UNCERTAINTY IN RELIABILITY PARAMETER ESTIMATES: INCLUSION IN THE GENERATION EXPANSION PLANNING (GEP) PROBLEM

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1. Abstract

What does uncertainty and nonstationarity in gas-fired generator reliability mean for the long-term reliability of our electricity system (and its optimal design)(In progress)? We anticipate that traditional methods significantly underestimate the riskiness of investment decisions and thus, overestimate system reliability, which potentially exposes consumers, generators, and system operators to greater risks of unmet demand. The contribution of our model to the literature is in the assessment of uncertainty and nonstationarity of the outage rate parameter on the optimal resource mix (as compared to existing methods). We anticipate that the composition, costs, and reliability resulting from our method will be quite different than existing methods, which rely on single point parameter estimates.

2. Introduction

The generation expansion problem (GEP) . . . [insert typical write-up]

Uncertainty incorporation in the generation expansion planning problem

Two general approaches are used to assess power system adequacy: deterministic and probabilistic criteria. Deterministic criteria include a planning reserve margin, which could be one of several measures including, setting the reserve margin to the size of the largest generation unit, percentage of system capacity, etc. However, deterministic approaches (e.g., planning reserve margin) do not account for stochasticity in unit behavior, account for unit size, etc. As a result, deterministic methods can lead to over-investment or inadequate system reliability (Aghaei et al. 2013).

Instead, stochastic methods naturally account for randomness such as unit forced outage rates, size, etc. but at the expense of an increasing computational burden (Aghaei et al. 2013). The adequacy of the deployed resources to meet demand can be incorporated into the GEP problem using: Loss of Load Expected (LOLE)[1], Loss

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[1]The LOLE is the expected number of hours in which demand is not satisfied and is calculated as $LOLE = \sum_{k=1}^{S} P_k \left(C_T - L_k \right) \times t_k$, where there are S sub-periods and each sub-period is of length t_k.

of Load Probability (LOLP)[2], Loss of Load Cost (LOLC), and Expected energy not served (EENS)[3].

Given it simplicity LOLE has been extensively used in the past, however, EENS does have certain advantages including that it encompasses the degree of the deficiency, as well as the likelihood (Murugan, Kannan, and Baskar 2009, p622). Typically, the LOLE and EENS are generated using Monte Carlo techniques (Roy Billinton and R. N. Allan 1996; Li and Zio 2012). It is typically built recursively using the Capacity Outage Cumulative Probability Table (COCPT).[4]

Assessing system adequacy using stochastic methods can lead to computational issues given the widely held belief that the GEP is actually a mixed integer non-linear program (Aghaei et al. 2013). As a result, several methods were developed to assess system adequacy. proposed the 'Z-Method' to evaluate system adequacy in the GEP problem, which replaces the stochastic adequacy assessment metric (i.e., loss-of-load probability (LOLP)) with a new constraint. The approach accounts for unit forced outage rates (FOR), system adequacy targets[5], uncertainty in expected load growth, as well as the size, type and number of units in the production mix (**"ldots** ; Aghaei et al. 2013).

The goal of this paper is to formulate the GEP problem as a ... The reliability metric (i.e., LOLE, LOLP, EENS, etc.) are highly sensitive to the EFOR parameter (i.e., a small change in the parameter estimate can lead to large changes in the reliability metric. GEP models have not explored the solution space that surrounds the EFOR parameter estimate.

The rest of this paper is organized as follows: in the second section we propose the mathematical formulation of the ... [insert problem type] problem. The third section ... [solution algorithm discussion?] In the fourth section we introduce our case studies before we discuss the results of our model formulation. In the final section we discuss some relevant conclusions of our work.

3. ... Generation Expansion Planning problem formulation

3.1. **Objective function**

3.2. **Constraints**

3.2.1. *Maximum construction limit* This constraint is a maximum allowable number, capacity, or investment amount for new generation sources to be built during period t given limited resources (i.e., capital, manpower, space, etc.).

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[2]The LOLP is the long-run probability of power system demand exceeding the capacity available (Endrenyi 1978). LOLP can be calculated using daily peak load (i.e. hour demand for a 24 hour period) or using daily peak loads for a 1-year period using a load duration curve (Endrenyi 1978).

[3]EENS is the expectation of the energy that the system is not capable of serving and is calculated as the following $EENS = P_k\left(C_T - L_k\right) \times \left(C_T - L_k\right)$.

