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Evaluating infrastructure resilience to extreme weather – the case of the Dutch electricity transmission network

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This paper reports the development and results of a model exploring the resilience of the Dutch electricity transmission infrastructure to extreme weather events. Climate change is anticipated to result in an increase in the frequency and severity of extreme weather events over the coming decades. Situated in a low-lying coastal delta, the Netherlands may be particularly exposed to certain types of extreme weather(-induced) events. The degree to which the country's electricity network may prove resilient in the face of these future events is an open question.

The model focuses on two types of extreme events – floods and heat waves – and assesses two types of adaptation measures – substation flood protections and demand-side management. The model employs a network-based approach in assessing infrastructure resilience – explicitly representing the structure and properties of the Dutch transmission infrastructure – and extends previous work by accounting for key power system characteristics such as capacity constraints and cascading failures.

From a practice perspective, the results offer a first indication of the vulnerability of the Dutch electricity transmission infrastructure in the context of climate change. These results suggest that the network displays some vulnerability to both floods and heat waves. Both types of adaptation measures tested are found to enhance resilience, though substation flood protection shows greater benefits. Whilst the model was specifically developed for the study of electricity networks, we anticipate that this method may also be applicable to other types of transport infrastructures.

Keywords: *climate change, electricity, extreme weather, modelling, network, resilience.*

1 Introduction

Electricity infrastructures are essential to the production and transport of electrical energy and the provision of basic human needs. However, recent years have seen several dramatic failures in electricity infrastructures sparked by extreme weather events – Hurricane Sandy in 2012 (8.5 million customers without power), the 2012 blackouts in India[3] (630 million customers without power), the 2003 European heat wave (temporary shut-down of multiple large generation facilities), and others.

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[3]Evidence suggests that the 2012 blackouts in India resulted partially from tardy monsoons that increased electricity demand for irrigation and air conditioning and decreased hydroelectric output (Morrison, 2012; Walsh, 2012)

A growing body of evidence suggests that extreme weather events like these may increase in severity and/or frequency over the coming decades. The Intergovernmental Panel on Climate Change (IPCC) indicates that the frequency and intensity of extreme heat events, the frequency of extreme rain events, the intensity of droughts and the maximum windspeeds of tropical cyclones are either likely or virtually certain to increase within this century (IPCC, 2012*a*). In Northwest Europe, projections suggest a likely increase in the intensity of extreme hot temperatures, together with an increase in heavy precipitation events and extreme wind speeds (Beniston et al., 2007; Tank et al., 2014). While much research indicates that these changes are likely to influence the supply, demand, transmission and distribution of electricity (Koch and Vogele, 2009; Linnerud et al., 2011; Mideksa and Kallbekken, 2010; Petrick et al., 2010; Rademaekers et al., 2011; Rothstein et al., 2008), less is known about the specific *country-level* impacts of changing extreme weather patterns on electricity infrastructures, and the potential of various measures to enhance infrastructure resilience.

Around the globe, electricity transport networks are segmented into high-voltage, long-distance *transmission networks*, and finer-grained regional and local *distribution networks*, to which the transmission networks connect. Together, these networks fulfil the function to transport electricity from location(s) of generation to end users. Our focus in this paper is on the electricity transmission network of the Netherlands.

As a low-lying coastal country situated at the mouth of three major European rivers, the Netherlands may be particularly exposed to certain effects of a changing climate, including an increased frequency and/or severity of river floods, heavy rainfall, sea floods, droughts and heat waves. Historically, the electricity network of the Netherlands is one of the most reliable in Europe, and has proven relatively invulnerable to extreme weather events. In 2012, weather was cited as the primary cause of only 0.6% of total interruptions (Netbeheer Nederland and Movares Energy, 2013). Still, the Dutch electricity network is far from impervious to the effects of extreme weather (KEMA, 2010; Stedin, 2012; Tennet, 2014), and climate change may exacerbate these effects.

How may long-term changes in weather extremes affect the vulnerability of the Dutch electricity network, and what measures can effectively support infrastructure resilience? In addressing these questions, historical data is an insufficient guide, as the network is constantly developing, and past meteorological conditions may not accurately reflect the range of future possibilities. Moreover, it is insufficient to deal with the infrastructure as a set of isolated components, as its *interconnectedness* may play an important role in affecting its resilience (Bollinger et al., 2014) – disturbances in one corner of the system may have far-reaching impacts elsewhere within the system.

In this paper, we seek to generate much needed insight into the resilience of the Dutch electricity infrastructure to extreme weather events, and to do so in a manner which accounts for the infrastructure's interconnectedness, as well as key features of real-world power systems largely lacking in previous studies. In the remainder of this paper, we introduce and present the results of a model for assessing the resilience of the Dutch electricity network to extreme weather events. The starting point for this model is a representation of the current Dutch electricity infrastructure, including major generators, transmission lines, substations and distribution grids, as well as the manner in which these components are connected. Our experiments with this model take the form of a resilience assessment focusing on two types of extreme weather events with particular relevance to the Dutch situation – *floods* and *heat waves*.

2 Background – extreme weather and electricity infrastructures

Extreme weather events may affect components of the electricity infrastructure in numerous ways. The primary effects of floods are on power generation facilities and on electrical substations. Flooding of power plant grounds may lead to the failure and contamination of electrical and electronic components. While overhead power lines and underground cables are relatively insulated from the direct consequences of flood events, substations contain high concentrations of sensitive electrical and electronic equipment – power transformers, breakers, capacitors and computers. Even very small quantities of moisture and dirt contamination can cause some of this equipment to fail (Kumagai, 2012). Seawater intrusion is a potentially more serious threat, due to its corrosive effect on electrical components. Restoring power to a substation after flooding can be a lengthy and arduous task. A submerged breaker, for instance, requires complete disassembly and thorough cleaning of each part, and acquiring a new transformer can take anywhere from 18 months to a couple of years (Kumagai, 2012).

Heat waves may be particularly pernicious in terms of their effects on electricity infrastructures due to their ability to simultaneously affect multiple types of infrastructure components across a wide geographical area. In terms of generation, heat waves may result in higher surface water temperatures, which may reduce the efficiency of thermal power plants drawing from these waters. Furthermore, restrictions on maximum surface water temperatures may in certain places limit possibilities for cooling water use under extreme temperature conditions. These effects were visible during the 2003 European heat wave/drought, during which a drop in the level of inland waterways and an increase in their temperature incited the temporary shut-down of several nuclear generators in France, and necessitated the issuance of temporary legal exemptions from water temperature limits for other plants (De Bono et al., 2004).

It is well established that the capacity of overhead transmission and distribution lines is reduced under higher temperatures, as resistivity increases and convective cooling decreases. Higher temperatures also contribute to *line sag* – the vertical displacement of an overhead power line – a result of thermal expansion on the part of the conducting material, usually aluminium or copper. This can increase the likelihood of a flash over to the ground or trees, resulting in line failure. The potentially significant consequences of a sag-induced flash over are apparent in the 2003 Italian blackout – the largest blackout ever to occur in Italy – which resulted in 180 GWh of lost load (Corsi and Sabelli, 2004).

Heat waves may also affect electricity demand, as additional electricity may be required for cooling purposes. Rothstein et al. (2008) identify a dual impact of heat waves on electricity consumption – (1) an increase in the intensity of electricity demand and (2) changes in the course of the electricity load curve. Higher total demand for electricity may be largely attributed to higher utilization of air conditioning and refrigeration. Complementing this work, Hekkenberg et al. (2009) identifies a positive relationship between temperature and electricity demand in the Netherlands during the months of May, June, September and October, with an increase in temperature of 1°C during these months resulting in an increase in aggregate demand by more than 0.5%.

While the focus of the research in this paper is on floods and heat waves, other extreme weather effects are also important. Of particular danger are high-intensity wind events and (extra-)tropical cyclones. High-intensity wind events are normally quite localized, but can result in the simultaneous failure of multiple transmission towers in a small area (Oliver et al., 2000). More widespread damage may be caused by (extra-)tropical cyclones, such as the Lothar and Martin storms which passed through northern Europe in 1999. This particular pair of storms caused “the greatest devastation to an electricity supply network ever seen in a developed country”, toppling 120 high-voltage pylons and one quarter of the total high-tension transmission lines in France (IPCC, 2012*b*).

3 Positioning of this research

A growing body of literature has sought in recent years to assess the vulnerability and resilience of electricity infrastructures to climate change and extreme weather events. One strand of this research has involved the use of regression models or physical (e.g. hydrological) models to discern relationships between climatic variables and electricity supply or demand (Bartos and Chester, 2014; Chandramowli and Felder, 2014; Hekkenberg et al., 2009; van Vliet et al., 2012). Via the use of integrated assessment models, a second strand of research has investigated the economic effects of combined supply- and demand-side climate change impacts on energy systems (Chandramowli and Felder, 2014; Mima et al., 2011). While these approaches enable estimations of climate change impacts on energy systems, they do not normally account for the structure of electricity networks, nor the effects of constraints in electricity transmission/distribution.

