Probabilistic Risk Assessment of Infrastructure Networks Subjected to Hurricanes

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ABSTRACT: An initial investigation towards a probabilistic risk assessment framework for infrastructure systems subjected to hurricanes is presented. An idealized probabilistic spatial-temporal hurricane model is proposed for the purpose of investigating infrastructure performance and redundancy. The investigated infrastructure is an electrical network, corresponding to a synthetic IEEE benchmark system, which is modeled by a physical power flow model. The response of the infrastructure network to hurricane events is evaluated in terms of the overall power loss, considering the power flow characteristics of the network and potential cascading failures. It is found that while the network component failure probabilities are strongly dependent on the hazard characteristics, this does not hold for the overall network damage after simulation of the cascading failures. The computed average power loss level tends to be rather insensitive to the number and combination of initially triggered network components.

1. INTRODUCTION

Modeling of damages and risks caused by natural hazards to infrastructure networks is an active field of research and development. The daily lives of millions of people necessitate reliable access to the resources and services that such networks supply: power, water, gas and oil, transportation and telecommunication. Even moderate service disruptions of these networks often lead to sizeable losses and affect public health and safety. This effect is pronounced in the context of natural hazards such as tropical cyclones, which can lead to large scale systemic damages. It has been estimated that in the US alone, power outages due to hurricane events lead to yearly nationwide costs ranging between 18 to 33 billion USD (Whitehouse 2013).

Multiple studies of the vulnerability of power networks and the occurrence of outages in hurricane prone regions have been conducted mainly for the US. Earlier studies developed regression models to predict the spatial distribution of power outages based on outage data from past hurricanes along with physical data and environmental conditions of the system component sites (Han et al. 2009; Liu et al. 2005; Liu et al. 2008).

Power outages often result from cascades of failures of individual network components (Crucitti et al. 2004). Triggering events such as hurricanes can lead to the damage of multiple components simultaneously, which then might lead to further line overloads (Koç et al. 2013). Often, diffuse overall network damages occur that are due to cascading failures after the initial triggering event(s). Some more recent studies accounted for cascading failures during hurricanes (Dueñas-Osorio and Vemuru 2009; Javanbakht and Mohagheghi 2014; Ouyang and Dueñas-Osorio 2012; Ouyang and Dueñas-Osorio 2014; Winkler et al. 2010).

Considering the importance of system dependencies in power networks, this paper presents a first idealized development and implementation of a probabilistic risk framework for the assessment of hurricane impacts, which incorporates such dependencies. This study addresses the difficulty of assessing the damages caused by a natural hazard as potential common cause for failure events of individual network components, while considering the physical dependency of these components. The suggested approach is applied to a synthetic transmission power system.

The paper is organized as follows: Section 2 introduces the methodology and Section 3 describes the numerical application. The results are presented in Section 4 while Section 5 provides conclusions and future research questions.

2. METHODS

2.1. Probabilistic risk assessment

Risk is commonly defined as the expected consequences of hazards. Consequences are a function of the exposure and vulnerability of the assets subjected to the hazard (Varnes 1984). The dependence of risk on hazard, exposure, and vulnerability can be expressed by the following generic equation:

$$R = \int_H p(h)\left[\int_D p(d|h)C(d,h)\mathrm{d}d\right]\mathrm{d}h \qquad (1)$$

$p(d|h)$ is the probability distribution of damage d conditional on a hazard intensity h; it describes the vulnerability. $C(d,h)$ is the cost as a function of damage and hazard intensity, it describes the exposure; $p(h)$ is the probability distribution of the hazard intensity.

In agreement with Eq. (1), risk is here quantified as the expected loss of power supply due to hurricanes. In Figure 1, the overall framework is visualized for hurricanes. The hazard model comprises a hazard genesis and hazard realization (Section 2.2). The infrastructure model includes the network inventory, i.e., location and characteristics of assets, and the vulnerability. The latter describes the component failure probability conditional on the hazard intensity, here: wind load. The resulting damage to the network in terms of power loss [%] is then simulated using a physical power flow model (Section 2.3 and 2.4). The exposure terms, i.e., the costs associated with the power loss and damages, are not part of this study and will be included in future applications.

