JOHNS HOPKINS UNIVERSITY

LONG-RUN ELECTRIC POWER SYSTEM PLANNING ENHANCEMENTS TO ADDRESS THE INEFFICIENCIES OF REACTIVE, CONFLICT-IGNORANT, DETERMINISTIC PLANNING

by

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ABSTRACT

The 21st century energy challenges of climate change and energy access call for enhancements in power system planning models. This thesis studies three enhancements that make planning models proactive, conflict-aware, and aware of exogenous uncertainties and estimates potential benefits for case studies from developed and developing countries. Chapter 1 starts with a brief history of power system planning and introduces the challenges that renewable energy poses on transmission planning; conflict risk on electrification efforts; and climate change uncertainty on deterministic planning models.

Chapter 2 compares traditional transmission planning practices — which invest in transmission to deliver energy from an assumed generation build-out — to a proactive transmission planning paradigm — which accounts for generators' response to transmission additions. It estimates the costs proactive planning could save for a stakeholder-agreed representation of the Eastern Interconnection. Chapter 3 proposes a conflict-aware power system planning framework. The framework considers civil conflict's multiple effects on power systems as well as uncertainty on how conflict will evolve. The results for a case study of South Sudan demonstrate how status-quo power system planning models underestimate the costs and unserved energy of conventional strategies due to omission of conflict. The results also show how a conflict-aware framework differentiates investment plans based on the conflict trajectory and finds postponement and diversification of investments worthwhile under specific circumstances. Chapter 4 compares Robust Decision Making (RDM) to Stochastic Programming (SP) across three criteria: practical applicability, modeling capability, and contribution to decision making. Both methods can handle climate change and other exogenous uncertainties in power system planning. Results indicate that while both methods can model the uncertainties that power system planning in Bangladesh faces, SP is more practical whereas RDM provides more information to decision-makers.

Using practical case studies, Chapters 2, 3, and 4 extend and assess enhancements to power system planning models that, in theory, improve their fidelity and usefulness. The results shed light on omissions and resulting unintended biases that status-quo models have. Chapter 5 concludes this thesis by discussing extensions of the three enhancements and additional enhancements analysts must implement to address the 21st century energy challenges.

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DEDICATION

To my teachers and mentors, who generously gave me knowledge & advice and encouraged me to set higher goals; no matter how (im)possible they seemed.

Special dedication to my father, who in a rather short life taught by example what a great teacher looks like, instilled in me a love for education and emphasized the role of education in alleviating social inequalities.

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CHAPTER 1

INTRODUCTION

Electricity is an essential commodity in modern societies — i.e., necessary to maintain a minimum standard of living [1]. Societies strive to provide electricity at an affordable cost [2]. As with other types of infrastructure, power system assets are capital-intensive, have long lifespans, and call for "smart" investment decisions with low anticipated regrets [3]. In the early years of electrification, consolidation of neighboring systems along with growth in demand encouraged investments in centralized units and led to declining costs of electricity due to economies of scale [4]. Centralized thermal and hydro power plants were clearly the most economical choices given the limited number of options available for electricity generation at that time.

As electricity infrastructure expanded and the system became more complex, several questions with no easy answers emerged. As a result, interest grew in using computer models to assess the benefits and costs of alternative power plant and transmission investments. Masse and Gibrat [5] addressed questions on the economic efficiency of tidal power and reservoir development in 1950s France. Existing methodologies at the time did not acknowledge the value of flexibility reservoirs could provide because each new investment was assessed according to its levelized cost per kWh. In levelized cost terms, development of a reservoir was unnecessarily expensive since it did not change the total amount of energy. Therefore, Masse and Gibrat [5] formulated the problem of electricity investment as a linear program that endogenously evaluated the system cost under alternative investment plans and recommended the least-cost investment plan. Their seminal paper offers the first instance of a computerized optimization model (also known as mathematical program) applied to assess investments in electricity infrastructure.

In the 1970s, US utilities were called to answer questions of similar difficulty and justify investment decisions in economic terms. An "anti-utility political constituency" emerged, criticizing past investments as wasteful and inefficient [4] and citing factors such as increasing fuel costs due to the 1973 oil embargo, rising construction costs, high demand forecast errors, and environmental concerns [4]. They called on utilities to consider alternative solutions such as energy conservation programs to limit the growth in demand. At the same time, new technologies such as gas turbines appeared promising and were included in the scope of utility investment planning [6]. This ferment led to the adoption of regular and explicit resource planning procedures with stakeholder participation in most states by the 1990s [3]. The formalized procedures signaled a need for sophisticated evaluation of expansion alternatives and spurred the development and application of several software programs such as WASP (Wien Automatic System Planning Package) by Oak Ridge National Lab [7]. The optimization methods — pioneered in the 1950's — were adapted to the new requirements of "integrated resource planning" by including multiple objectives, risk, environmental concerns, demand-side as well as generation and transmission investments [8].

Today, planning procedures with varying degrees of stakeholder participation aided by computerized optimization models have been adopted by national governments, state authorities, local utilities and international donors. Mathematical programs for power system planning have been evolving in two areas: (1) refinement of physical system representation (generation, transmission, and load characteristics) and (2) representation of contextual information, such as environmental policies, institutional framework, market rules and structure. In the first area, the complexity of the physical system means that the mathematical problem is not a linear program. Simplifications are usually necessary because the resulting models are complex — for instance, Mixed Integer Non-Linear Programs — and the number of variables involved is large — multi-decadal horizon with thousands of nodes, leading to millions of decision variables. Continuous advances in mathematical programming enable analysts to formulate larger and more complex models that have more refined spatial and temporal resolution and that represent the physical structure and properties of power systems more accurately. Given the high cost of the power system planning problem, even incremental improvements in computational power and algorithmic procedures can lead to sizeable savings [9]. In the second area, recent discussions have focused on the integration of policy targets, institutional framework, uncertainties [10], market rules [11], and market structure [12].