Filling this gap, various *network-based* approaches have been used to study the vulnerability/resilience of electricity transport systems to extreme weather events. Foremost amongst these are empirical approaches, which use historical data to identify vulnerabilities and quantify the resilience of electricity delivery systems (Chang et al., 2007; Reed et al., 2009, 2010). A strength of these approaches is their link to real-world observations. However, empirical approaches are often limited in their ability to discern vulnerabilities in the case of future events. Next to empirical approaches are topological approaches. These approaches are generally used to quantify vulnerability or resilience using network metrics (e.g. giant component size) or to identify optimal or improved network topologies (Buldyrev et al., 2010; Holmgren, 2006*a*; Sterbenz et al., 2013).

Topological approaches offer a more generic understanding of network performance under extreme weather conditions, and have also been combined with empirical approaches to establish a firm basis in real-world observations (Winkler et al., 2010). However, a downside of purely topological approaches is their exclusion of certain power system features that may significantly influence vulnerability or resilience (Hines et al., 2010). Amongst others, these include the capacity constraints of power system components and the dynamics of cascading failures. Features such as these are commonly represented in the models of power system researchers (Bompard et al., 2011; Chang and Wu, 2011; Chen et al., 2010), but thus far have not been applied to assess the vulnerability and resilience of real-world electricity infrastructures to extreme weather events. Via the approach used in this study, we seek not only to provide insight into the extreme weather resilience of the Dutch electricity transmission infrastructure, but also to demonstrate the use of an approach capturing the effects of these key features.

4 Approach

The approach of this study involves the development of and experimentation with two models – a *flood resilience assessment model* and a *heat wave resilience assessment model*. Specific emphasis in these models is placed on representation of the electricity transmission network, the portion of the electricity system responsible for transporting power from production centres to distribution networks, and linking distribution networks with one another.

We use each of the models first to evaluate the resilience of the *current* network; then to evaluate a set of hypothetical *future* networks in which a set of selected adaptation measures have been implemented. The purpose is to gain insight into the extreme weather resilience of the infrastructure under current conditions, and to complete an ex-ante analysis of various measures to enhance the network's resilience. Details of the selected adaptation measures are described in more detail below.

In developing these models, we build on the technique of *structural vulnerability analysis*. This technique is used to assess how the successive removal of nodes or edges from a network affects its performance, and has been widely employed in the study of power systems (Albert et al., 2004; Chen et al., 2009; Holmgren, 2006*b*; Rosas-Casals et al., 2007; Wang and Rong, 2009). Experimentation with each of the two developed models involves repeatedly exposing the represented infrastructure network to extreme weather events of successively increasing magnitude and evaluating performance.

In the case of both floods and heat waves, we define the magnitude of an extreme event in terms of the *number of infrastructure components affected by the event*. This manner of incorporating extreme weather events allows us to sidestep the necessity to include detailed representations of possible extreme event scenarios, while allowing us to focus on the infrastructure-related aspects that are core to this investigation. Additionally, it allows us to simulate the effects of a wide range of possible disturbance scenarios, rather than only those which may have occurred historically or which may be considered most probable.

The procedure for evaluating infrastructure resilience is as follows:

1. **Instantiate the infrastructure network:** A representation of the Dutch electricity transmission infrastructure is instantiated. The details of this representation are described in the following section. Depending on the experiment, this representation may be augmented with a given (set of) adaptation measures.
2. **Disable components of the network:** To represent an extreme weather event, the properties and/or composition of the network is altered so as to represent the failure of a specific set of network components. In the case of the flood resilience assessment, the failed components are generators. In the case of the heat resilience assessment, they are generators.
3. **Evaluate network performance:** Using this modified representation of the infrastructure as a basis, the respective model calculates the network's performance in terms of the *fraction of demand served* (elaborated below). This performance calculation takes the form of a combined power flow analysis / cascading failure analysis, which determines the power flow magnitudes across the lines of the transmission network and the quantity of power delivered to each distribution network.
4. **Repeat:** By repeating this procedure numerous (1000) times to represent different extreme weather scenarios, we obtain information about the network resilience as a function of event severity, accounting for different network states and different loading conditions.

This procedure is illustrated in in Figure 1. The individual elements of this procedure are described in more detail in the following section.

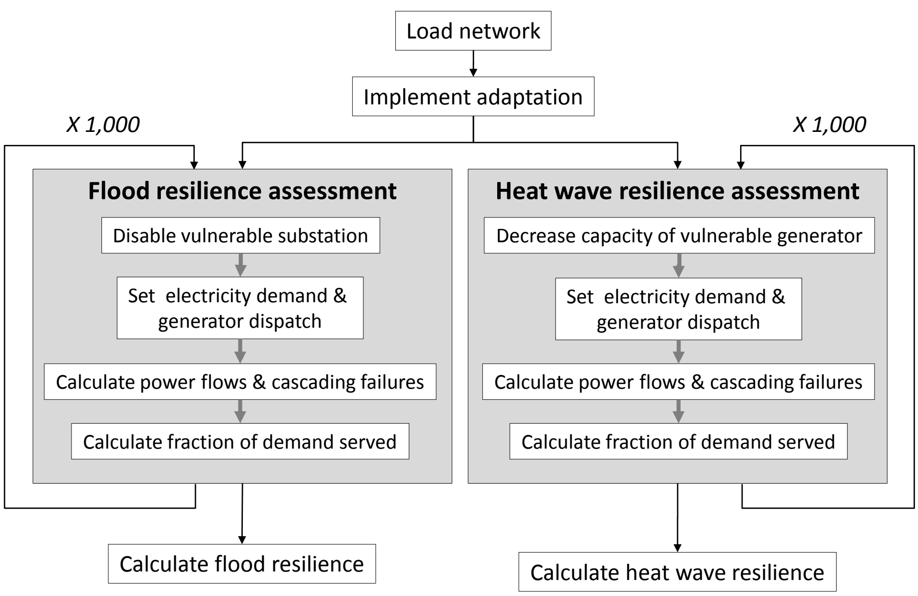

Figure 1. Flow diagram summarizing the model procedure.

Implementation of this procedure accounts for the relative vulnerabilities of different network components. Components that are more vulnerable to flooding – located in flood-prone areas and lacking sufficient defences – for instance, will fail more readily than those that are less vulnerable. And components that are not vulnerable at all will not fail at all. In this manner, we seek to identify the *range* of consequences that may be engendered by various types of extreme weather events. By performing similar analyses for different infrastructure configurations – reflecting different adaptation measures – we seek to explore the relative benefits of different adaptations.

The term *resilience* has been defined in many ways (Folke, 2006; Holling, 1973; Hollnagel, 2009; Mili, 2011; Sudakov and Vu, 2008), and various approaches to quantifying the resilience of infrastructure networks have been proposed (Ash and Newth, 2007; Dekker et al., 2008; Prasad and Park, 2004; Reed et al., 2009). For the purpose of this investigation, we define resilience as *the propensity of a system to remain unaffected upon exposure to a disturbance*. In the case of infrastructures, it is logical to define system performance in terms of the *degree of service provision* – the degree to which an infrastructure is able to fulfil the function for which it has been constructed. For electricity infrastructures, a useful measure of the degree of service provision is the *fraction of demand served* – the fraction of power received by customers versus that which was demanded. To quantify the resilience of an electricity infrastructure, we need to consider how system performance (fraction of demand served) may be affected by various disturbances, in this case extreme weather events of different types and magnitudes. Based on this, we define resilience as the *mean fraction of demand served across the range of possible extreme event magnitudes*. Mathematically, this may be expressed as follows:

$$R_I = \frac{\sum_{m=0}^{M} \Theta_m}{M} \tag{1}$$

where R_I is the resilience of the infrastructure, θ_m is the mean fraction of demand served under conditions of an extreme event of size m, and M is the maximum size of an extreme event.

5 Model design

The Dutch electricity infrastructure is represented in the model as a set of connected technical elements, including: 86 generators[4], 238 distribution grids[5], 402 transmission lines operating at four different voltage levels, 312 domestic substations, 8 foreign substations, 29 transformers and 9 international interconnectors. In combination, these components constitute a unified electricity network – an abstract representation of the Dutch electricity infrastructure, including interconnections with neighbouring countries. Each of the defined components is assigned a set of key properties, indicated in Table 1. The dataset is illustrated in Figure 2.

Table 1. Key properties of elements represented in the input dataset describing the Dutch electricity infrastructure.

Component type	Properties
Generators	Generation capacity (maximum real power output), coupled substation, fuel type, cooling method
Distribution grids	Peak demand, coupled substation(s)
Substations	Voltage level, latitude, longitude
Transmission lines and interconnectors	Connected substations, voltage level, nominal capacity, total length, underground length
Transformers	Connected substations

5.1 Representation of electricity demand and supply

The magnitude and geographical distribution of electricity demand are set in accordance with known peak and mean consumption values for the Netherlands for 2010 (the defined base year for the model). The precise value of aggregate demand each run is set randomly between a defined maximum and minimum. This variability is intended to reflect both daily and seasonal variations in electricity demand.