[4]COCPT assumes that the failure of a unit is "independent of the operating level, system load, and the outage pattern of other units" (Goel presentation, 2011).

[5]In the GEP formulation framework the modeler would select an acceptable level of service (i.e., industry standard is an insufficient capacity with a frequency of 1-in-10 years)(). The model would then calculate the appropriate reliability statistic using the EFOR (i.e., the number of hours of unit failure as a percentage of all available hours) for each generation unit type and size.

3.2.2. *LOLP constraint*

(1) $$lolpc_t \leq lolps_t \forall t \in T$$

The $lolpc_t$ is the loss-of-load probability at stage t and $lolps_t$ is the loss-of-load probability limit (i.e., the reliability target selected by the user) (**dragoon:2006aa**). The equivalent Z constraint is . . .

3.2.3. *Non-negativity constraints*

4. . . . [Name of solution algorithm

As a result, Planning and investment in power generation capacity expansion is difficult given the competing objectives for power producers (i.e. minimization of investment costs and maximization of reliability); uncertainty in a number of parameters (i.e. costs, demand, regulation), physical and technical constraints, complex mix of regulated and deregulated market structure across the country, and, large and lumpy investments, to name a few. One tool used in the long-term power planning process is Generation Expansion Planning (GEP) problem, which provides a framework to optimize generation investment.

The GEP model determines how best to meet expected future demand through the selection of plant size, production technology, and location, as well as timing over a planning horizon, usually between 10 - 30 years (Hemmati, Hooshmand, and Khodabakhshian 2013). To ensure that adequacy requirements (i.e., minimum level of service) are maintained the GEP problem formulation typically includes reliability constraints.[67]

5. Methodology

The generation expansion planning (GEP) model we present here is based upon a toy model presented in (Ehrenmann and Smeers 2011). We build upon the toy model through the inclusion of (i) multiple nodes, (ii) a complete transmission network, and (iii) stochastic demand, fuel inputs, and reliability. The individual generator is a price taking firm that maximizes profit by choosing an optimal capacity investment (y_{hi}) and generation (x_{hli}) given marginal costs of production (C_h), electricity prices (pi_{li}), and investment costs (I_h). Demand varies across the year using a load duration curve representation that decomposes annual demand into several load segments. In the next few sections we walk the reader through model development activities to date. Model development has proceeded incrementally to ensure the accuracy of results.

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[6]Reliability and adequacy are considered early in the planning process, typically well before stability and fault analysis. These factors are a necessary component of any long-term planning process; otherwise, there is no guarantee of having adequate supply to meet system demand.

[7]The determination of the adequate generation supply capacity can be divided into two areas: static and operating capacity requirements (R Billinton and R. Allan 1984). In this study, we focus on the static capacity requirement, which is the capacity that must be planned and installed in advance of system demand (i.e., as a part of a long-term planning process) (R Billinton and R. Allan 1984). Static capacity must be able to provide for outages and regularly scheduled maintenance, in addition to anticipated load growth (R Billinton and R. Allan 1984). Operating capacity, which we mention only for completeness, determines the capacity necessary to meet actual short-term load and is used in different frameworks, such as unit commitment problems (R Billinton and R. Allan 1984).

P_{11}

1

P_{12} P_{21} P_{31} P_{13}

P_{22} **2** P_{23} **3** P_{33}

P_{32}
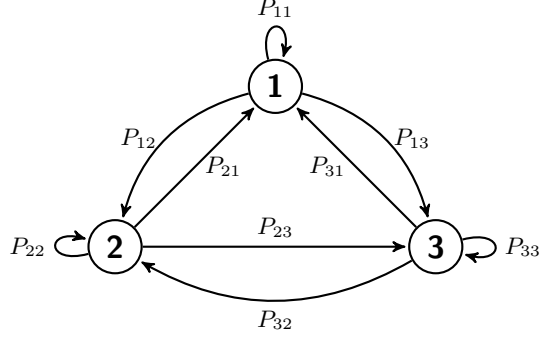
5.1. **Introduction.** Addressing the inherent uncertainty of the EFOR parameter is a well studied problem even if the results aren't well incorporated into the typical GEP formulation. A significant literature exists that has continued to evolve and incorporate advancements in other fields of study. Barbosa 1977, Mohanta et al. (2007); Silva et al. (1988); Suhartono, Zika, and Sasaki (2000) treats the forced outage rates as a random variable with a certain mean and variance to approximate confidence limits around the LOLP. Patton and Tram (1978) investigate sensitivities of reliability indices to variations in particular parameters in order to help planners identify the most important parameters and generators on the reliability indice. Hamoud and Billinton (1981) use Fourier Transform methods to incorporate the uncertainty of parameters into the calculation of the LOLE index for a single area system. Sahinoglu et al. (1983) derived probability density functions for the loss of load and unserved energy reliability indices using classical and Bayesian statistical inference. Singh and Kim (1992) use a weighted composite of three gamma distributions (i.e., six parameter estimates) to generate a reliability probability distribution. Billinton (1993) compares the accuracy and computing requirements of three analytical methods for computing reliability: load modification technique, cumulant method, and the segmentation procedure. Noor and McDonald (1996) used expert elicitation and fuzzy set theory to estimate the forced outage rates of generating plants. Oliveira, Melo and Pinto use Monte Carlo simulation methods to determine the effect of uncertainty in equipment reliability on composite reliability at the bus level. Amjady and Ehsan (1999) use artificial neural networks in the estimation of forced outage rates.