These planning procedures are being revised in the context of two challenges for the global energy agenda in the 21st century: energy access and climate change [13]. In 2018, the population without access to electricity fell below 1 billion for the first time since it has been tracked [14]. But the world remains off-track to achieve universal electrification by 2030 [14]. It is estimated that approximately 650 million people will lack access to electricity in 2030 and the vast majority of population without access (~600 million people) will be in Sub-Saharan Africa [15]. The access deficit has stimulated discussion of weaknesses of existing planning procedures and models (Section 1.2). The leapfrogging observed in the telecom industry in the developing world has also inspired discussions on the potential of novel solutions for electrification in Sub-Saharan Africa [16] and elsewhere in rural areas in the developing world. Consequently, there is a call for enhancement of power system planning models to make them more relevant for the developing country context [17].

Meanwhile, concerns over climate change have drastically changed the landscape of electricity expansion. The electricity sector must mitigate its emissions contributing to climate change [18] as well as adapt to the effects of climate change [19]. Policies aimed at greenhouse gas mitigation have been major drivers of new investments [20]. Renewables are playing an increasingly important role in electricity generation [21]. The growth of renewables introduces new sources of uncertainty and variability and calls for a higher degree of coordination among regions and between transmission and generation investments [3]. Existing planning procedures inadequately capture the interdependencies of transmission and generation investments and are being revisited (see Section 1.1). At the same time, climate change affects power systems in multiple ways — among them, rising temperatures leading to lower Carnot efficiencies in thermal power plants and greater air conditioning demands, and changing patterns of water availability for cooling and hydropower production [22]. New features such as resiliency must be added to a long list of desirable features of the future power grid [23]. Climate change introduces new uncertainties in resource planning models [3], and planners are called to adopt new methods that explicitly handle this uncertainty and can better assess adaptation strategies (see Section 1.3).

This dissertation contributes to the literature of power system planning by proposing and assessing enhancements to power system planning models. These enhancements will lead to improved power system plans that aid policymakers in addressing the 21st century challenges of energy access and climate change. Chapters 2–4 each apply novel modeling frameworks and discuss the benefits of those enhancements through illustrative applications. The remainder of Chapter 1 (Sections 1.1–1.3) introduces three needs for improved methodologies for power system planning. Section 1.1 explains how alternative designs of transmission planning procedures affect system costs and integration of renewable resources. That discussion provides background for Chapter 2's analysis of alternative transmission planning procedures, and its estimates of the economic benefits that planners could obtain by using models that endogenously account for complementarities between transmission and generation investments. Section 1.2 discusses progress towards universal electrification. The slow progress recorded in fragile and conflict-affected countries necessitates novel planning approaches to achieve universal electrification in those countries. Chapter 3 addresses that need by proposing a framework for evaluation of electricity investments that accounts for conflict risk. Section 1.3 points out that new methodologies are necessary to evaluate adaptation efforts in the power sector. Fortunately, multiple methods have been proposed to capture uncertainty related to climate change adaptation decisions. However, at present, the literature provides only an ambiguous and vague basis for choosing among those methods. To correct this deficiency in the literature, Chapter 4 applies two popular methods on power system planning in Bangladesh and documents insights resulting from a cross-comparison with respect to relative strengths and weaknesses of each method. Section 1.4 briefly introduces the basic operations research and software programs I employ within the models used in the dissertation, and then summarizes the scope of the remaining chapters.

1.1 TRANSMISSION PLANNING PROCEDURES

Chapter 2 focuses on transmission planning procedures. Transmission planning procedures aim to assess and approve transmission investments required for a cost-efficient and reliable power system [24]. In principle, transmission planning procedures are technology-agnostic — i.e., they do not pick winners and losers from among transmission and energy supply based on a prior definition of favored resources, but rather they select investments based on their impact on system net benefits. The design of transmission planning procedures is the cornerstone for a technology-agnostic practice [25].

Over the past few decades, the design of transmission planning procedures has evolved in incremental steps and does not necessarily effectively achieve the basic goal of reliably meeting demand at least cost [26]. The proliferation of goals (reliability, economic, public policy) for transmission procedures along with increasing renewable penetration led ISOs to adopt changes in procedures [27], [28].

Renewable energy legislation, for example, mandated ISOs to reconsider their assumptions concerning future generation mix — traditionally ISOs assessed transmission investments assuming a fixed generation mix including existing and planned investments — for at least two reasons. First, renewables have shorter construction time than transmission lines [29]. So, at the time transmission investments are evaluated, the location and size of renewable projects that might use those facilities at the day the line becomes operational are unknown. Second, quality of renewable generation is geographically-dependent and good resources are often located in areas far from the load. For instance, high quality wind resources in the Great Plains could provide energy to coastal regions in the Eastern United States with high load [30]. However, wind developers will not plan additional wind projects in the Great Plains unless transmission lines are available, leading to a "chicken-and-egg" problem [29].

ISOs could have improved their generation assumptions either by redesigning their procedures to endogenously account for complementarities of transmission and generation investment (so-called proactive planning [12] or co-optimization) or by improving their projections of the generation mix. ISOs followed the latter approach [26], foregoing system benefits that the first approach could offer [26].

Chapter 2 discusses three alternative designs of transmission planning procedures, their relative strengths and weaknesses. It aims to estimate the system benefits planners achieve under alternative transmission planning procedures, with a focus on the value of co-optimization of transmission and generation. For that purpose, I formulate alternative transmission procedures as mathematical programs for a realistic system — the Eastern Interconnection — and compare system costs, renewable penetration, and transmission investments under alternative transmission planning procedures.