The magnitude and geographical distribution of generation are set in accordance with the known capacities and geographical locations of large generators (greater than 10 MW) in the Netherlands.

[4]Distributed generation is also accounted for, based on data concerning the total magnitude of distributed generation in the Netherlands and assumptions about its geographical distribution.
[5]The internal composition of distribution grids is not represented.

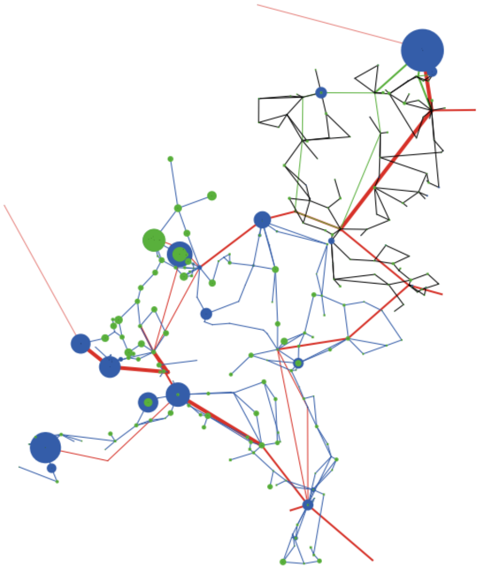

Figure 2. Geographically explicit representation of the employed dataset describing the Dutch electricity infrastructure. Blue circles represent (clusters of) generators. Green circles represent distribution grids. Edges represent transmission lines and international interconnectors (red = 380kV+, green = 220kV, blue = 150kV, black = 110kV). Substations lie at the connection points of transmission lines. The size of generators and distribution grids is determined by the relative magnitude of their generation capacity or peak demand, respectively.

Each model run, each of these generators is assigned to produce a random (uniformly distributed) amount of power less than or equal to the known capacity of the generator, such that the sum of demand (plus imports and minus exports) equals the sum of generation. This manner of representing generation dispatch thus accounts for the known capacities of generators, but ignores minimum output constraints of individual generators as well as economic factors which may lead certain generators to be dispatched more or less frequently[6].

When the integrity of the infrastructure is compromised, re-dispatching of power plants may occur. More specifically, if one or more active generators fails or is otherwise cut off from the grid, the dispatch pattern is altered such that all remaining generators (including available foreign suppliers) increase their power output in proportion to their available capacity until parity between supply and demand is again reached. This process essentially assumes perfect balancing capability of the transmission system operator (TSO) – the owner and operator of the electricity transmission network – within the constraints of available transmission capacity. If insufficient additional capacity is available, load shedding will occur – the power supplied to each customer is reduced in proportion to their demand.

Imports and exports from/to the neighbouring countries of Germany, Belgium, Great Britain and Norway are incorporated in a manner similar to domestic demand and generation. Using known maximum and minimum export/import values for these countries in 2010 as boundaries for a (uniform) random distribution, we (each run) assign each country a random demand or supply level. These demand/supply levels are taken into account in the aforementioned procedures for calculating generator (re)dispatch.

[6]In leaving out the economic factors that determine power plant dispatch, we allow for exploring a greater range of generator dispatch scenarios, which also captures situations of planned or unplanned availability of various generators. Inclusion of these economic factors may affect the distribution of results, but not the range of observations.

5.2 Representation of electricity transport

The transport of electricity from points of production to points of consumption is represented using a power flow module, which calculates real power flows across each of the lines of the modelled transport network based on a given distribution of generation and consumption, determined as described above. The power flow module employs the MATLAB-based power system simulation package Matpower (Zimmerman et al., 2011) and solves a DC approximation of the power flow problem[7]. If, as a result of this calculation, the power flow across any line is determined to exceed 1.2 times its nominal capacity – the assumed maximum allowable flow – the line fails and the power flow calculations are executed again. This process is repeated until no lines are exceeding their allowable flows. In this manner, we capture the dynamic of cascading failures.

In the Dutch power system, congestion in the transmission system is dealt with by the transmission system operator via strategic upward and downward regulation of generators with the aim of ensuring network integrity. In the model, the process of congestion management is represented in the form of the following two-step algorithm:

1. If a line overload is projected under given demand/supply conditions, a new random generation dispatch pattern and the resulting power flow pattern are calculated.
2. This process of "re-dispatching" is repeated until a dispatch pattern is found which will not result in line overload, up to a maximum of 100 times (sensitivity analysis shows that further re-dispatching attempts beyond this value do not significantly affect the results).

This algorithm for representing congestion management approximates the real-world process of congestion management in that it does not directly represent the economic factors which affect its outcome. In representing this process as a repeated random draw, however, we seek, to some degree, to mimic the outcomes of this process.

5.3 Representation of extreme weather events

The developed model represents extreme weather events in an indirect manner. Rather than explicitly representing the meteorological circumstances constituting such events, we map them in terms of their effects on infrastructure components. As described above, flood events are thus represented in terms of the number and locations of substations that fail; heat waves are represented in terms of the engendered capacity loss at affected generators. Both of these types of events may influence the transport of electricity: the failure of substations directly affects the transport capabilities of the network, and reduced capacity of generators may affect the distribution and/or magnitude of electricity flows through the network.

5.3.1 Floods

Floods are represented in terms of their effects on electrical substations. Each substation is assigned a *flood vulnerability* level based on its geographic location and on publicly available flood risk data for that location. Flood risk data for the geographic area of the Netherlands has been obtained from GBO-provincies (2013), and constitutes maximum water depths over the geographic area of the Netherlands. For a visualization of this data, we refer to the reader to `http://nederland.risicokaart.nl/risicokaart.html`. These water depth values have been determined using a variety of (externally developed) flood models which collectively simulate a range of dike breach scenarios across the Netherlands. Substations situated in locations with higher maximum water depths are assumed to have a higher vulnerability level than those in locations with lower depths. It is assumed that substations are protected to water depths up to 2.5 meters. Thus, substations at

[7] The DC approximation is a simplified version of the AC problem which ignores the reactive power component of a power flow and assumes negligible line resistance.

locations with maximum water depths of less than 2.5 meters are assigned a vulnerability of zero[8]. Substations outside the geographic area of the Netherlands are assumed to have a vulnerability of zero. The locations of vulnerable substations based on this analysis are illustrated in Figure 3 (left pane).

A single model run constitutes the successive removal of random vulnerable substations until all substations with a flood vulnerability greater than zero have failed. Following the failure of each successive substation, the performance of the infrastructure is evaluated as described above. The order in which substations fail during the course of a single run is affected by the substations' relative flood vulnerability, with substations featuring a higher vulnerability more likely to fail before those with a lower vulnerability[9]. It is assumed that substations with a vulnerability value of zero will not fail.

Conceptualized a different way, this manner of representing the effects of floods essentially constitutes successively increasing the flood magnitude (represented as the number of substations failed) until the maximum possible infrastructure effect has been realized (all vulnerable substations have failed). With each successive increase in flood magnitude, the performance of the infrastructure is evaluated. Due to embedded randomness in terms of the order of substations removed (as well as the aforementioned randomness in demand magnitude and generator dispatch), this process of gradually increasing flood magnitude until all vulnerable substations have failed is repeated numerous (1000) times. This provides us with knowledge of infrastructure performance degradation under a large range of possible flood scenarios.

5.3.2 Heat waves

Heat waves are represented in a manner similar to floods, except that they affect generators rather than substations, thus affecting the distribution and/or magnitude of electricity flows through the network. Each generator is assigned a *heat wave vulnerability* level based on knowledge concerning its location (coastal or inland), the type of generator (thermal or other) and the cooling method (presence of a cooling tower). The vulnerability level for a generator (V_G) is calculated as follows.

$$V_G = T_G \times W_G \times C_G \tag{2}$$

where T_G is a binary variable representing whether the generator is a thermal power plant (1 if yes, 0 if no), W_G is a binary variable representing whether the power plant draws from an inland water source (1 if yes, 0 if no), and C_G is a variable representing whether the power plant has a cooling tower (0.5 if yes, 1 if no)[10]. Together, these variables provide an estimate of a generator's heat wave vulnerability. The vulnerability values for generators in the Netherlands are illustrated in Figure 3 (right pane). Each circle in this plot represents a group of generators attached to a particular substation. The size of the circles represents the magnitude of vulnerable capacity attached to that substation, determined as follows:

$$M_{V,s} = \sum_{n=1}^{N} V_{G,n} \times M_{G,n} \tag{3}$$

[8] Due to the resolution of the utilized flood data, it is not possible to distinguish between water depth gradations between 2 meters and 5 meters. We therefore assume that all substations at locations with projected water depths greater than 2 meters are vulnerable.
[9] Technically, this is accomplished using a weighted random sample, with the weights set in accordance with the flood vulnerability values of the substations.
[10] Our choice of 0.5 for the positive value of A_T reflects the claim of Rademaekers et al. (2011) that the temperature sensitivity of an air-cooled nuclear generator is half that of a water-cooled nuclear generator.