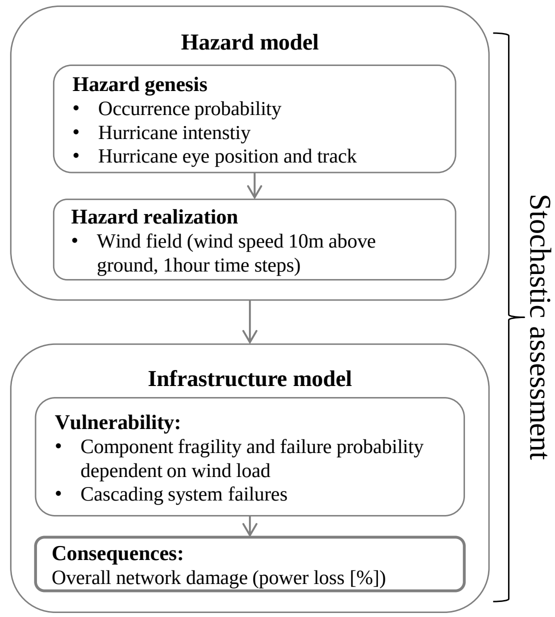

Figure 1: Overall modeling approach.

The assessment of the vulnerability of an infrastructure network is challenging, primarily because of the large number of components and their mutual dependencies. The exhaustive assessment of the effect of all combinations of component failures on the system performance is computationally intractable already for smaller networks. As an example, the network considered in Section 3 of this paper has 58 components, which results in 2^{58}=2.9E17 combinations of binary component states, posing challenges with respect to computational treatability.

2.2. Hurricane hazard model

For the purpose of this initial investigation, a simple hypothetical hurricane model is introduced. A hurricane event is treated as a random process in space, time, and intensity. The occurrence of hurricane events is modelled by a Poisson process with an occurrence rate λ that is assumed constant for the total study area.

Hurricanes are categorized according to their intensity, following the Saffir-Simpson Scale. This scale categorizes hurricanes by their maximum wind speeds into five categories. The (site-specific) probability of the hurricane falling into any one of these categories is according to Table 1.

Table 1: Site specific probability of hurricane intensity given hurricane occurrence; data based on Ouyang and Dueñas-Osorio (2014).

Hurricane intensity [m/s]	P(Intensity| Hurricane)
1 [33-42]	0.53
2 [43-49]	0.19
3 [50-58]	0.15
4 [59-70]	0.08
5 [>70]	0.05

A function $w(r)$ is fitted to the observed static gradient wind fields of hurricanes Katrina, Wilma, and Ivan (NOAA 2013), to model the wind field (Eq. 2). See Figure 2 for the appropriate maximum wind speed model for hurricane Ivan. $W(r)$ is the one minute directionless wind gust speed at 10 m open terrain at each site of interest within the study area, as a function of the distance r from the hurricane center.

$$w(r) = \frac{2r \cdot r_{max}(w_{max} - f)}{(r^2 + r_{max}{}^2)} + f \qquad (2)$$

As specified in Eq. (2) and illustrated in Figure 3, the model generates a circularly shaped wind field. It uses three parameters: maximum hurricane wind speed w_{max} [m/s], the distance of the maximum wind speed to the hurricane eye r_{max} [m], and offset f [m/s], which is the asymptotic decay level of the wind field at great distances (infinity). W_{max} is defined conditionally on the hurricane intensity, by a uniform probability distribution within the wind speed intervals according to Table 1. For a hurricane of category 5, an interval of 70 to 90 m/s is assumed. R_{max} and f are also modeled by independent uniform distributions.

