow patterns change within the system, and depending on the value of $\alpha$ some nodes will be unable to handle the redistribution and will also fail because $C(v) < L(v)$. These additional failures require a new redistribution of loads, which either stabilizes and the failures are locally absorbed, or grows until a large number of nodes are compromised in terms of functionality.

The parameters to monitor the performance of the power system focus on quantifying the effects of the cascading failures. A simple parameter to measure the cascade size is denoted as $S$ and defined as the fraction of demand nodes that do not experience load curtailment $n_D'$ with respect to the total number of demand nodes $n_D$ in the original system:

$$S = \frac{n_D'}{n_D} \quad (4)$$

Another parameter corresponds to the cascade susceptibility $C_s$ which measures the vulnerability to cascading after failure of some nodes during the triggering event. Essentially, this parameter relates the number of nodes failed during the disruptive event $n_{Trigger}$, and the total number of nodes failed after the cascade stabilizes $n_{Cascade}$:

$$C_s = 1 - \frac{n_{Trigger}}{n_{Cascade}} \quad (5)$$

The effect of cascading failures can also be monitored for performance metrics that relate to the reliability assessment of power transmission and distribution systems. On going work is aimed at quantifying cascading effects in transmission systems by means of the Expected Frequency of Load Curtailment (EFLC) in occurrences per year, and the Expected Duration of Load Curtailment (EDLC) in hours per year. Analogous customer-based parameters for distribution systems correspond to the System Average Interruption Frequency index (SAIFI) and the System Average Interruption Duration index (SAIFI). These parameters measure expected frequency and duration of interruptions per customer, respectively.

## 4. System performance

Since vertex betweenness $B(v)$ captures the flow patterns within the network, each of the benchmark systems is initially subjected to a targeted disruption based on their most loaded vertex—the node with $B(v)_{max}$. The removal of this loaded node triggers a redistribution of flow that is recorded as a function of time, where time is represented by the number of steps in the cascading sequence. The evolution of network response in terms of $S$ is simulated for three distinct values of the tolerance parameter $\alpha$. Figure 2 displays the different regimens in which the networks operate after removal of their most loaded node.

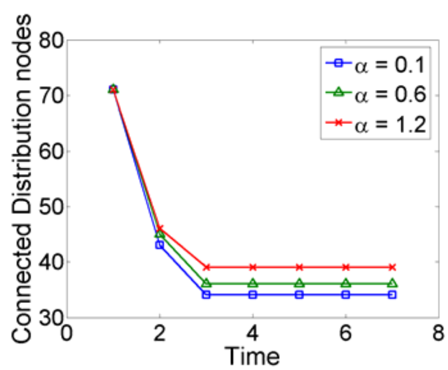


*Figure 2: Evolution of cascading failures for networks with different tolerance $\alpha$.*

The results of the figure are reported for the TD power model where the differences are confined to the marked regimens induced by the tolerance $\alpha$. Low tolerance drives the system to a critical state where it is difficult to locally absorb any perturbation. The system response stabilizes after a few time steps, implying that most changes in state are due to the triggering event effects. As $\alpha$ increases, the ability of the system to redistribute flow without collapsing also increases. Figure 3 presents the performance of the systems in terms of cascade size $S$ as a function of the tolerance $\alpha$. The plot displays the steady-sate response of the network after the cascade has taken place. The triggering events consist of the removal of a single node according to their maximum betweenness $B(v)_{max}$ and their maximum vertex degree $d(v)_{max}$.