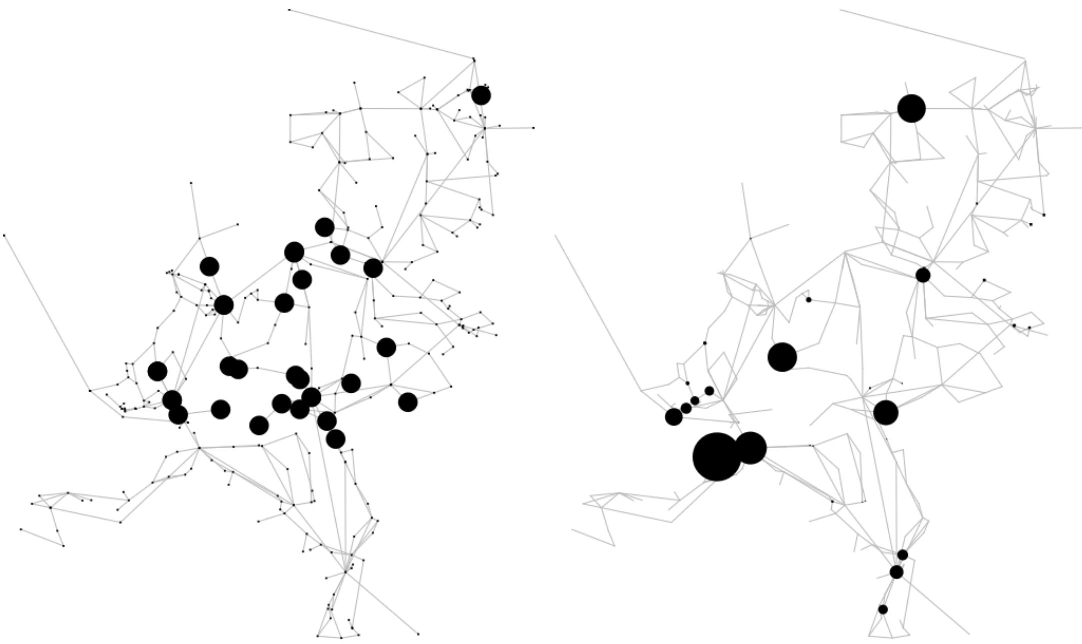

Figure 3. Vulnerability of technical components of the Dutch electricity infrastructure. The left pane shows the flood vulnerability of substations in the Netherlands, based on an assumed protection level of 2.5 meters. Large circles indicate substations with projected maximum flood heights exceeding their protection level. Small circles indicate substations with projected maximum flood heights below their protection level. The right pane shows the heat wave vulnerability of generators in the Netherlands. (Groups of) generators are represented by circles, which are sized according to the magnitude of their vulnerable capacity. Larger circles represent (groups of) generators with more vulnerable capacity. Generators are grouped according to the substation to which they are coupled.

where $M_{V,s}$ is the magnitude of vulnerable generation capacity attached to substation s, N is the number of generators attached to substation s, $V_{G,n}$ is the vulnerability of generator n (calculated according to the equation above), and $M_{G,n}$ is the total generation capacity of generator n.

A single model run constitutes the successive reduction of generation capacity in increments of 100 MW from random vulnerable generators until all vulnerable generation capacity has been eliminated. The vulnerable capacity of a generator is defined as the vulnerability of the generator times its generation capacity. Following each successive reduction in generation capacity, the performance of the infrastructure is evaluated as described above.

In addition to the gradual reduction in available generation capacity, several other known effects of heat waves on infrastructure components are included in the model. First, the capacity of transmission lines is reduced to reflect the effects of extreme temperature conditions, reflecting the direct effects of heat waves on the transmission network. As a basis for adjusting the capacity of transmission lines, we use the *IEEE Standard for Calculating the Current-Temperature of Bare Overhead Conductors* (*IEEE Standard for Calculating the Current-Temperature of Bare Overhead Conductors*, 2007)[11]. Second, we alter peak and mean demand values to reflect summertime conditions[12] and to reflect the effects of temperature. To capture the effect of temperature on demand, we use as a basis the findings of Hekkenberg et al. (2009) that electricity demand in the Netherlands (during summer

[11] In implementing the procedure defined in this standard, we assume low-wind conditions, a maximum conductor temperature of 100°C, a line rating temperature of 25°C, a rate of radiated heat loss equivalent to the rate of solar heat gain and an ambient temperature of 33.2°C (the mean peak temperature of heat waves in the Netherlands between 1901 and 2013 (KNMI, 2013))

[12] As a basis for this, we use daily demand values published by TenneT (2013*b*)

months) increases on average by 0.5% for every 1°C increase in ambient temperature[13].

Due to the multiple sources of randomness embedded in the model, the process of gradually increasing heat wave magnitude until all vulnerable generation capacity has been eliminated is repeated numerous (1000) times. This provides us with knowledge of infrastructure performance degradation under a large range of possible heat wave scenarios.

5.4 *Representation of adaptation measures*

The Dutch electricity network is already well protected in numerous ways from extreme weather events. Many lines of the transmission system, and nearly all lines of the distribution system are underground. Moreover, many of the largest thermal generators are located in coastal areas, and several inland generators are equipped with cooling towers. Despite these and other existing measures, the Dutch electricity network remains vulnerable to certain types of extreme weather events. Via the developed models, we assess the effectiveness of two types of adaptation measures – *enhanced flood protections* at key transmission substations and a *demand-side management* mechanism. The paragraphs below provide an introduction to these measures and the manner in which they are implemented in the developed model.

Primary components of substations in the Dutch transmission system are generally protected to an on-site water depth of 2.5 meters (Wester, 2013). While in many instances this degree of protection may suffice to preserve substation functionality under the full range of possible flood scenarios, in other instances it may not. One possible form of adaptation involves the outfitting of substations located in flood prone areas with enhanced flood defences. Measures may include, for instance, the construction of dikes to surround vulnerable substations, the elevation of sensitive equipment above anticipated peak water levels or the repositioning of substations to higher ground. Regardless of the exact mechanism, the essential effect of such measures is to raise the critical water level – the on-site depth above which primary equipment may be affected. The first set of proposed adaptations addressed involve the implementation of such measures for substations vulnerable to high water levels.

Electricity demand in the Netherlands varies in a generally predictable way both seasonally and daily, peaking in the winter and in the afternoon/evening and dipping in the summer and during the night. In the case of critical generation shortages that threaten the ability of the system to supply for this demand, the TSO has several measures at his disposal. These include, for instance, the contracting of emergency power and load shedding. Another measure not currently widely employed in the Netherlands is that of *demand-side management*, which encompasses a range of incentive mechanisms to encourage specific modifications in demand patterns. These measures may take many forms, such as time-of-use pricing, demand bidding and direct load control. Such mechanisms have been successfully deployed on a small scale in several places around the globe (EnerNOC, 2013; Lowfoot, 2013).

For each type of extreme weather event implemented, experimentation with the model involves evaluating the effectiveness of a set of adaptation measures. For the case of floods, these tested measures entail the implementation of various degrees of improved flood defences at vulnerable substations. Improved flood defences are represented by increasing the protection height of the substation in question to a level equal to the maximum projected water depth at that location – essentially reducing the substation's flood vulnerability to zero. Several degrees of improved flood defence are tested, ranging from the implementation of defences at 0% of vulnerable substations to the implementation of defences at 100% of vulnerable substations.

We test two strategies for enhancing substation flood defences. Under the first strategy, substations are selected for improved flood defences in order of their *vulnerability* – substations with a higher flood vulnerability are protected first. Under the second strategy, substations are selected for im-

[13]For the purpose of modifying demand, we assume an ambient temperature of 33.2°C

proved flood defences in order of their *criticality-adjusted vulnerability* – the product of a substation's vulnerability and its criticality. Criticality is determined by the magnitude of reduction in system performance caused by the failure of a given substation. Substations whose failure, on average, results in a larger drop in system performance, are assigned a higher criticality value[14]. The relative criticality and criticality-adjusted flood vulnerability of substations – as calculated according to this procedure – are illustrated in Figure 4.