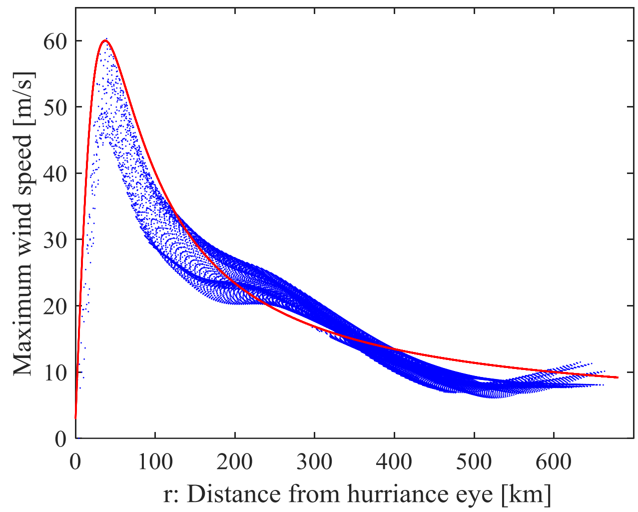

Figure 2: Modelled maximum wind speed curve, red (Eq. 2), together with data from hurricane Ivan, blue.

The temporal component of the model is implemented as time steps of 1 hour after landfall (x_0, y_0, t_0), as the hurricane center is assumed to move 12 hours inland with a translational speed of 15 km/h (Javanbakht and Mohagheghi 2014). The initial landfall location of the hurricane eye at the study area's lower boundary (coastline) is chosen according to a uniform distribution. At each time step, the eye location is updated according to hurricane track direction β, which is assumed to follow a normal distribution centered on the south-to-north direction. At each time step and at each location of interest, the wind speed value is calculated according to Eq. (2). An overview of all variables and assumptions is given in Table 2.

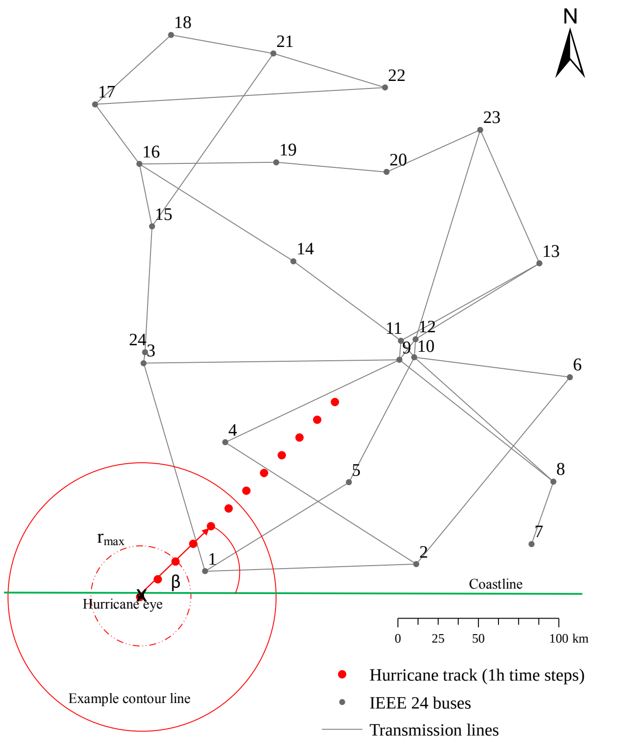

Figure 3: 2D contour lines of one realization of the wind field at landfall (x_0,y_0,t_0), indication of 1 hour time steps of hurricane eye track, and georeferenced power network in a 300x300 km² study area.

2.3. Infrastructure model

2.3.1. Power grid inventory

A power system has three main functional parts: power generation, power transmission between generators and substations, and power distribution system. In a graph representation of a power grid, nodes represent generation, transmission, and distribution buses, substations and transformers, while lines model the transmission lines/cables and transformers, which are weighted by the admittance (impedance) values.

2.3.2. Vulnerability: Component fragility models

The component fragility models describe the damage probability of the individual network components as a function of the hazard characteristics. Here, fragility models are based on the 10 m wind gust speed alone, independent of direction and duration. As a further simplification, no distinction is made between different node types and each node is seen as a single unit. The same holds for the transmission lines.