Kim and Singh (2002) use fuzzy set theory to calculate the ?possibilistic? reliability indices based upon the uncertainty in the underlying data using the probability-possibility consistency principle algorithm. Wu (2004) establishes a procedure for estimating Bayesian reliability in fuzzy environments (but doesn?t apply it to FOR). (**mohanta:2005aa**) Mohanta, Sadhu, and Chakrabarti (2005) uses a probabilistic Markov model in conjunction with fuzzy set theory to incorporate maintenance scheduling, failure-repair cycle, and aging of generating units in the generation of state probabilities. Billinton and Li (2007) compare the EFOR (i.e., two state outage model) to a multi-state generator outage model in a composite system adequacy assessment. Previous work has shown that the EFOR model can be overly pessimistic. Chowdhury et al. (2007) incorporated uncertainty in the forced outage rate parameter of the generation adequacy assessment through a sensitivity analysis (varying the parameter 25Bhatkar et al. (2008) use fuzzy sets to incorporate data uncertainty into the calculation of the forced outage rate (and the well-being

of the generating system). Abdelfatah et al. (2011) determine trends in the hazard function while assessing the reliability of transformers in the Egyptian Electricity Transmission Company. Dent and Bialek (2011) model both random and systematic error in unit availability probabilities, which allows them to specify error bars around the reliability index produced. The authors show that small changes in the unit availability can lead to large changes in the reliability index. Awadallah and Milanovic (2013) divide the uncertainty into aleatory (i.e., related to a random process) and epistemic (i.e., related to a lack of information) to quantify uncertainty representation (also have a good lit review). They use second order probability and evidence theory to quantify the uncertainty. NERC 2014? uses a three stage technique to identify the reliability metrics under different modeling assumptions.

The world is changing around the electric power industry, as a result of changes in the domestic energy economy. Much of the recently built and proposed power plants are either renewable or natural gas, which has made the power production sector the largest consuming sector of natural gas domestically (NERC 2011a). Natural gas-fired growth is expected to increase by an average 1.3% annual increase between 2012 and 2040 (US EIA 2014).[8] By 2040, an additional 1,600 million megawatthours (MWh) of generation is projected to be available in the contiguous United States (US EIA 2014). The changes in the electricity production mix are largely the result of environmental regulation and the increased domestic availability of natural gas, as a result of shale gas discoveries. The electricity production mix is phasing out coal-fired resources in favor of natural gas-fired resources, renewable energy resources (e.g. solar, wind, etc.), demand side management programs, and nuclear (NERC 2011b). For some regions (i.e., SERC and RFC), which cover portions of the southeastern and mid-western US, coal is expected to remain the largest generation source by fuel type (US EIA 2014). However, elsewhere much of the existing coal capacity retirements will be replaced by natural gas-fired resources (US EIA 2014).

Gas-fired resources are particularly vulnerable to fuel supply disruptions as a result of characteristics of the gas pipeline industry, natural gas itself, and gas-fired generators. (1) Natural gas is not easily stored on-site and as a result, real-time delivery of natural gas is necessary for plant operation (NERC 2013). (2) Gas-fired plants tend to have one connection to the pipeline network and as a result, are at risk from any disruptions in the connection (NERC 2013). (3) Gas-fired plants tend to have interruptible pipeline capacity contracts in place instead of firm capacity. Interruptible service is the lowest priority and can be interrupted for a number of reasons (NERC 2013). The increased demand is increasing the likelihood in some regions of pipeline capacity issues for natural gas-fired generation (NERC 2013).[9] Options are available to reduce the supply security risk (e.g. storage, firm fuel contracting, additional pipelines, dual-fuel capabilities, additional transmission lines, etc.) (NERC 2011a). However, for many plants these options have not yet been implemented.