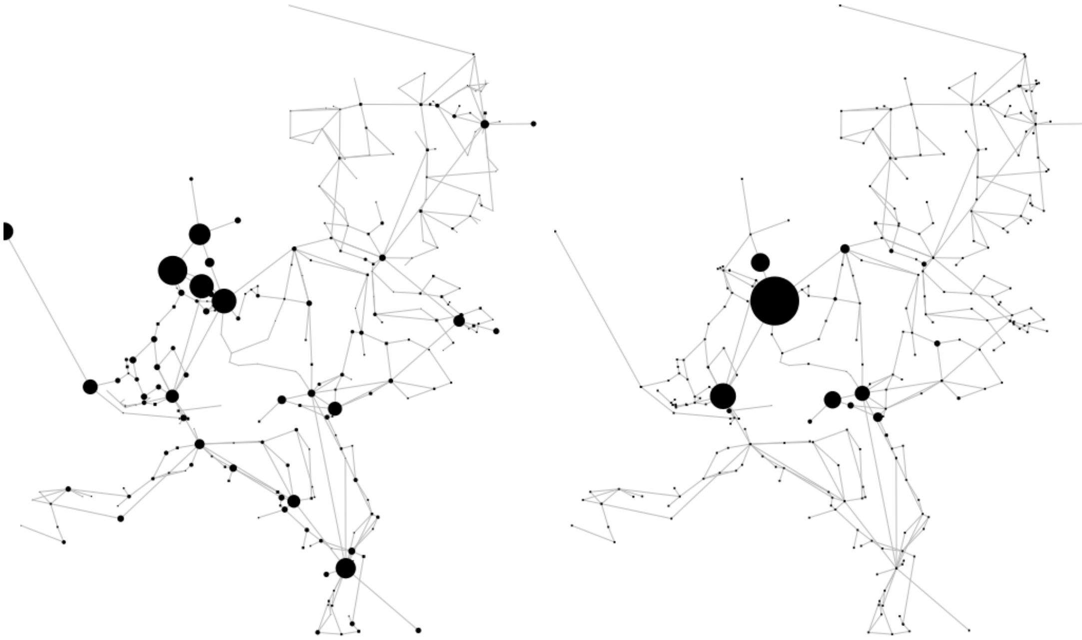

Figure 4. Illustration of the Dutch transmission system, with substations sized according to their criticality (left pane) and criticality-adjusted flood vulnerability (right pane). Substations with a higher criticality/vulnerability are larger.

For the case of heat waves, the tested measures entail the implementation of demand-side management. Demand-side management is represented by a percent-wise reduction in demand, distributed evenly across the distribution grids. The model does not capture the precise mechanism by which this reduction in demand is achieved. Several degrees of demand-side management are tested, ranging from 0% to 25% reduction in demand.

Table 2 summarizes the tested adaptation measures.

Table 2. Summary of adaptation measures tested in the developed model.

Measure	Unit	Min	Increment	Max
Improved flood defences (substations protected in order of vulnerability)	% of vulnerable substations protected	0	20	100
Improved flood defences (prioritization of critical substations)	% of vulnerable substations protected	0	20	100
Demand-side management	% reduction in demand	0	5	25

[14]Specifically, the criticality of substations is calculated by successively removing substations in random order, and recording the drop in performance engendered by the removal of each successive substation. This procedure takes into account patterns of power flow through the system and possible cascading failures, as described above. System performance is quantified in terms of the fraction of demand served. This procedure is repeated 1000 times, after which the mean drop in system performance resulting from the removal of each individual substation is calculated. The mean drop in system performance engendered by the removal of a given substation is then normalized to generate a quantification of the substation's relative criticality.

6 Validity of the developed model

The validity of the developed model has been tested by comparing its results to the results of power flow calculations published in TenneT's *2010–2016 Quality and Capacity Plan* (TenneT, 2009)[15]. Specifically, we compare the results of TenneT's power flow calculations under a *no-fault state*[16] with the results of the developed model under a no-fault state. Results are compared on the basis of the transmission line *utilization rate* – the percentage of line capacity used. TenneT (2009) provides the results of power flow calculations under several generation dispatch and import/export scenarios. From these results, we extract the mean, minimum and maximum utilization rates for each of 29 transmission lines (selected based on the availability of sufficient data) and compare them with the mean, minimum and maximum utilization rates of the same 29 lines in the developed model. This procedure provides insight into the degree to which the magnitude and geographical distribution of power transported over the modelled network under normal conditions corresponds with reality.

The results of this analysis suggest that the developed model may somewhat *underestimate* the magnitude of power flows under a no-fault state. For 83% of the tested lines, the mean utilization rate as calculated based on the model results lies below that calculated based on TenneT's results – with an average magnitude of deviation of about 7%. While the mean utilization rate in the developed model generally lies below that of TenneT's calculations, the model more often manages to capture the *range* of utilization rates observed in TenneT's calculations. For 49% of the tested lines, the range of values produced by the model fully captures the range of values observed in TenneT's data. For most of the lines where this is not the case, the model slightly underestimates the maximum utilization rate, though usually not significantly. For further details of the results of the validation procedure, we refer the reader to Appendix B.

The identified deviations in the results of the developed model compared with those of TenneT's model(s) may be attributed to several factors – differing demand/supply scenarios, slightly differing assumptions concerning the constitution of the network, and differing calculation methods. The results of our test confirm that there is no order-of-magnitude difference between the results of the developed model and those of TenneT's models. However, they indicate that the developed model generally underestimates the utilization rates of lines, suggesting that the model may somewhat *overestimate* infrastructure resilience. Additional data would be necessary to more precisely determine the source of this discrepancy, but is not available at the time of this study.

7 Results and analysis

In this section, we present and analyse the results of the developed model. We begin with the results of the flood resilience assessment, and follow this with the results of the heat wave resilience assessment.

7.1 Flood resilience

Figure 5 (left pane) illustrates the performance of the defined network exposed to flood events of each possible magnitude, with no adaptation measures in place. The gray lines show the results for each of the 1000 runs of the model. The thicker black line shows the mean performance across these 1000 runs. As expected, these results indicate that the performance of the network (fraction of demand served) tends to decrease with increasing event magnitude. As the gray lines illustrate, this drop in performance is anything but smooth. In some cases the failure of a single substation results in a 10%+ drop in performance; in other cases, it results in no performance drop at all. This reflects the reality that some nodes in an electricity network are more critical than others. While

[15]TenneT is the Dutch TSO, the owner and operator of the Dutch electricity transmission system.
[16]A no-fault state corresponds to a state in which all elements of the system are functional

the Dutch network is built in accordance with an n-1, and in some cases n-2, criterion, these results indicate that the potential for situations in which load curtailment is necessary.

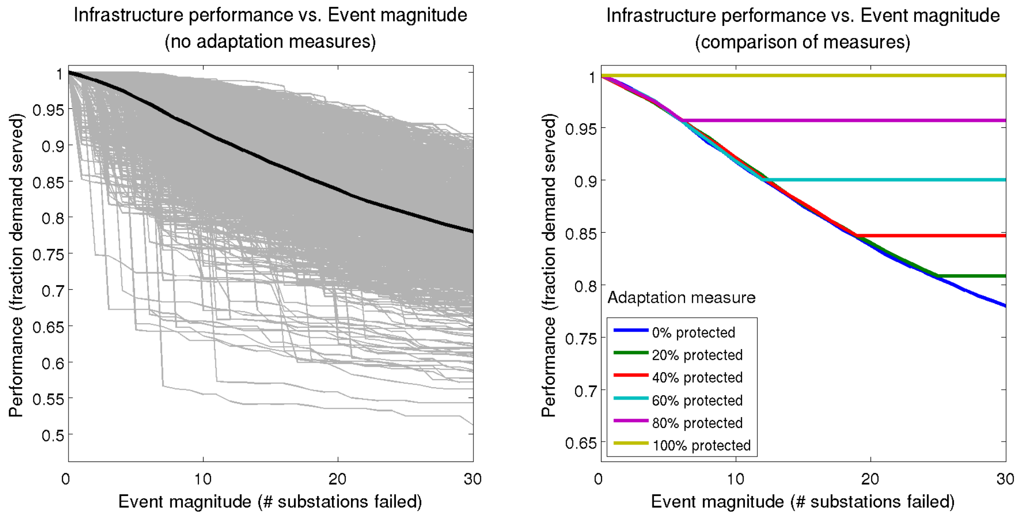

Figure 5. Performance of the modelled infrastructure vs. magnitude of the flood event. The left pane illustrates infrastructure performance with no adaptations in place. The right pane compares infrastructure performance with different adaptations implemented. The gray lines in the left pane indicate the results of individual model runs, and the thicker black line shows the mean of these results. The lines in the right pane indicate the mean performance across all runs for each adaptation scenario. Please be aware of the differing vertical axis scales between the two plots.

On average, the performance of the system drops by about 12% with the failure of half of the vulnerable substations and 22% with the failure of all 30. Nearly all runs of the model produce minimum performance values greater than 0.65. A handful of outliers generate minimum performance values below this, as low as 0.51. These outliers correspond to situations in which the failure of several critical substations incites a massive failure cascade that propagates throughout the system.

Figure 5 (right pane) compares the performance of the network across the range of tested adaptation measures. As expected, increasing the percentage of protected substations also tends to increase overall network performance. The general shape and slope of the performance degradation curve is similar regardless of the measure implemented. However, the event magnitude at which performance degradation halts decreases as more substations are protected.