Table 2: Model variables, probability distributions and assumptions

Variable	**Probability distribution and assumptions**	**Comments and data source**
Hurricane occurrence	Poisson distribution	$\lambda = \frac{0.5}{year}$; Ouyang and Dueñas-Osorio (2014)
Landfall position	Uniform distribution	Location on lower boundary of study area (coastline, 400km length)
Hurricane intensity	Pr(Intensity| Hurricane)	Ouyang and Dueñas-Osorio (2014); see Table 1
Max hurricane wind speed, w_{max} [m/s]	Uniform distribution	The given hurricane intensity determines the regarding range
Distance eye to w_{max}, r_{max} [m]	Uniform distribution	Range 10 to 100 km
Offset, f [m/s]	Uniform distribution	Range 5 to 15 m/s
Track direction, β [degree]	Normal distribution	Emphasis on south-north directions; μ=90°;σ=15°
Component damage state, d_{ij}	Fragility Pr($d_{ij}\|w$) following Eq. 3	Parameters according to Figure 4.
Component failure, F_i		
Line segment	Pr(F_{ij}=yes|d_{ij})= [0.001, 0.01, 0.1,0.2,0.6]	
Node	Pr(F_{ij}=yes|d_{ij})= [0.0001,0.001,0.01,0.1,0.5]	

For four predefined damage levels (minimal, moderate, severe, and major damage), lognormal fragility curves describe the probability of the ith node to have reached a damage state d_j as function of wind speed w:

$$\Pr\left(D_i \geq d_j | W_i = w\right) = \int_0^w \frac{1}{\sigma_j \sqrt{2\pi} w} \exp\left(\frac{-\left(\ln(w) - \mu_j\right)^2}{2\sigma_j^2}\right) \mathrm{d}w \quad (3)$$

The fragility functions are summarized in Figure 4. The probability of failure of a network component given wind speed $\Pr(F_i | W_i = w)$ is calculated according to Eq. (4):

$$\Pr(F_i | W_i = w) = \sum_{d_{ij}} \Pr(F_i | D_i = d_{ij}) \Pr(D_i = d_{ij} | W_i = w) \quad (4)$$

The conditional probabilities $\Pr(F_i | \mathrm{d_{ij}})$ of component failure given the damage state are summarized in Table 2 .

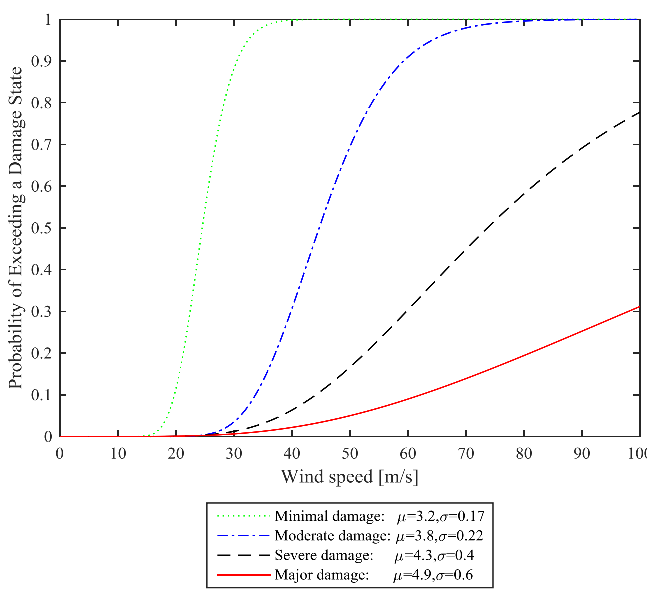

Figure 4: Fragility curves for four damage states, d_j (minimal, moderate, severe, and major damage).