1.2 POWER SYSTEM PLANNING FOR UNIVERSAL ENERGY ACCESS

It is estimated that 1.7 billion people did not have access to electricity in 2000 [31]. A wide gap between electrification rates in developed and developing countries had formed: 64% and 73% of the population in developing countries and the world as a whole had access to electricity respectively, while developed countries achieve nearly 100% access. Approximately 1 and 0.5 billion people without access to electricity resided in developing Asia and Africa in 2000, respectively. In 2011, the United Nations launched the "Sustainable Energy for All" campaign [13] and later in 2015 adopted "Sustainable Development Goal 7: Universal access to clean energy by 2030" [2].

The estimated population without access to electricity fell to less than 1 billion people in 2017 [14]. However, the progress towards universal electrification has been uneven around the world. Developing Asia is now home to ~0.4 bn people without access to electricity, but is on track to reach almost universal electrification by 2030 [31]. On the other hand, the population without access to electricity in Sub-Saharan Africa (SSA) instead increased by 0.1 bn over the last 16 years because of population growth. According to IEA [31], 36% of population in SSA will lack access to electricity in 2030. Thus, accelerated and novel electrification efforts are necessary in SSA.

SSA — the epicenter of the energy poverty challenge [32] — consists of some of the poorest and most fragile countries [33]. Collier [34] argues that conventional development strategies are condemned to fail in fragile countries. Development strategies for electricity also need to be novel. He argues that incremental de-centralized investments are more appropriate in a fragile environment and can significantly improve the energy access in the short term, fueling growth.

Existing power system planning models overlook fragility and the risk of conflict; they do not recommend different investments plans according to the fragility status of a country. In fact, the impact of conflict on power system expansion is not well studied. As I will later explain in Chapter 3, past literature has a narrow focus on single effects of conflict on power systems (such as sabotage of transmission towers, thereby ignoring other effects such as other types of sabotage, reduced maintenance, and fuel shortages) or specific technologies and does not capture the multi-faceted phenomenon of conflict nor the full range of options for managing power systems under conflict. Thus, in Chapter 3 I provide a comprehensive summary of conflict effects on power systems. I review state-of-the-art methods for conflict projections and propose a novel framework for evaluation of power system investments that integrates conflict risk. The framework is applied to planning the power system under conflict uncertainty in South Sudan.

1.3 CLIMATE CHANGE UNCERTAINTY IN POWER SYSTEM PLANNING

The interest in adaptation to climate change has recently increased [35] since mitigation efforts (defined as efforts to lower greenhouse gas emissions or to remove those gasses from the atmosphere) will not fully eliminate adverse impacts of climate change [36]. Decision makers are called to devise adaptation plans while they are still uncertain about the pace and local effects of climate change, costs of adaptation actions, and the magnitude of damages in case of inaction.

New tools that explicitly consider uncertainty are necessary for evaluation of adaptation investments [37]. Research has been conducted on methods for including general uncertainties in power system planning, such as fuel costs, load growths, and policy changes. These methods include decision trees, stochastic programs [38], robust decision making [39], and others [40], [41]. In his 1989 review, Crousillat [42] concluded that no method for integration of uncertainty into power system planning is superior to others. More recent literature ([40], [41], [43]) discusses the relative strengths and weaknesses of various methods. However, recommendations with respect to applications are vague and ambiguous. Systematic comparisons of methods are lacking discussion on the appropriateness of methods to the problem at hand, or theoretical validity, nor are there careful analyses of whether results from different methods differ significantly. As a result, planners do not have the information they need to best match the method to their problem.

Two methods — Robust Decision Making and Stochastic Programming — are frequently applied in power system planning under climate change uncertainty ([44], [45]). One would expect that reported practical experience with these methods would aid planners better understand the mechanics of each method and choose a method. Instead, as discussed in detail in Chapter 4, the literature on these applications is likely to confuse practitioners even further since in many cases methodological choices are not justified or contradictory rationales are provided.

In order to remove ambiguity on the relative strengths and weaknesses of the two methods, Chapter 4 applies both methods on the same practical example. The problem is generation planning in Bangladesh over the next two and a half decades in the face of climate, fuel price, and other uncertainties. The vis-à-vis application highlights choices and assumptions made by analysts under both frameworks. Based upon lessons learned from past applications of each method, Chapter 4's cross-comparison is designed to be as informative and objective as possible. Finally, another novel aspect of the application presented in Chapter 4 relates to the integration within planning of a careful characterization of flooding risks for power plants.

1.4 TOOLS AND SCOPE

I created multiple mathematical programs and automatic routines in order to study the problems described in Sections 1.1–1.3 for realistic case examples. For chapters 2–4, I formulate the power system planning problem as an optimization model (also called a mathematical program). In particular, I formulate mixed integer linear programs for Chapters 2 and 3 and a linear program for Chapter 4. I employ slightly different formulations for each chapter to accommodate for different contexts and information availability. For example, the transmission network is not represented in the case study of Chapter 4. For all case studies, I gathered information from publicly available resources such as past studies or reports. For the case studies of Chapters 3 and 4, some of the input data were provided by sophisticated models projecting conflict and flooding, respectively. Python and Matlab routines were also developed to process geographical information in ArcGIS, fit data to probabilistic distributions, parallelize model runs, and process input and output data.

There are three projects in this dissertation, organized into Chapters 2, 3, and 4. Alternative designs of transmission planning procedures are compared in Chapter 2. Section 2.1 introduces the problem and is followed by a literature review in Section 2.2. Section 2.3 lists the assumptions of the case study and explains the rationale behind them. Basic features of the case study are presented in Section 2.4 and a detailed model formulation is provided in Section 2.5. I document the experimental design for the comparison of alternative designs for planning procedures in

Section 2.6. Section 2.7 discusses the results of the comparison and major conclusions are highlighted in Section 2.8.