Using the method for resilience quantification described above – the *mean fraction of demand served across the range of possible extreme event magnitudes* – we can quantify the flood resilience of the infrastructure. The mean resilience of the infrastructure with no adaptation measures in place amounts to a value of approximately 0.88. Figure 6 (top pane) compares the calculated resilience values for each of the six adaptation scenarios (corresponding to different percentages of protected substations), with substations protected in order of their vulnerability. This plot shows that the improvement in resilience is relatively negligible when 20% of vulnerable substations are protected, but increases more clearly thereafter. With 100% of substations projected, a flood resilience of 1 is achieved. It is interesting to note, however, that while the median resilience value generally increases with a greater number of substations protected, low outliers are still observed. Even at a protection level of 80% – where we observe a median resilience of 0.98 – we also observe a single run with a resilience value of 0.71.

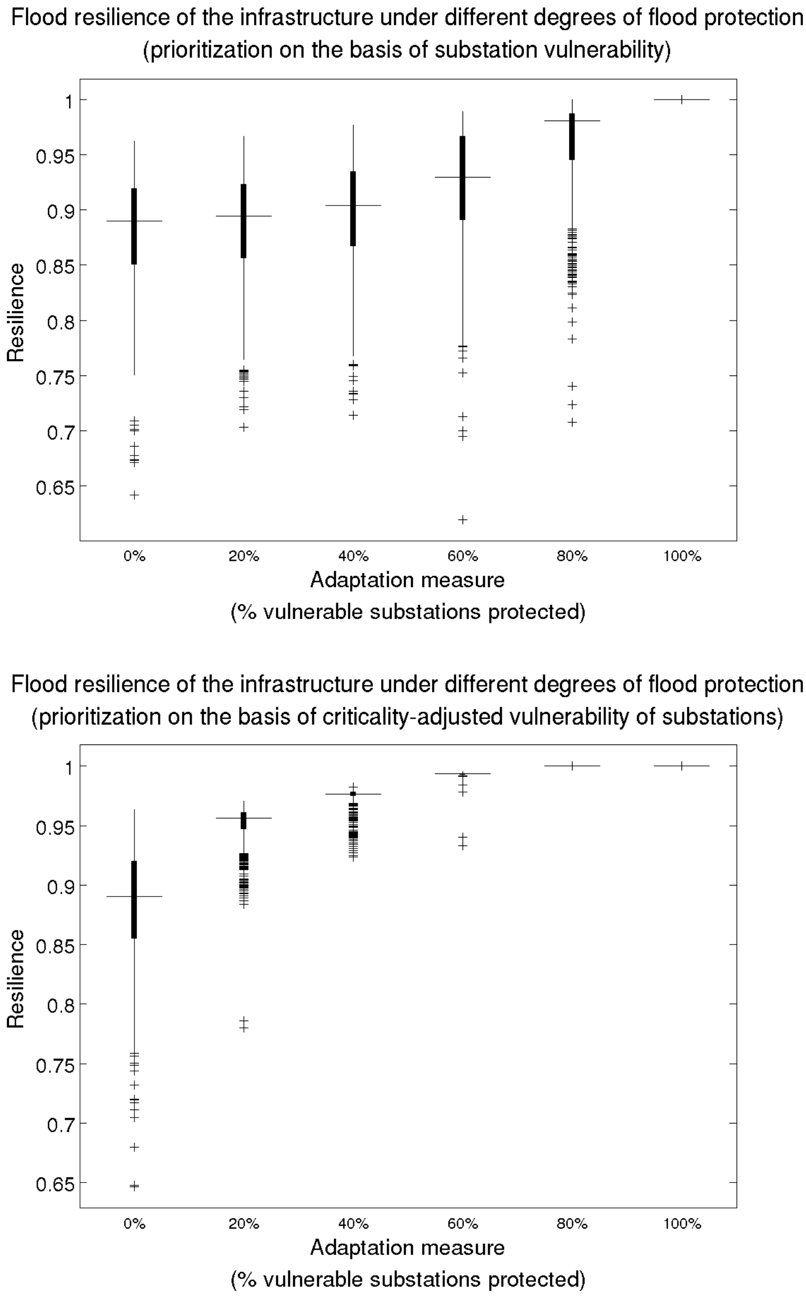

Figure 6. Comparison of resilience values obtained under the different flood protection strategies – with substations protected in order of their vulnerability (top pane) and in order of their criticality-adjusted vulnerability (bottom pane). The ends of the dark box indicate the 25th and 75th percentiles; the "whiskers" extending from the boxes include the most extreme data points not considered outliers; outliers are plotted individually as crosses.

Figure 6 (bottom pane) compares the calculated resilience values for each of the six adaptation scenarios, this time for the case in which priority is given to the protection of *critical substations*. Compared with the previous case – in which substations are protected in order of their vulnerability – we see here relatively larger improvements in resilience with the protection of a smaller fraction of substations. With 20% of vulnerable substations protected, for instance, we see an increase in mean resilience of about 0.07 relative to the no adaptation case – compared with a negligible increase in the previous case. In addition to a more rapid rise in mean resilience with an increasing fraction of protected substations, we see a more rapid dissipation of low outliers – with 60% of vulnerable substations protected, we observe a minimum resilience value of 0.93. With 80% of substations protected, the system achieves perfect flood resilience (a value of 1), with no low outliers.

7.2 *Heat wave resilience*

Figure 7 (left pane) illustrates the performance of the defined network exposed to heat wave events of each possible magnitude, with no adaptation measures in place. Gray lines show the results for each of the 1000 runs of the model, and the thicker black line shows the mean performance across these 1000 runs. These results indicate that the performance of the network (fraction of demand served) tends to decrease with increasing event magnitude, though the decrease is relatively slight compared with the flood case – the minimum performance value observed across all runs is 0.78. In fact, most of the runs (90%) display essentially no drop in performance at all, even at large event magnitudes.

A closer look at the results reveals that this drop in performance is due to a combination of insufficient generation capacity and insufficient line capacities. In some situations, the gradual disabling of generation capacity eventually creates a situation in which remaining supply is simply insufficient to cover demand, resulting in a drop in infrastructure performance commensurate with this supply deficit. In other cases, the gradual disabling of generation capacity results in a situation in which the distribution of generator dispatch produces power flows in excess of line capacities. This latter situation may be most damaging to the performance of the infrastructure, as it sometimes results in failure cascades that disable additional system components.

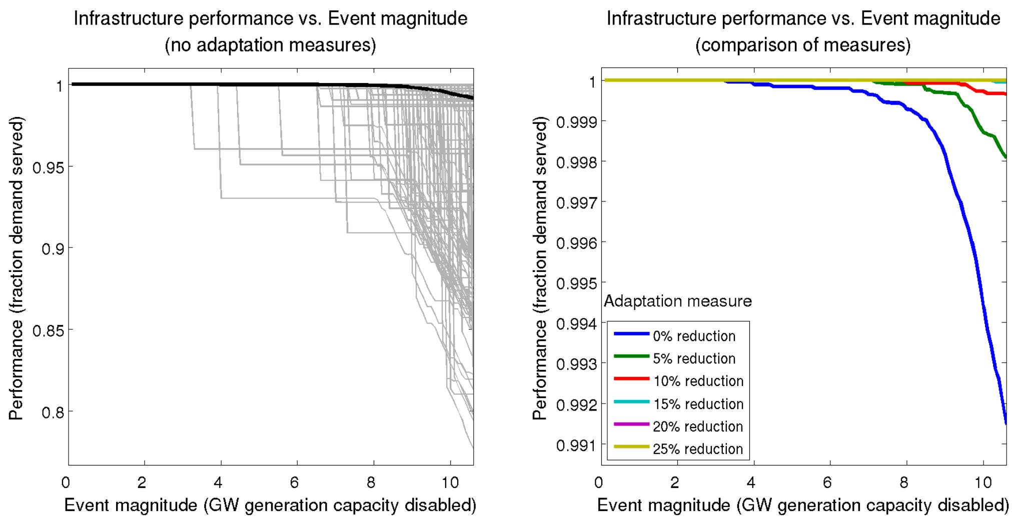

Figure 7. Performance of the modelled infrastructure vs. magnitude of the heat wave event. The left pane illustrates infrastructure performance with no adaptations in place. The right pane compares infrastructure performance with different adaptations implemented. Please be aware of the differing vertical axis scales between the two plots.

Figure 7 (right pane) compares the performance of the network across the range of tested adaptation measures. As expected, increasing the percentage of demand reduction also tends to increase the mean network performance. However, this effect is only observed up to levels of demand reduction of less than 20%, at which point the performance of the network is no longer affected by heat wave events of any magnitude.

Using the same method of resilience quantification employed in the flood case, the mean heat wave resilience of the infrastructure (with no adaptation measures) amounts to a value of approximately 0.999 – suggesting nearly perfect resilience. Across the 1000 runs of the model, the minimum observed value is 0.94 and the maximum is 1.00. Figure 8 compares the calculated resilience values for each of the six adaptation scenarios. This plot indicates that the improvement in resilience observed with increasing fraction of demand reduction is due not to a shift in the median values, but rather to a gradual elimination of low outliers. At 20% demand reduction and above, these low outliers are completely eliminated.