The reliability evaluation of a transmission line is performed by spatial segmentation of the line. Each segment is assumed to have fully correlated performance, and is subjected to the wind speed at its midpoint. Different segments are considered to have independent performance for given wind speed. Each line is treated as a series system that fails if one line segment fails. The definition of the segment length has high importance. As the number of segments increases, the reliability of the lifeline decreases (Selçuk and Yücemen 1999). For the time being, a segment length of 10 km is used in this study.

2.3.3. Consequences: Network response model

In earlier studies, different approaches to account for changes in the power flow after potential component failure events were used. Some studies apply topological measures and properties of networks. Motter and Lai (2002) estimate the load at a node by the total number of shortest paths passing through the node (betweenness), which is altered, as soon as a node of the network fails. A topological network model has been used by Winkler et al. (2010) to model cascading failures in forthcoming hurricane events. As a result of this, reliability could be linked to topological features, such as meshedness, centrality and clustering. The more compact and irregular a network is built, the more reliable it is.

To overcome constraints of a purely topological model, the power flow in the network can be computed with a physics-based model. This allows accounting for the dependency of network components and to estimate if, and to which extent, initial component failures cascade through the network and cause partial or overall network collapse. Physical models estimate power flows across the grid according to Kirchhoff's laws. Here, the applied model is built on direct current (DC) power flow equations that are linearized approximations of the alternating current (AC) power flow equations and only consider flow of active power; see e.g. Van Hertem et al. (2006) for more detailed explanations.

The maximum power flow that a line can tolerate is the line capacity C_i, defined as the product of tolerance parameter α_i and initial load $L_i(0)$. In case of a line overload, the line is here assumed to be deactivated deterministically, e.g., by a circuit breaker, neglecting the possibility that protection devices could also suffer a (hidden) failure.

The failure of one or more components changes the topology of the power grid and eventually subdivides the grid into several unconnected sub-grids. The following algorithm assesses the consequences of the cascading failure in terms of overall power loss [%] and active link loss after a potential hurricane event has affected the study area:

1) Line and node threat determination; in case a node fails, all lines connected to it are also deactivated.
2) All threated lines are cut from the topology (zero line flow). As a result of the removal, some parts of the grid may end up to be split into disconnected sub-grids. In each sub-grid, it is checked whether power generating sources are still available or not. If there are none, the sub-grid is inactive as a whole. If there is power generation available, the power is redistributed among the remaining nodes, which may cause successive line overloads and thus further line removals from the grid. In this process, load shedding is not accounted for, i.e. the potential ability of the network operator to intentionally interrupt supply to certain areas in order to contain overall damage.
3) The (isolated) networks are reevaluated by repeating step 2 until convergence is reached.
4) The resulting damage, after the iterating algorithm finishes, is quantified by the fraction of the not-satisfied power demand (power loss [%]).

The described physical flow algorithm (steps 1 to 4) is implemented in MATCASC, an open source MATLAB tool for modeling cascading failures in power grids (Koç et al. 2013).

3. NUMERICAL APPLICATION

The synthetic IEEE 24-bus power system (UW 1999) is georeferenced by projecting it onto a 300x300km^2 study area. Each substation and transmission line segment is assigned a x,y-coordinate; the complete network is shown in Figure 3. The substations capacities and the technical parameters for the transmission lines, such as reactance and capacity, are obtained from the test case file (UW 1999). Figure 3 depicts the test case network in a georeferenced context, together with an example hurricane realization.

Hurricane scenarios are simulated using Monte Carlo simulation, thus generating information about landfall position, track direction, and hurricane intensity parameters for 1000 random hurricane events.

3.1. Results

3.1.1. Hazard and power system simulation results

Based on MCS, we find that there is only a 7% probability of the network remaining completely intact after a hurricane. The probability that component failures occur but do not result in power loss is 0.11 (resilience). 82% of hurricanes lead to a power loss in the system of some sort. The overall average (expected) power loss is 69%. Conditional on a power loss occurring, the expected power loss is 73%. With 0.12 probability, the overall power loss is greater than 90%.