Chapter 3 proposes a novel framework for power system planning in fragile and conflict-affected countries. The motivation for this project is discussed in Section 3.1. I concisely discuss the observations from the literature review on conflict projections, conflict effects on power system, and integration of conflict risk in power system models in Section 3.2. In Section 3.3., I articulate the proposed framework step by step, outlining the purpose of each step and choices practitioners should make. I demonstrate the applicability of the framework on a case study in South Sudan in Section 3.4. Then, I follow the experimental design described in Section 3.5 to provide results in Section 3.6 that illustrate model features. I discuss the results in Section 3.7 and summarize major conclusions in Section 3.8. Appendix A contains detailed information on assumptions and results of the South Sudan case study.

In Chapter 4, I compare Robust Decision Making to Stochastic Programming for integration of climate change uncertainty along with other uncertain factors in power system planning. The problem is introduced in Section 4.1, followed by background information on both methods in Section 4.2. Upon reviewing relevant literature in Section 4.3, I describe the case study in Section 4.4. Then, I explain the experimental design in Section 4.5 and discuss the results of the cross-comparison in Section 4.6. Conclusions are summarized in Section 4.7. Appendix B provides supplementary information on assumptions, results, and models used in the Bangladesh case study.

The overarching conclusions that can be drawn from the projects comprising this thesis are presented in Chapter 5. Each project suggests one enhancement of the power system planning framework that will aid decision makers to better address the two challenges of our century: climate change and energy access. I have also published results from each project in scientific journals and technical reports. In a 2017 article in the IEEE Transactions on Power Systems [46], I discuss key results and take-aways from the project presented in Chapter 2. In a forthcoming article in Nature Energy, I present results and conclusions from the project of Chapter 3. Key results and insights from Chapter 4 have been reported in a 2017 World Bank technical report [47]. The key message from all projects is that models need to integrate contextual information and uncertainty in order to suggest relevant investment plans. Adoption of off-the shelf modeling approaches will not yield the same benefits as context-aware modeling approaches that represent the institutional framework and relevant risks. Finally, directions for future research are also discussed in Chapter 5.

CHAPTER 2
BENEFITS OF PROACTIVE TRANSMISSION PLANNING

Transmission planning has traditionally followed a "generation-first" or "reactive" logic, in which network reinforcements are planned to accommodate assumed generation build-outs. The emergence of renewables has revealed deficiencies in this approach, in that it ignores the interdependence of transmission and generation investments. For instance, grid investments can provide access to higher quality renewables and thus affect plant siting. Disregarding this complementarity increases costs. In theory, this can be corrected by "proactive" transmission planning, which anticipates how generation investment responds by co-optimizing transmission and generation investments. I evaluate the potential usefulness of co-optimization by applying a mixed integer linear programming formulation to a 24-bus stakeholder-developed representation of the U.S. Eastern Interconnection (EI). Cost savings from co-optimization are estimated by comparing co-optimization to both reactive planning and an approach that iterates between generation and transmission investment optimization. I also evaluate three congestion metrics as screens for reducing the number of candidate transmission investments. They each improve solution times, but the proposed Estimated Potential Benefit metric is much more effective in identifying cost-effective lines than the others.

2.1 INTRODUCTION

Transmission investments have grown significantly over the past decade in the USA [48]. They are expected to be sustained at high levels in the near future [49], [50] as policymakers and industry recognize the significant benefits of transmission upgrades and expansion [51], [52]. There are multiple categories of benefits. Among benefits, the improvement in system reliability and cost are most frequently quantified. Whereas, other benefits such as enablement of a competitive and more liquid market environment might be more difficult to quantify [53].

Prior to restructuring of the electricity sector in parts of the USA, vertically integrated utilities identified investment needs at the generation and transmission level to satisfy projected electricity needs [54]. As a result of restructuring of electricity markets in parts of the USA, generation investments have become more market-driven while transmission investments have largely continued to be made on a regulated cost recovery basis [55]. In this framework, Independent System Operators (ISOs) — not-for-profit organizations formed by groups of transmission owners, responsible for the reliable and cost-efficient operation of power systems in their jurisdiction — play a central role in identifying and/or approving transmission projects.

The unbundling of generation and transmission services explains the ISOs' focus on transmission investment decisions. ISOs chose to use reliability criteria to evaluate and justify transmission investments. Thus, most transmission development in the past addressed reliability issues and facilitated interconnections [12]. However, FERC Order 890 [24] established economic planning studies as one of the nine planning principles for transmission providers. To comply with FERC Order 890, ISOs integrated production cost modeling in their economic planning procedures. Congestion analyses were also incorporated in the ISO economic planning procedures, examining past and projected congestion [56]. To economically evaluate the benefits of transmission expansion plans through production cost simulation and congestion analysis, planners had to assume a generation mix. Because of that assumption, the transmission planning approach has been called "reactive" or "generation-first" planning, since the transmission planner "reacts" — decides on transmission investments — to a pre-defined generation fleet [12].

More recently, FERC Order 1000 [57] required a high degree of interregional coordination of planning processes and consideration of non-transmission alternatives. Considering non-transmission alternatives is not straightforward given that most planners rely on fixed assumptions about the levels of non-transmission alternatives. For example, the procedures cannot capture benefits such as deferral of capacity needs and changes in the composition of cost (e.g., shifts from capital to operational cost and vice versa). Despite submission of compliance fillings by the ISOs for FERC Order 1000, economic evaluation of non-transmission alternatives through ISO planning procedures is still relevant as demonstrated by the formation of a working group at the California ISO that discusses storage as a transmission asset [58].