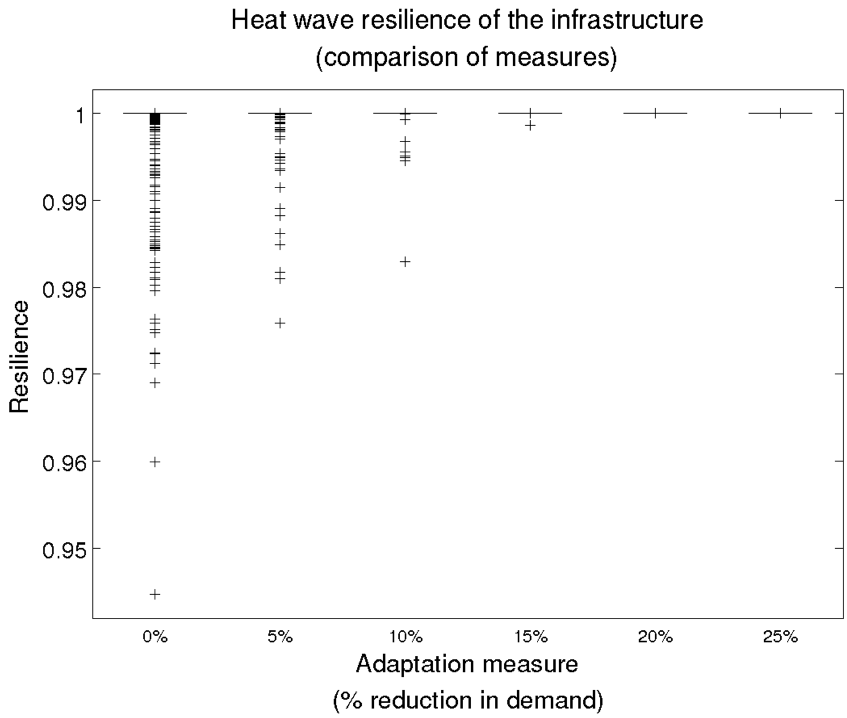

Figure 8. Comparison of resilience values obtained across the tested adaptation scenarios. The ends of the dark box (horizontal line in this case) indicate the 25th and 75th percentiles; outliers are plotted individually as crosses.

8 Discussion

The results described above suggest that the modelled infrastructure displays some vulnerability to both flood events and heat wave events, within the range of possible event magnitudes. They also suggest that the infrastructure is relatively less vulnerable to heat wave events than flood events. In the case of heat waves, the maximum possible drop in mean system performance is almost imperceptible – a result chiefly attributable to the coastal locations of most large generators in the Netherlands. In the case of floods, the maximum drop exceeds 20%. Taken as a whole, these results suggest a highly resilient Dutch infrastructure – an infrastructure that remains largely functional even in the face of highly unlikely large magnitude events.

Most of the tested adaptation measures demonstrate a clear ability to reduce, and in some cases even eliminate, the infrastructure's vulnerability to floods and heat waves. If substations are protected in order of their vulnerability, enhanced flood protection of vulnerable substations shows increasing returns with a successively increased fraction of protected substations. With a protection of 20% of substations, the resilience benefit is negligible. With protection of an additional 20%, we observe a resilience benefit of about 1.7% relative to the base (no adaptation) case. And with protection of an additional 40% of substations, we observe a resilience benefit of 4.6% relative to the base case. This suggests that larger investments in substation flood protection measures may be proportionally more beneficial than small investments. The argument for such investments at all, however, depends on the cost of such measures relative to the expected cost of inaction.

If we take into account the criticality of substations, the story is different. By prioritizing the protection of more critical substations, we observe larger increases in resilience with less investment – already a 7.8% increase in mean resilience and a significant reduction in low outliers with 20% of substations protected. In this case, smaller investments in substation flood protection measures are seen to be proportionally more beneficial than large investments – although even relatively large investments generate more resilience benefit than in the previous case.

This result is not unexpected. It is logical that prioritizing the protection of critical substations should be a more efficient strategy than protecting only on the basis of vulnerability. However, this is not always the strategy adopted by TSOs, who often prefer to combine investments in flood defences with major renovations or refurbishments to substations. In other words, prioritization often occurs on the basis of factors unrelated to a substation's criticality, such as its age. Such no-regret measures are efficient in a different sense, but not necessarily optimal from flood protection standpoint. The developed model provides a quantitative basis for comparing these different strategies.

The resilience benefit of a demand-side management mechanism for dealing with heat wave events is less substantial than in the flood case. With a reduction in demand of 5%, we observe a mean resilience benefit of only 0.08%, and with a reduction of 15% a benefit of 0.10% (relative to the base case). This is not necessarily an argument against a demand-side management mechanism – again, this depends on the cost of such measures relative to the expected cost of inaction (also considering potential co-benefits[17]) – though it indicates that the likely benefit in terms of system performance during heat wave events is likely to be minor.

9 Limitations and future research

Model development inherently entails simplifications of the real-world system and assumptions concerning the relevant aspects of its dynamics. As such, the results described above must be viewed in light of certain assumptions and simplifications that have deliberately been made in the design of our model. The paragraphs below detail several key resulting limitations.

A key simplification in our model is the manner in which the flood vulnerability of electrical substations is determined. We have used the maximum flood depth at substation locations as a proxy for flood vulnerability, though other factors clearly play a role in the real world. One key excluded factor is the anticipated flood return time at a given location, determined amongst others by the design specifications of the dike rings within which a substation is situated. Also excluded in this case are the geographical dynamics of flood progression, which may enhance the likelihood that clusters of substations within a given geographic area fail simultaneously. Accounting for these factors may improve the flood vulnerability estimates of transmission substations, and lead to a more accurate assessment of overall system resilience to floods.

A second key simplification is exclusion of the flood sensitivities of generators and distribution grid substations from the flood resilience assessment[18]. In light of these exclusions, the flood resilience assessment results should be viewed as an evaluation of transmission infrastructure resilience, rather than an evaluation of the resilience of the infrastructure as a whole. Inclusion of

[17] An argument in favour of demand-side management is also reduced necessity for investments in peaking plants and/or grid capacity.

[18] The model indirectly captures the flood sensitivity of generators in terms of the sensitivity of the substations to which they are connected. However, these substations are not always co-located with the respective generators, which means that the sensitivity of the generators themselves are not always adequately represented.

distribution grid elements would likely result in a reduction in the magnitude of identified flood resilience values, given that the protection heights of these substations tend to be significantly lower than those of transmission substations. On the other hand, it is unlikely that disturbances at the distribution level would propagate to the transmission level, meaning that the consequences of individual failures would likely be more limited, and would not affect the stability of the transmission system. Adequately incorporating distribution system elements in national level models is challenging for several reasons, including the large number of components in these networks and a lack of available data concerning component properties and network topologies. One approach to alleviate this involves the use of synthetic distribution networks, as employed by Thacker and Hall (2014).

A third key simplification entailed in our model is that the vulnerabilities of individual power plants are currently based on approximations that do not account for the specific hydrological characteristics of different inland water bodies or the distinct sensitivities of different thermal generation technologies to changes in air and water temperature. Initial progress in these respects has been made using cycle-tempo models and historical temperature data for different water bodies in the Netherlands (Karamerou, 2014). This research has not yet been coupled with the model described above, but may be incorporated into future work to facilitate a more accurate quantification of generation vulnerability to heat waves.

Fourth, the model in its current form does not quantitatively address how the frequency and magnitude of extreme events may change under different climate scenarios, and how these changes may subsequently affect the frequency and magnitude of infrastructure failures. Nor have we attempted in this study to quantify the probability of different levels of performance under conditions of climate change. These may be useful steps in enabling a comparison of the benefits and costs of various adaptation options, but they are complicated by the difficulty of assigning objective probabilities to many of the underlying variables. A possible alternative to a probabilistic approach is an approach based on *robust decision making* (Lempert et al., 2003), in which the aim is not to identify optimal strategies, but rather strategies that perform "well enough" across a range of possible futures. Application of this approach to the selection of investment strategies in infrastructure networks has been demonstrated by Bollinger (2014).

Finally, the present study has investigated the effects of a handful of hypothetical adaptation measures, but has not considered how the Dutch electricity infrastructure may develop more broadly over the coming decades. Given the rapidly changing socio-technical composition of this infrastructure – in particular driven by climate change mitigation concerns – this is a key aspect for future consideration. In an extension of the work described in this paper, we have explored possible scenarios in terms of the co-evolution of electricity supply, demand and transmission to 2050, and assess the affects of these developments in terms of the system's resilience to extreme weather events.

10 Conclusions

This paper has described the development and results of a model exploring the resilience of the Dutch electricity transmission network to extreme weather events. We have developed a method to represent an electricity infrastructure network, and a structured model design and experimentation strategy to assess current and future network resilience to extreme weather events. The developed model features a data-rich representation of the Dutch infrastructure, and represents a novel application of the technique of structural vulnerability analysis and a novel method for assessing infrastructure resilience – taking into account both the environmental sensitivities of infrastructure components and the consequences of their interconnectedness.