When looking at the dependence of the number of deactivated lines after cascading failures on the number of initially triggered components, a positive correlation can be found with a correlation coefficient of 0.63. Nevertheless, already for small numbers of initially failed components, the total number of failures after considering the cascading failures may be large. This effect has also been stated in Motter and Lai (2002), especially when the tolerance limits alpha for single parts of the grid or for the network as a whole are small. Because of this effect, the resulting power loss is not very sensitive to the number of initially failed lines, as evident from Figure 5.

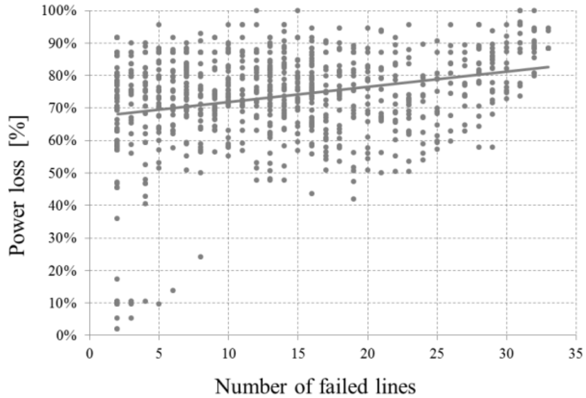

Figure 5: Dependence of power loss on number of initially failed lines.

Figure 6 shows the probability of line and node failure and average percentage of active lines after cascading failure conditional on the different hurricane classes.

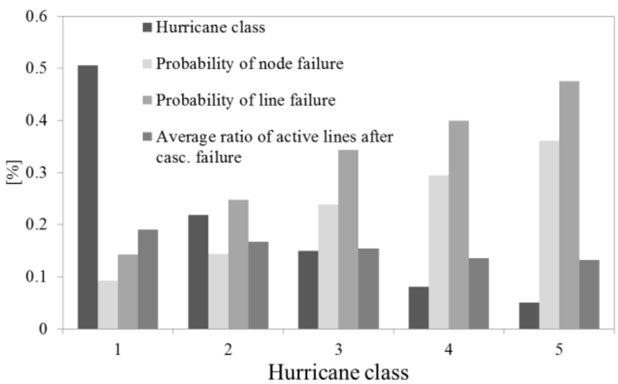

Figure 6: Hurricane intensity levels and regarding probability of node/line failure.

3.1.2. Impact of hurricane parameters on component and network failure

To investigate the dependence of initial components failure events on different model parameters, receiver operating characteristic (ROC) curves are shown in Figure 7. A ROC curve plots model sensitivity against the complement of the model specifity. The sensitivity is defined as the probability of a model to predict correctly a failure event (*true positive rate*). The specifity is the probability that a model correctly predicts non-failure events (*true negative rate*). The greater the area underneath the ROC curve (AUC), the higher are specifity and sensitivity, and thus the better the corresponding model explains the failure event (Mason and Graham 2002).

The highest AUC value is reached for a model combined of the following variables with increasing prognostic character: offset, hurricane class, r_{max}, wind speed at node 1 (near the coastline). The wind speed at node 1 (see Figure 3) differentiates very well between remote and critical hurricane tracks. The hurricane's offset has only negligible influence on the failure event of single network components.

The dependence of the overall system performance (power loss) after hurricane events and subsequent cascading failure on the individual parameters of the hurricane model is significantly less pronounced than for component failures (Figure 8). The low impact of the hurricane parameters mainly stems from the fact that values of power loss predicted by the applied physical network model are insensitive to the number of component failures, given that at least one network component failed (see Figure 5).