At the same time, the growing amount of renewables — driven by policy incentives — has complicated the forecasting of future generation siting for at least two reasons [59]. First, high quality wind resources are often located at remote areas with weak or no transmission connections under the current network configuration [60]. The economic effectiveness of such resources depends in part on the expense of the new transmission needed to deliver them, which may be highly uncertain until detailed transmission plans are made. Second, wind generators have shorter construction times than transmission, and generation expansion plans might change depending on where the transmission planner decides to expand the grid [29]. To overcome those challenges, transmission planners have developed new approaches to account for wind siting in reactive planning procedures. For example, Midcontinent Independent System Operator (MISO) conducted the Regional Generation Outlet Study (RGOS) to facilitate renewable integration [27]. RGOS identified wind zones and ranked them using criteria such as proximity to load and capacity factor. Then, RGOS developed wind siting scenarios by allocating equal amounts to zones starting from the top ranked zones until the renewable requirement for each region was satisfied. Electric Reliability Council of Texas (ERCOT) pursued a similar study "Competitive Renewable Energy

Zones" (CREZ) [28] to develop wind siting assumptions for its planning procedures. ERCOT designed four scenarios for wind siting and estimated costs for each scenario. Consulting with stakeholders, the regulator decided to build the transmission plan identified by one scenario [61].

In summary, the restructuring of electricity sector along with mandates imposed by FERC orders and the growing amount of renewables have triggered tremendous evolution of transmission planning procedures in the past two decades. Practice illustrates the efforts of planners to enhance planning procedures through addition of steps/modules within a traditional reactive, generation-first planning framework. As Kahn [26] points out, this general approach still does not capture the trade-offs between transmission investment costs and generation mixes. By decomposing the problem into two separate and successive sub-problems (wind siting and then transmission planning), the interactions of these decisions are only partially captured, and the planner is unable to determine if the overall strategy selected is indeed least-cost. With this approach, the planner can only conduct "what-if" analyses and simulations of the system under a few wind siting scenarios. Thus, significant cost savings that might be gained from co-optimization of generation and transmission planning may be overlooked.

Another problem of the reactive approach is that it does not account for the response of generator investors to transmission plans. That response might differ from the assumed generation projection. To account for generators' response, some planners follow an iterative approach in which two optimization models, one for generation and one for transmission, are alternately applied until convergence is achieved (e.g., WECC's Long Term Planning Tool [62]).

However, as demonstrated in Section 2.6.4 , such an iterative approach cannot guarantee convergence to the joint transmission-generation optimum. This joint optimum, though, can in theory be identified by a co-optimization planning approach (which is equivalent to proactive or anticipative transmission planning under certain assumptions as proved in Section 2.5.2) [12], [63]. That approach optimizes generation and transmission investment simultaneously on a system-wide basis, and so endogenously accounts for any interdependency between transmission and generation investments.

Despite the proven result [12] that proactive planning, in theory, leads to superior results compared to traditional approaches, papers estimating the practical improvements in net benefits compared to traditional planning practice are lacking. As discussed in Section 2.2, most of the existing academic literature acknowledges the general benefits of proactive planning, and has focused on: 1) resolution of the computational problems arising because of the Mixed Integer Non Linear Program (MINLP) nature of the generation and transmission planning problem in case strategic behavior is assumed [64], [65], [66] and 2) model enhancement through addition of new features such as outage contingencies [67]. In practice, though, no transmission planners have adopted a proactive planning framework such as the one described in [12].

Thus, this chapter aims to contribute in literature by addressing two topics. First, I compare all three planning procedures (proactive, reactive, iterative) in theory (see Section 2.6.4) and through a case study that quantifies the benefits of more complex models, in terms of improved plans. Case studies such as the one presented here might help planners to decide whether changes to the planning framework are worthwhile and comprise a convincing case for changing transmission practice needs. To the best of my knowledge, only one paper presents relevant benefit estimates [63], in that case for a simplified 13-zone US network. In contrast to [63], this chapter employs a more detailed network (24-bus representation of a real system (the Eastern Interconnection (EI)) and scenario assumptions that were developed by stakeholders participating in Eastern Interconnection Planning Collaborative (EIPC) [68], [69]. In summary, the first research question addressed here is "How do plans and total system costs resulting from traditional planning approaches (reactive or iterative) compare to costs under full co-optimization of transmission and generation investment?"

Second, I assess the effectiveness of congestion-based screening metrics in reducing the pool of candidate transmission investments without diminishing the benefits of co-optimization. The size and complexity of the model for proactive planning might prove challenging for a real system, discouraging the adoption of the proactive approach. Thus, effectiveness of available screening metrics is important for planners that consider changing their practice. Most screening metrics rely on shadow price information, which may misestimate the benefit of the expansion of an interface because they do not consider the extent of the interface expansion and its interaction with potential augmentation of other interfaces. To quantify the potential inefficiencies introduced by those screening procedures, I compare the solution of the co-optimization model considering a full set of alternatives with solutions that only consider subsets of interfaces that survive screening by the three criteria considered here.

The rest of the chapter is structured as follows. Section 2.2.1 reviews literature on transmission planning procedures focusing on methods that consider the interaction between generation and transmission investment. Section 2.2.2 reviews screening metrics for transmission candidates. Section 2.3 describes the assumptions for the methodological analysis of this chapter. Section 2.4 summarizes key features and assumptions of the case study. Section 2.5 summarizes the model formulation and proves the equivalence of co-optimization to proactive transmission planning under the assumptions of Section 2.3. Section 2.6 explains the experimental design, demonstrates the theoretical relationship among the three methods considered here and defines the screening metrics I use. Section 2.7 presents the results of transmission planning under all cases listed in experimental design, followed by conclusions in Section 2.8.

2.2 LITERATURE REVIEW

2.2.1 Review of coordination of generation and transmission investments

Researchers and practitioners have acknowledged the importance of coordination between the generation and transmission investments as demonstrated by the multiple papers I review in this section. Based on the extent of coordination, I classify the proposed methods in three categories:

(1) methods that fully coordinate transmission and generation investments, (2) methods that anticipate the response of generator investors to announced transmission investments, and (3) methods that overlook the interdependencies between generation and transmission investments.

The first category includes methods that find the joint optimum of transmission and generation expansion. The second category refers to methods that identify a transmission plan which induces generators to invest in a way that is identical to the generation assumptions made to evaluate the transmission investment plan. The third category of methods has been already discussed in Section 2.1 as the status-quo approach, followed by most planners and commonly called "reactive" or "generation-first". In the following paragraphs, I present some key methods proposed under each category.