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[8]the information in this paragraph is from this article on eia today in energy http://www.eia.gov/todayinenergy/detail.cfm?id=17571#

[9]The pipeline capacity expansion process is currently based on firm capacity only (NERC 2013). FERC will not provide the required certificate without sufficient firm capacity demand in place (NERC 2013). Thus, there exists a disconnect between the pipeline expansion mechanism and the rising demand for natural gas by electricity producers (this has been addressed in some regions by changes in contracting practices).

But is this actually an issue? In 2014, the Polar Vortex exposed previously unknown or underestimated energy security issues in the Northeastern United States. Shutdowns were related to two factors: energy supply curtailment and ambient conditions resulting in forced outages or deratings (in particular during startup) (Gugel et al. 2015). Natural gas power plants were forced to shut down as a result of insufficient fuel supplies after there pipeline capacity was curtailed. During the worst of the polar vortex more than 35,000 MW of outages existed in the Eastern and Texas Interconnections (Gugel et al. 2015).

One issue with the existing literature is that it assumes the stationarity of the data. The role of natural gas-fired generators is changing in the production mix (i.e., higher capacity factors) and more frequent ramping as a result of more renewables with unknown consequences on maintenance schedules and reliability [add citation]. Generators are experiencing increasing O&M costs as a result of increasing power plant cycling given larger deployments of variable generation, especially for plants designed as baseload units (**nrel:2012aa**). Cycling means operating the plant in response to system load requirements (i.e., load following, varying load levels, etc.); as opposed to operating it as a baseload resource (**nerc:2012aa**). Each cycling exposes equipment to pressure and thermal stresses that can damage equipment and subsequently, lead to shorter component life expectancies, higher equivalent forced outage rates (EFOR), and shorter life expectancies (**nerc:2012aa**).

The natural gas industry is deploying more electric compressors throughout its pipeline system (NERC 2011a). And as a result of these changes, the natural gas and electricity generation industries are increasingly interdependent. More natural gas fired plants means more exposure of the bulk power system to supply security issues (i.e. natural gas supply and delivery issues) (NERC 2011a). Therefore, not only is there uncertainty in the EFOR parameter estimate but it might be changing. Changes in the domestic energy economy, as well as in the climate require additional techniques to identify the trends in the data and incorporate them in additional analyses (i.e., GEP).

The question put forward here is whether existing methods are capturing the true (and changing) risk to the bulk power system brought about by changes in the domestic energy economy. By risk in this case, we mean specifically the ability to deliver electricity demanded with a certain reliability. Uncertainty in GEP formulations tends towards uncertainty in load demands, fuel input prices, investment and operating costs, electricity prices, amongst others. () demonstrated the importance of the forced outage rate (FOR) in generating the COCPT. Shirvani (2012)[add citation] looked at the sensitivity of the EENS to the FOR through the COCPT and showed that it has a direct effect on the reliability of the system. The FOR, defined as $FOR = \frac{\sum downtime}{\sum downtime + \sum uptime}$ and EFOR are measures of unit unavailability (i.e. outage rates). The FOR represents the availability of a unit across an entire period of time (e.g. a one-year period), while the EFOR is the availability of the unit during periods when the unit is needed. However, FOR provides a skewed sense of reliability given that we are more interested in the ability of a unit to meet demand when it is actually required to do so (Phoon, 2006, p19). The North American Reliability Council (NERC) tracks the EFOR and FOR for in the Generating Availability Data System (GADS).

We have not seen work dedicated to a sensitivity study of the equivalent forced outage rates (EFOR) on the LOLP. In particular, we have not seen work looking

into the energy security concerns of the increasing gasification of the electricity production industry. First, we show that small changes in the EFOR can have large changes on the LOLP for a small toy system. A one percent change in the EFOR for each unit is associated with a ... change in the LOLP of the power system. Then we propose to incorporate uncertainty of the EFOR for gas-fired resources as a result of changes in the domestic energy economy using Bayesian methods. Next using the posterior density for the EFOR parameter we assess the range of LOLP for the PJM Interconnection region. Finally, we discuss next steps.

5.2. **Data.** One approach would be to test the methods on the IEEE Reliability Test system (**billinton:1994aa**). We use the IEEE Reliability Test System as an example system topology ().