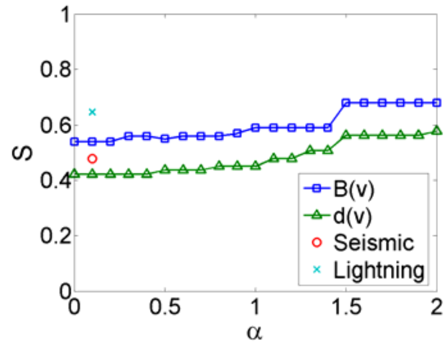


*Figure 3: Steady-state response of TD power model after cascading failure as a function of $\alpha$.*

Increasing the tolerance parameter $\alpha$ has a visible impact in the response of the system when subjected to targeted disruptions. Since tolerance is directly associated with flow capacity, its gradual increase has a global effect of protecting the network from cascading failures. Increased tolerance has a similar effect in improving networks whose removed element is the most connected. However, $S$ for $\alpha < 0.1$, which causes the largest cascades, is lower for degree-based disruptions suggesting that network structure plays a more relevant role in their reliability. Vertex degree has an important function in ensuring *accessibility*, but not necessarily in flow capacity. Hence, robustness to cascading failures depends not only on the tolerance, but also on the *topology* of the system. According to the plot, to improve cascading resistance for a typical infrastructure network it is necessary to increase $\alpha$ to impractical values. A better approach is to also modify the connectivity patterns of the most connected nodes by decentralizing the node with $d(v)_{max}$.

The response of the power system to natural hazards is estimated daily during 10 years, where each day has a probability of hazard occurrence governed by their hazard functions. If an earthquake or lightning storm occurs, vulnerable elements are removed from the systems with a probability associated to their structural fragility and limit states. These elements form a variable triggering set during each trial. Simulations are performed for the power transmission models running at a critical tolerance of $\alpha_c$ = 0.10. The average of the natural hazards effects on cascading size are included in Figure 3 as single points. These average values provide a preliminary indication of the performance boundary that governs their effect on cascading failures. For instance, seismic hazards are closer to the degree-based disruption due to the vulnerability of multi-component electric substations, whereas lightning hazards are above the milder load-based disruption. Overall, a single failure of a highly connected node is worse than any other targeted or natural hazard for the hazard rates and limit states of considered in this study. Lightning hazard has the least effect on system unreliably due to their effect on transmission lines, which have better odds of being rerouted as compared to rerouting around entire electrical substations after earthquakes or targeted disruptions.

The size of the triggering event for the steady-state response has been a constant $n_{Trigger}$ = 1. Figure 4 presents the cascading size as a function of tolerance $\alpha$ for the TD model with load-based disruptions and $n_{Trigger}$ = 1, 2, and 3. Simultaneous removal of two or the three of most loaded nodes results in a system that is unable to function even with levels of tolerance that imply a fictitious capacity of twice the maximum load. Loaded nodes are likely to fail more frequently due to their continued operation near their design capacity. Hence, scenarios when more than one heavily loaded node fail can be common as flow demand increases. This results calls for improved capacity and *additional* lines or nodes to *decongest* the system. Increased capacity is a temporary fix, whereas enhanced topology has not only more permanent effects, but also alleviates stresses from other disruptive events. For instance, additional lines in the neighbourhood of highly connected nodes can help decentralizing them and improving cascading resistance to vertex degree disruptions or natural hazards.

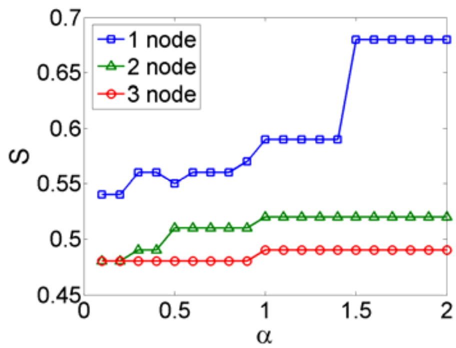


*Figure 4: Cascading size for different load-based triggering sets as a function of α.*