A seminal paper in the first category is [12], where Sauma and Oren explain how a proactive network planner that anticipates generation investments is helpful for recovery of part of the welfare losses introduced by unbundling of generation and transmission. They assume that the transmission planner has an objective of maximizing net market surplus and prove that the proactive planner will lead to superior solutions in terms of market surplus compared to the reactive network planner's approach but inferior compared to an integrated (or composite) resource planner [70]. In the applications presented in [12] and [71] , they do not solve the full proactive problem but instead use it as a framework to evaluate investments on transmission lines, considering one transmission investment at a time.

The computational complexity of the proactive framework proposed in [12] might explain why the authors did not attempt to find the optimal transmission investment plan. Their framework implies a multi-level structure with the lower number of levels being three. At the upper level, the transmission planner decides on transmission investments anticipating the decisions of middle and lower levels. At the middle level, generators decide on generation investments anticipating system operation. Finally, at the lower level operational decisions are made with respect to commitment, dispatch, and power flows. The lower level might be extended to comprise of two levels itself in case generators are strategic in their operational bids. Its multi-level structure along with generator's strategic behavior introduces non-linearities. Whereas, the discrete level of transmission investments introduces non-convexities.

The non-linear and non-convex nature of the problem is challenging for available solution procedures. Assumptions about the market environment and degrees of flexibility have been used by researchers to render the problem tractable. For example, authors of [64] adopt a set of assumptions that allows them to formulate the proactive problem as a Mixed Integer Linear Problem. In particular, they assume perfect competition at the lower level, which allows them to replace the lower level by a linear complementarity model. The bilinear terms of the complementarity model are linearized through disjunctive, "big M" constraints. Moreover, the authors of [64] assume discrete levels of generation investments, which allow them to handle non-linearities at the middle and upper level through binary expansion and use of "big M" constraints.

In contrast, authors of [65] do not attempt to make the formulation more tractable. Instead, they propose a combination of solution methods and a set of criteria that would allow planners to determine if the optimal plan has been identified. In particular, they assume multiple generator companies (genco) behaving as Cournot competitors in both investment and operational levels. In that case, an EPEC (Equilibrium Problem with Equilibrium Constraints) describes the multi-genco game. Authors state that the solution to the complementarity reformulation of the EPEC is not necessarily an optimal solution to the multi-genco game because of non-convexity. However, authors use the complementarity reformulation and solve the problem as a Mixed Integer Non Linear Program (MINLP) with an off-the-shelf solver. Then, for a given transmission plan (the one identified by MINLP) the diagonalization method is used to determine the equilibrium among generators. Depending on the result of the diagonalization method, more iterations of the scheme might follow. The MINLP problem with additional cuts is then used in subsequent iterations to identify alternative transmission plans (different from previous iterations). Alternative plans have better market surplus than solutions found in earlier iterations because of relevant constraints in the MINLP problem. Iterations between the MINLP and the diagonalization method stop when the MINLP is no longer feasible. Note that this method belongs to the second category because it cannot guarantee convergence to the joint optimum but identifies a transmission plan, anticipating the generators' response.

The approach followed in [66] is similar to [65] given that no assumptions on the market environment that would simplify the model are made. It is also similar to [12] and [71] in that the benefits of a pre-determined set of transmission investment plans are estimated. In this case though, authors use agent-based methods to determine generator bidding at the operational level and search-based algorithms to identify the generation investment. The approach in [66] also belongs to the second category since it does not necessarily identify the joint optimum and it actually uses an objective function for the transmission planner that differs from social welfare.[1]

On the other hand, Gu et al. [72] limit the scope of the generation investment problem to wind investments and assume only one generation company. Their planning procedure starts with generation planning; then, given the generation investments identified, the procedure continues with transmission planning. After defining a tentative set of transmission investments, it adjusts the generation investment plan, and continues iterating between the two planning modes (generation, transmission). The iterative approach guarantees that the joint optimum is found through addition of optimality cuts at the transmission planning level, which take into account the sensitivity of costs in the generation planning problem through Langrage multipliers.

A similar procedure is followed by WECC's LPTP model [62]. In [62] though, instead of optimality cuts, estimates for the transmission investment each generator requires are added in the generation planning problem. Those estimates are updated at each iteration based on the latest solution of the transmission planning problem. Note that this procedure is iterative but

[1] There are multiple social welfare functions in the literature [315]. In this thesis, the term "social welfare" refers to the sum of the individual utility functions of all market participants.

convergence to the joint optimal is not guaranteed. Therefore, the procedure belongs to the 2nd category.

Finally, I would like to note that the transmission planning literature extends beyond the traditional structure where the ISO has a critical role in evaluating the benefits of candidate projects and approving them. For example, in [73] a deregulated market is investigated where the transmission investments are made by merchant transmission and the role of the ISO is limited to overseeing network security criteria and issuing capacity payments to guarantee network security. In [73], merchant transmission and generation investors are simultaneously considered in the same step where they individually decide on proposed investment plans. Then the ISO processes plans submitted by market participants and performs the following functions: (a) check if security criteria are met, (b) choose an investment plan that minimizes capacity payments to generation and transmission in case multiple plans are feasible; and (c) project prices for the optimal operational problem. Here, the ISO broadcasts two types of signals to coordinate the iterative procedure: capacity payment signals to guarantee compliance with security criteria; projected LMPs and FMPs (Locational and Flowgate Marginal Prices, respectively), which help market participants evaluate if the proposed investments are profitable. Investors react to those signals, submit updated plans and the procedure iterates until a defined stopping criterion is met. In [73], authors look at the difference between costs in subsequent iterations to decide if the iterations have converged. Note that the cost is defined as the sum of capacity payments by the ISO to market participants and the operational cost of the system at optimal dispatch. This procedure does not aim for optimality in social welfare or capacity payments; and it is not guaranteed to converge.