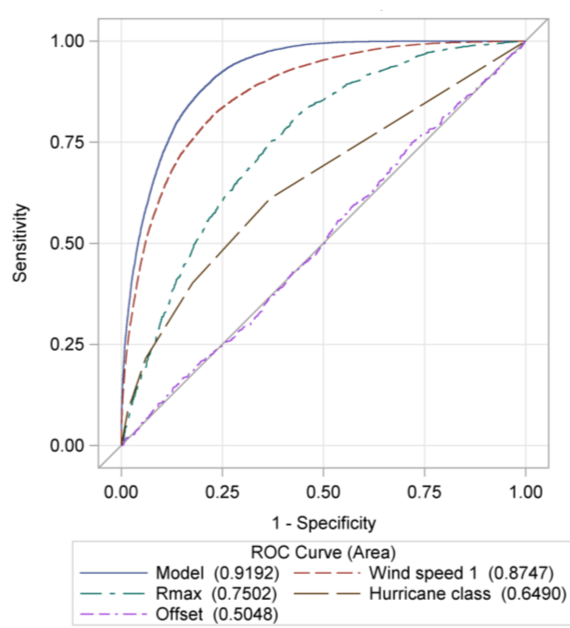

Figure 7: ROC curves: Influence of hurricane model parameters on the component failure event.

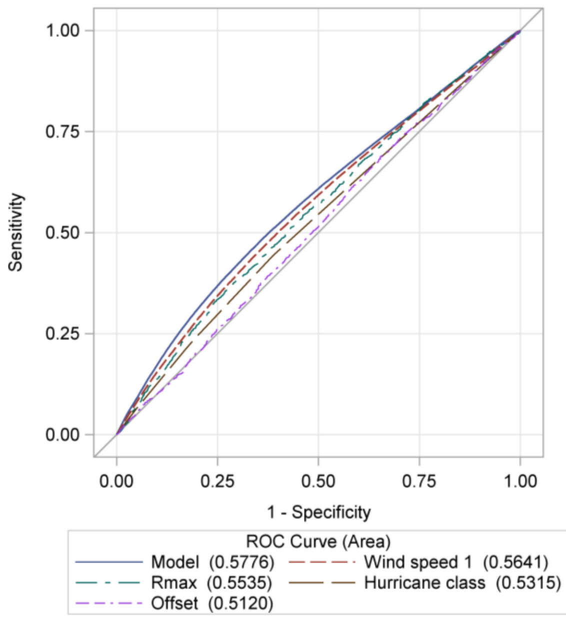

Figure 8: ROC curves: Influence of hurricane model parameters on the overall network damage (power loss).

4. CONCLUDING REMARKS

The main focus of this work is the inclusion of a physically-based system failure model within a hurricane simulation context. With the assumed model parameters, the network components have high probability of failure. Further, the physical power flow response model produces high overall system damage values in most cases, i.e. it does not differentiate between different hazard scenarios as already the failure of one or few component(s) lead to high power losses due to cascading effects. Consequently, more sensitive physical models will be considered in the future. This could be aided by comparing different alternative models, e.g. more complex AC models (Javanbakht and Mohagheghi 2014) and different performance metrics as they are discussed in Cavalieri et al. (2014).

In relation to the dynamic hazard model and in order to aim for a (near-)real time model, the implementation of a dynamic component into the power flow model is needed, so that the cascading failure evolvement can be evaluated in accordance with the hurricane time steps. For the time being, only the overall damage after hazard occurrence is assessed.

For real applications, the idealized hazard model must be replaced by state-of-the-art models, and system-specific fragility curves should be used. A further refinements is the reconsideration of the segmentation method for modeling the reliability of transmission lines, e.g. according to suggestions in Selçuk and Yücemen (1999) and SelÇuk and Yücemen (2000). Furthermore, the cost and follow-up consequences of power losses should be added to the model. Ideally, the model would also include required restoration efforts (time and costs), as carried out for instance in Ouyang and Dueñas-Osorio (2012) and in Ouyang and Dueñas-Osorio (2014).

Finally, in order to draw conclusions about the risk in monetary terms, and in order to express the potential overall costs during a defined time period, the distribution network in a given study area would have to be assessed similar to Winkler et al. (2010). The inclusion of percentages of households and businesses without power after a disruptive event would facilitate complete cost quantification dependent on outage localization and size.

5. ACKNOWLEDGEMENTS

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