The changing electricity generation mix requires that industry personnel gain more experience with "generating resource technology behavior, operating characteristics, and optimal planning approaches in order to properly assess reliability or improve performance analysis" (NERC 2011b). Understanding the reliability and performance of existing and new production technologies is necessary to understand the reliability of the bulk power system in North America (NERC 2011b). It is also important to electric utilities since poor performing units can result in higher operating costs (i.e., loading units out of economic order), a need to purchase power, and/or installing additional capacity ()(GADS Introduction material). The industry, as a result, created the Generating Availability Database (GADs) as a means to share information on the causes and effects of unavailability, in addition to the development and improvement of strategies to prevent or mitigate availability losses that have proven useful to others ()(GADS intro material).

The North American Electric Reliability Corporation (NERC) compiles the Generating Availability Data System (GADS), which is an annual summary report for power stations located in the United States and Canada (**nercgads**). GADS contains information about the type of equipment used, performance characteristics, and descriptions of events (i.e. equipment failures). Four types of events are reported in GADS: outages, deratings, reserve shutdowns, and non-curtailing events (Gugel et al. 2015). It also contains data on the reliability, availability and maintainability of power plants (i.e., outage data). The dataset includes the equivalent forced outage (EFOR), which is defined as the hours of unit failure (i.e. unplanned outage hours and equivalent unplanned derated hours) as a percentage of total available hours (i.e. unplanned outage, unplanned derated, and service hours)(wikipedia, GADS).[10] Outages can be divided into planned – scheduled maintenance, versus unplanned outages – unscheduled outages.

GADS began in 1979 as an extension of a data collection process that begin during the 1960s ()(GADS, The generating availability data system (GADS): Application and benefits, 1995). The database began as a voluntary with each participating utility providing detailed reports of each units operation and performance. However, since January 1, 2013, it is mandatory for conventional generating units with a nameplate capacity $\geq$ 20 MW to report reliability information to GADS ()(GADS frequently asked questions). Variable energy sources are not required to report reliability information; a taskforce is currently underway to assess the best data collection methods for solar ()(GADS frequently asked questions). The reports

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[10]EFOR is calculated using IEEE Standard 762 definitions (Gugel et al. 2015).

include quarterly information on the design information, types of outages and de-
ratings, energy produced, fuel use, etc., which are then summarized in the annual
Generating Availability Report () (GADS, The generating availability data system
(GADS): Application and benefits, 1995). It has involved to include data collection,
data maintenance and support, in addition to data processing and reporting (i.e.,
trends in industry availability).

The GADS contains operating histories for more than 7,700 generating units lo-
cated in North America ($\approx 90\%$ of all installed generating capacity)()(Generating
Availability Data System: Data Reporting Instructions, 2015). Events are defined
as any time the operating status of a generator changes and include: outages,
derates, reserve shutdowns, and non-curtailing events ()(Generating Availability
Data System: Data Reporting Instructions, 2015). The event report will include
informaiton on the event magnitude, primary cause, and, additional causes or com-
ponents worked during the event ()(Generating Availability Data System: Data Re-
porting Instructions, 2015, pIII-2). In Figure **??** we show the Unit States diagram
from the ()(Generating Availability Data System: Data Reporting Instructions,
2015, pIII-5).

Resources can first be categorized by whether they are active or inactive. Inac-
tive resources are in one of three potential states: inactive reserve (IR), mothballed
(MB), and, retired (RU). An inactive reserve, mothballed, or retired unit is a unit
whereby the unit is unavailable for an extended period of time for reasons unre-
lated to the equipment ()(Generating Availability Data System: Data Reporting
Instructions, 2015, pIII-5). Active states include: available and unavailable, which
can be further broken down into unplanned outages and planned deratings for avail-
able resources, as well as unplanned outages and planned outages for unavailable
resources () (Generating Availability Data System: Data Reporting Instructions,
2015, pIII-6). "An outage exists whenever a unit is not synchronized to the grid
system and not in a reserve shutdown state. An outage starts when the unit is ei-
ther desynchronized from the grid or when it moves from one unit state to another
(for example, goes from a reserve shutdown to a maintenance outage). The outage
ends when the unit is synchronized to the grid or moves to another unit state"
(Generating Availability Data System: Data Reporting Instructions, 2015, pIII-6).

In the GADS database an interruption in fuel supply, for example, as a result
of interruptible supply of fuel as part of a fuel contract would be considered as
events caused by external economic factors with a cause code 9131 () (Generating
Availability Data System: Data Reporting Instructions, 2015, Appendix B - pB-
FS-29). .