2.2.2 Background on transmission candidate selection

The proactive transmission planning framework is computationally difficult as discussed in Section 2.2.1. The large size of the problem also contributes to model intractability. The number of binary variables grows linearly with the number of candidate transmission lines. Thus, screening candidates for transmission investments is usually performed prior to evaluation of alternative transmission plans. Screening is widely used by ISOs to select projects submitted by stakeholders for detailed analysis.

Screening aims to reduce the set of candidate transmission lines to a subset that appears particularly promising and should be studied in more detail. Screening should ideally:

a) require significantly less time than the full problem,
b) have zero false negative rates, i.e., resulting to a reduced set that does not exclude lines that would be chosen for investment by the full model's optimal solution, and
c) have a relatively low false positive rate; that is, the resulting subset is much reduced compared to the original set of lines to reduce the effort required and improve the computational efficiency in subsequent analyses.

Congestion metrics are frequently used by transmission planners as screening metrics. A transmission line is considered congested when the power flowing over it is equal to its available capacity. Thus, it seems reasonable that a line that is frequently congested and/or is characterized by high difference between the prices at its two ends would be a candidate for expansion resulting in market benefits. There are at least three different metrics used by the ISOs to measure congestion: (1) binding hours (2) congestion cost (3) total shadow price of each transmission interface. PJM [74] provides to stakeholders the first two metrics in order to help them identify transmission projects that improve market efficiency: (1) the number of binding hours — also called congestion frequency— and (2) congestion cost — also called market congestion. SPP [75] uses a congestion score that is equal to the product of the average shadow price of the congested lines multiplied by the number of binding hours. SPP selects for further review a maximum number of projects that have a congestion score above a specified threshold.

However, congestion metrics have flaws. For example, congestion frequency is not informative by itself because congestion frequency might be high but the shadow price for the line (indicating the cost penalty of congestion) might be low. On the other hand, congestion cost contains aggregated information for both frequency and the price differential. Congestion cost performs poorly because it uses existing capacity of lines in its calculations. In that case of lines with differing existing capacity, a metric such as shadow price (which expresses congestion cost per unit of MW capacity) might be more appropriate. However, both shadow price and congestion cost rely on the shadow price of the transmission constraint (i.e., the constraint that does not allow flows over lines to exceed the capacity of lines). Shadow prices are only accurate on the margin (and in the case of degenerate solutions might not be accurate even for marginal costs [76]). To clarify, when a solution is nondegenerate, the shadow price equals the marginal difference in the objective function (here cost) resulting from a marginal increase in the right-hand side of the constraint (here the transmission capacity constraint).

Acknowledging the weaknesses of existing screening metrics, researchers from MISO have proposed a metric called Estimated Potential Benefit (EPB) [52]. EPB also relies on the shadow price, but it additionally approximates the magnitude of a useful expansion of the line. To be more specific, calculation of EPB requires an additional production cost run where the line has unlimited capacity and the flow over the line is recorded. Exact formulations for EPB and all other metrics are provided in Section 2.6.3. The authors of [52] compare congestion metrics based on their ability to reflect the rank order implied by the Actual Potential Benefit (APB) of interface expansions and conclude that EPB outperforms all other metrics. Note that APB refers to the reduction in system cost estimated by a production cost model after expanding an interface and is used by MISO to determine benefits of transmission expansion. However, later in Section 2.7 it will become clear that APB is of limited value when multiple interdependent expansions are considered.

2.3 ASSUMPTIONS

In this section, I describe the assumptions made in this chapter. I also discuss how realistic my assumptions are based on present US market design and any limitations the reader should be aware of when they attempt to interpret results.

2.3.1 Assumptions concerning the institutional framework and scope of transmission planning

This chapter is dedicated to transmission planning in restructured US markets where the investments in generation are made by market participants and ISO has a central role in identifying, approving, and guaranteeing the cost recovery of transmission projects aiming at improvement of system costs. ISOs typically identify transmission needs as arising from three different purposes of transmission: (1) reliability improvement, (2) market efficiency, and (3) needs imposed by policy goals. Projects are usually identified separately for each purpose except in the case of MISO's multi-value process [77]. Benefits, though, should be calculated for all three categories when the ISO assesses the investment, since a transmission line built primarily for one purpose may affect the other two purposes as well. The focus here is on the last two categories because I formulate a problem that minimizes system cost, which includes the cost of carbon tax, subject to constraints imposed by renewable portfolio standards.

The purpose of reliability is only considered in this chapter though provisions of surplus capacity above the projected peak demand. In practice, though, reliability covers multiple issues such as contingency events (N-1 criteria), system stability, voltage support that are not taken into account here. Adopting an approach that could consider all three needs in a single procedure would be much more efficient, but also very complex considering available computational power. The approach to the economic and policy objectives followed here is a standard paradigm in the industry for identifying promising trade between regions and is usually followed by detailed analyses that look into compliance with reliability standards.

ISO transmission processes can also be differentiated by their horizon, addressing either short/medium-term needs or long-term needs. This chapter here falls in the latter category because it aims to propose conceptual transmission plans with promising economics.

This chapter deviates from present US practice in that I assume that there is seamless collaboration of the planning procedures of multiple ISOs. In effect, I assume that a single planner is responsible for the transmission planning for the entire Eastern Interconnection. To the contrary, multiple ISOs as well as states and provinces with non-restructured vertically integrated utilities constitute the Eastern Interconnection of the US and Canada, and coordination among these entities is far from perfect. It is true that FERC Order 1000 [57] mandates interregional transmission planning processes and development of methods to allocate transmission costs among regions. However, present processes are in an early stage, far from seamless collaboration [78]. Even if collaboration is seamless, allocation of transmission costs might prove tricky, requiring side payments among ISOs or groups of market participants. I adopt this assumption though since it allows me to find the most promising projects for the entire Eastern Interconnection.