## 5. Infrastructure risk assessment

The operation of geographically distributed infrastructures is sensitive to their topology and tolerance in flow capacity. However, current operating practices and deregulated markets push them to work closer to their maximum design regimens. This factor heightens the probability of observing more frequent and larger cascading failures. In addition, traditional countermeasures focus on improved tolerance of congested elements, which alone does not guarantee robustness to cascading failures. Infrastructure systems are rather vulnerable to failures in the nodes that enable local connectivity, and to failures in multiple nodes that operate close to their maximum flow capacity. These unique factors produce significant network collapses even when the triggering event is perceived as a benign factor, such as the removal of a *single* node. Figure 5 presents the probability of observing load curtailments of increasing sizes given natural hazards. The plot includes the size of the affected distribution nodes for cases with and without cascading failures. The probability trends are crucial for risk assessment. Defining risk simply as the product of the size of the cascade or cost $C(k)$ and the probability of observing a cascade of size $k$ or $P(k)$, clearly indicates the relative higher risk induced by cascading failure modes. These failure modes are neglected in current connectivity-based reliability methods for networked systems.

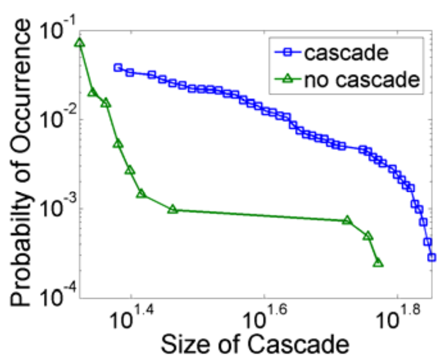


*Figure 5: Probability of outage size for TD systems with and without cascading effects.*

## Conclusions

Conventional connectivity-based reliability assessment for infrastructure systems can lead to significant underestimation of their risk. Connectivity-based methods focus on finding enough connected components within the network so that supply and demand of commodities can be balanced. However, these methods are unable to capture flow dynamics within the network.

When flow dynamics are included in reliability assessment, the systems are like to undergo large-scale cascading failures. These failures are caused by flow redistribution after disruptive events. Since most engineered systems are designed to operate close to their capacities, any growth in flow demand decreases the tolerance of their components. This phenomenon slowly drives the systems to a critical state where a *single* component failure can trigger large disruptions, such as blackouts in the power grid.

The tolerance to flow overload in power systems displays a critical value $\alpha_c < 0.1$ for triggering failures based on total flow or load at each component, and based on their connectivity. Increasing the tolerance beyond the critical value improves robustness to cascading failures. However, the improvements from tolerance increase occur at a slow rate, implying that only increasing the tolerance of existing systems is not an effective solution. Increasing tolerance does not improve the pre-existing topology of the networks, which affects their accessibility. Hence, improving topology will have a positive effect not only in increasing robustness, but also in decongesting the system, decentralizing it, and increasing the number of alternative routes in case of natural hazards that compromise extensive portions of the network.

For a tolerance $\alpha$ close to the critical value, seismic-induced "slight" damage on several nodes does not trigger on average any cascading failure larger than cascading failures induced by removing *one* node with high connectivity. The reason is that the random nature of the event does not necessarily affect the most connected or most loaded elements. Seismic induced failures are rather observed within the larger set of nodes that are not highly ranked in connectivity or flow transmittal. Lightning hazards trigger failures more frequently, but their consequences are not sizable because they mainly affect transmission lines that cover large distances, which in general have alternative routes.

The susceptibility of infrastructure systems to decreased tolerance and reduced local connectivity leads to more frequent cascading failures. These failures manifest as a power law probability of exceeding a particular size of cascading effect. This algebraic regime has an important effect on the estimated risk for infrastructure systems: large-scale cascades are more common than implicitly assumed in connectivity-based reliability. This observation implies that cascading failures are correlated and that the systems operate near critical states. Hence, the risks of service impairment even from simple disruptions can be exceedingly large. This critical behaviour is typical of complex systems and can be captured by generic transmission and distribution models such as the proposed TD model. Such model can be used to explore mitigation actions, which in complex systems need to simultaneously address frequent and infrequent events to avoid the effects of long term correlations where the mitigation of small-scale frequent failures can lead to more frequent large-scale failures in the long run.

## Acknowledgements

The work reported here has been funded in part by the Department of Civil and Environmental Engineering at Rice University. This support is gratefully acknowledged.

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