The underlying data, used to calculate the annual summaries, is not publically
available. Data sharing in GADS works via the following mechanism: an electric
utility would share information for the types of power plants in its portfolio of assets.
In GADS it would then have access to more detailed (and not publically available)
reliability information concerning only those types of power plants. The Generating
Availability Report contains 17 categories of statistics for generating units and
related equipment, which can be viewed at an annual or five-year cumulative basis.
The generating units are grouped by type, size (i.e., nameplate rating), and fuel
(i.e., primary fuel used).

5.3. **Methods.** We propose to use the GADS dataset to build a Bayesian regression
model to estimate a posterior distribution around the EFOR parameter for each

type (and size grouping) of power plant. Reliability is known to be a function of or at least correlated with the size and type of power plant. In our regression model we will control for confounding factors (i.e., weather, location, etc.) and trends (i.e., capacity factor, etc.) in the dataset.

Each generation unit can be represented by its capacity and its unavailability and each unit has only two states: on or an outage. One disadvantage of the model is that it is a two-state system (i.e. up or down) while generating units are necessarily more complex in that they may experience partial failures in which they operate at reduced capacity levels (i.e. a 3- or even multi-state model). The capacity is a random variable in reliability analysis (Phoon, 2006, p19).

$$P(X = x_i) = \begin{cases} 1 - q & x_i = capacity_i \\ q & x_i = 0 \end{cases}$$

where, q is the equivalent forced outage rate (EFOR) The capacity out of service then is multinomially distributed. There are 2^n possible states, where n is the number of generating units. And the likelihood of capacity greater than a particular value is $P(X \geq x_k) = \sum_{i \geq k} p(x_i)$. In other words, we sum all of the outcomes in which capacty exceeds a particular value and repeat this from the smallest unit capacity to the total system capacity value. The likelihood of different capacity outages of the system, which is the basis of the COCPT.

References

Aghaei, Jamshid et al. (2013). "Multiobjective generation expansion planning considering power system adequacy". In: *Electr. Power Syst. Res.* 102, pp. 8–19. ISSN: 0378-7796. DOI: 10.1016/j.epsr.2013.04.001.

Barbosa, Fernando Pires Maciel (1977). "Confidence limits on loss of load probability method". PhD thesis. Victoria University of Manchester.

Billinton, R and RN Allan (1984). *Reliability evaluation of power systems.* Plenum Press.

Billinton, Roy and Ronald N Allan (1996). "Reliability assessment of electric power systems". In: *University of Saskatchewan, Canada, S7N OWO.*

Endrenyi, J. (1978). *Reliability Modelling in Electric Power Systems.* John Wiley & Sons.

Gugel, H et al. (2015). "Polar vortex analysis with Generator Availability Data System (GADS) data". In: *Power & Energy Society General Meeting, 2015 IEEE.* IEEE, pp. 1–5.

Hemmati, Reza, Rahmat-Allah Hooshmand, and Amin Khodabakhshian (2013). "Comprehensive review of generation and transmission expansion planning". In: *IET Gener. Transm. Distrib.* 7.9, pp. 955–964. ISSN: 1751-8687. DOI: 10.1049/iet-gtd.2013.0031.

Li, Yanfu and Enrico Zio (2012). "Uncertainty analysis of the adequacy assessment model of a distributed generation system". In: *Renewable Energy* 41, pp. 235–244.

Murugan, P, S Kannan, and S Baskar (2009). "NSGA-II algorithm for multi-objective generation expansion planning problem". In: *Electric Power Systems Research* 79.4, pp. 622–628.

NERC (2011a). *2011 Special Reliability Assessment: A Primer of the Natural Gas and Electric Power Interdependency in the United States*. Tech. rep. Atlanta, GA: North American Electric Reliability Corporation.

– (2011b). *Gnerating Availability Data System: Mandatory Reporting of Conventional Generation Performance Data*. Tech. rep. Atlanta, GA: North American Electric Reliability Corporation.

– (2013). *2013 Special Reliability Assessment: Accomodating an increased dependence on natural gas for electic power. Phase II: A vulnerability and Scenario Assessment for the North American Bulk Power System*. Tech. rep. Atlanta, GA: North American Electric Reliability Corporation.

US EIA (2014). *Annual energy outlook 2014*. Tech. rep. Washington, DC: US Energy Information Administration.