Our results demonstrate that the network displays more vulnerability to floods than to heat waves, but some vulnerability to both. The resilience benefit of substation flood protection measures was generally found to be greater than that of demand-side management. Moreover, it was found that prioritizing the protection of critical substations can significantly enhance the efficiency of substation flood protection measures – suggesting a clear trade-off to the no-regret measures sometimes favoured by TSOs.

The immediate policy applicability of these results is limited by certain elements of the model design, especially the manner in which the vulnerabilities of individual substations and generators are determined and the exclusion of the electricity distribution system. We have pointed to several improvements and extensions to the model design that can address these limitations and in doing so enhance the contribution of this work to policy development. Despite these limitations, the present results offer a first indication of the vulnerability of the Dutch electricity infrastructure in the context of climate change, and of the potential of various measures to enhance resilience. Moreover, the employed approach – which accounts for the interconnectedness of infrastructure components as well as key power system characteristics largely absent from previous studies – represents a demonstrable advance in modelling capabilities and a novel method for assessing infrastructure resilience to a range of extreme event scenarios.

Extreme weather events may directly and simultaneously affect the generation and transport of and demand for electricity. Feedbacks amongst these elements mean that even minor disturbances can sometimes result in larger scale failure cascades. These effects may be compounded when extreme weather events occur in tandem with other types of disturbances – an eventuality not explored in this paper. Such simultaneous effects and feedbacks between network elements may also be observed in other types of transport infrastructures – road, rail, gas, etc. In light of these similarities, we anticipate that the method described in this paper may also be applicable to other types of transport infrastructures – a fruitful direction for future research.

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Appendix A: System description – the Dutch electricity infrastructure

The Dutch electricity infrastructure is responsible for delivering electricity to approximately 8.1 million customers spread throughout the geographical area of the Netherlands (Energie-Nederland and Netbeheer Nederland, 2011). As of 2010, electricity generation in the Netherlands comprised 42 generators with a production capacity greater than 60 MW (Energie-Nederland and Netbeheer Nederland, 2011), as well as numerous smaller generators. The current technological composition of the Dutch generation portfolio comprises approximately 16.5 GW natural gas-fired power plants, 5.9 GW coal-fired power plants, 2.4 GW wind and 0.5 GW nuclear (European Wind Energy Association, 2013; TenneT, 2013*a*).

The majority of electricity produced in the Netherlands is used for commercial and industrial purposes, with household consumers comprising approximately 24% and heavy industry approximately 28% of total consumption (Energie-Nederland and Netbeheer Nederland, 2011). Electricity consumption in the Netherlands generally peaks in the cold, dark winter months, with the peak load on the grid usually occurring in December or January (Energie-Nederland, 2012).

The components of the Dutch electricity grid can be divided into a transmission system and a distribution system. As of 2010, the transmission system included 8,829 km of lines operating at four different voltage levels – 110 kV, 150 kV, 220 kV and 380 kV (Energie-Nederland, 2012). The distribution system of the Netherlands comprises approximately 145,000 km of lines contained within 238 distribution grids operating at voltages of 0.4 kV to 50 kV (Energie-Nederland, 2012; TenneT, 2009). While many lines of the transmission grid are above ground, nearly the entire length of the distribution system (99.88% as of 2007) is underground (Energie-Nederland, 2012), making this system less susceptible to meteorological circumstances.

The Dutch electricity infrastructure is linked with the infrastructures of neighbouring countries by way of a handful of extra high-voltage interconnectors. These interconnectors link the Dutch grid directly to the grids of Germany, Belgium, the United Kingdom and Norway. Amongst these countries, the most interconnection capacity is with Germany, with three interconnectors comprising a total of 4,715 MVA of interconnection capacity (TenneT, 2009). In all years between 2000 and 2010, the Netherlands was a net importer of electricity, with an average net import volume of 15.2 million MWh per year (Energie-Nederland, 2012).

The Dutch electricity market was liberalized in 2004, which has resulted in a separation of ownership between the processes of electricity generation and transport as well as many new market entrants. The operation of the Dutch electricity infrastructure is facilitated by way of several markets, including the electricity retail market, electricity wholesale markets and balancing markets. Wholesale trading in electricity in the Netherlands occurs via several mechanisms, including bilateral contracts, over-the-counter (OTC) contracts and spot market exchanges. Spot exchanges of electricity take place within the APX day-ahead and intra-day markets, and futures trading takes place within the power derivatives exchange ENDEX.

Appendix B: Validation results

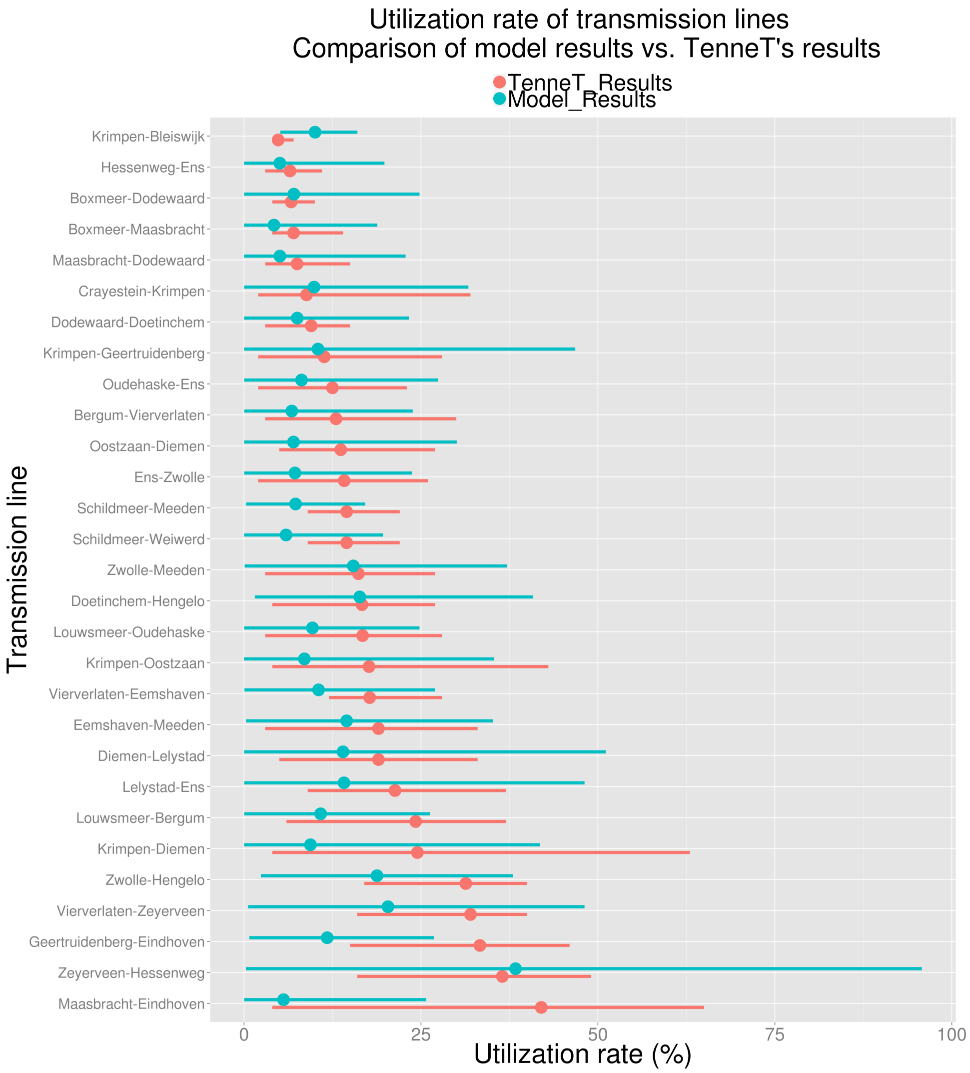

Figure 9. Comparison of results of the developed model to the results of TenneT's calculations as published in TenneT (2009). Circles represent the mean utilization rate of the respective transmission lines. The ends of the horizontal lines represent the minimum and maximum utilization rates. The model results generally underestimate the utilization rate of transmission lines under no-fault conditions, but capture the range of observed utilization rates relatively well.

Appendix C: Software implementation

The developed model is implemented in MATLAB, and makes use of the MATLAB-based power system simulation package Matpower (Zimmerman et al., 2011). In addition to the Matpower code, the model consists of three Matlab M files. The first of these (*EvaluateNetworkResilience.m*) includes high-level code for setting demand and supply and calculating and plotting the flood and heat wave resilience of the represented infrastructure, both with and without the aforementioned adaptation measures. During the course of its execution, this file calls the other two supporting M files. The first of these (*LoadNetwork.m*) is responsible for loading, parsing and formatting the input data files, which contain the infrastructure configuration data and component vulnerability values. The second supporting M file (*CalculatePowerFlows.m*) incorporates code for generation redispatch, power flow analysis and cascading failure analysis. The model code and accompanying input data is freely available and can be found at `https://github.com/ABollinger/ResilienceAssessmentModel_NLVersion`.