Moreover, in this chapter I view the ISO as a social planner who is aiming to maximize social welfare considering all transmission projects at once. In practice though, ISOs do not optimize market efficiency. They usually evaluate projects one at a time by comparing their costs and benefits, which may be narrowly defined. As [71] discusses, various economic criteria might lead ISOs to select transmission plans different from the one that maximizes the social welfare.

2.3.2 Assumptions concerning the market environment

I make two important assumptions about the market environment: (1) perfect competition exists among generators at both investment and operational levels and (2) demand is inelastic. The first assumption is based on the premise that the Federal Energy Regulatory Commission, Public Utility Commissions and ISO procedures effectively oversee and facilitate the competitive operation of the market. For ISO-operated markets, several indexes such as Herfindahl-Hirschman Index and mark-up premiums relative to a competitive benchmark are published every year by the Independent Market Monitors (see [79]) — independent agencies that report to FERC. Those indexes suggest that present electricity markets are largely competitive, although there are times, places, and market products that occasionally experience the exercise of market power e.g. [80].

Demand is assumed to be inelastic. To be more accurate, demand curtailment is allowed at a price of $750/MWh. At that price, consumers might rely on their own resources, curtail use, or, in the long run, find it beneficial to do investments in higher energy efficiency. Moreover, the inelastic demand assumption applies to all representative hours of the year. Thus, deferral of loads or shift to other time periods which would result to change of the chronological load profile are not allowed. As I will explain later in the approximations, the assumption of no load shifting is not very restrictive because of the low temporal resolution of the model. In general, though, elastic demand might affect the cost and siting of transmission investments [81].

2.3.3 Technical approximations

Planning models such as the model of this chapter attempt to model continental-scale power systems, which consist of thousands of buses, transmission lines and generator units. Moreover, the planning horizon consists of multiple decades, including hundred thousand hours of operation. It is inevitable that several approximations of the system are made in order to formulate a computationally tractable problem. Thus, continental-scale tools aim to capture system details that significantly affect the results while keeping models manageable. Consistent with George Box's quotation that "all models are wrong, but some are useful" [82], my presumption for all continental-scale power system models is that details not captured within models will not significantly change investment decisions, which is the desirable output of this type of model.

Several continental-scale models have been developed and are maintained by different institutions. Examples of widely used continental-scale planning tools are IPM [43], which is used for both policy making and planning, and ReEDS [44], which is applied by the National Renewable Energy Laboratory to investigate power system futures, set federal research and development goals, and support policymakers at federal, state or city administration. While in this particular application, I focus on benefits that society might enjoy if the proposed co-optimization model is adopted by transmission planners, other parties might find it useful in their policymaking or decision making processes. Examples include but are not limited to generation investors who might apply the model for market intelligence purposes, and regulators or ISOs who could use the model when reviewing applications for new transmission facilities.

Typical approximations shared among continental-scale planning tools which are also adopted in the model used here are the following:

(a) Each year (8760 hours) is approximated by a set of few representative hours. Development of methods to select the set of representative hours is an active field of research ([83], [84], [85]).

(b) The network is reduced to a representative network with a tractable number of (usually) aggregated nodes and lines.

(c) Generator units are aggregated in representative units based on their technology, age, type of fuel. As a result, an average heat rate is considered for each generator ignoring its heat rate curve.

Note that as of now all continental-scale planning tools use a method for selection of representative hours that does not preserve the chronological order of hours. This simplification means that the impact of storage resources may be mischaracterized. Moreover, given that generating unit-level data are not preserved, all operational constraints that are chronologically dependent at the unit level such as ramping constraints, minimum on and down time are not considered.

Another simplification is that planned and unplanned outages of generating capacity and transmission are not explicitly modeled, are only taken into account through average outage rates (i.e., "derating" of capacity). A final simplification is that, no other products than energy such as regulation, spinning, and non-spinning reserves are considered. The result of this simplification might be that the generation mix is suboptimal in cases in which resources have different capabilities for providing ancillary services and the revenue streams from those products are significant.

2.4 CASE STUDY

The database for the original EIPC study were developed by a collaborative stakeholder process [86] and the assumptions and results of that study have been used or analyzed in follow-on studies [87], [88], [89].Therefore, I retain the original EIPC assumptions, except where noted, in order to make the results of this chapter as comparable as possible to previous studies.

2.4.1 Representation of Eastern Interconnection through a reduced network

For all results reported in this chapter, I use the 24-bus representation of the Eastern Interconnection [68] as defined by knowledgeable experts from planning coordinators through a multi-stakeholder process. In the original study, this network was judged sufficient for generating conceptual transmission plans that would capture the fundamental economics of interregional transmission and be of sufficient interest to justify further study.

I provide a list of key system characteristics assumed in this chapter below:

(a) The EI is represented with 24 nodes (set N) where Balancing Authorities are aggregated to nodes. Internal congestion within the regions is ignored. Nodes are connected through 47 interfaces (set L). A single interface between any two regions is assumed where applicable instead of multiple lines at different voltages and locations. I omit regions outside of the EI in this case as the interchanges between them and the EI are relatively small. Note that I assume that trade between Quebec and EI will continue at historical levels.

(b) Transfer limits are approximate estimates of the maximum power that could be transmitted between any adjacent nodes in 2020. The transfer limits were estimated in the original study by a variety of methods depending on stakeholder preferences. In brief, the following methods were used: linear transfer analysis, first contingency incremental transfer capability (FCITC), operating limits (actual or augmented) to account for additions, and historical data.

(c) Transmission capital costs are estimated based on EIPC data on costs per MW-mile for eligible configurations (345 kV single and double circuits, 500 kV, 765 kV), adjusted for regional differences.

(d) Interface lengths are approximated using distances between center points of regions.

(e) To represent wheeling cost and power trading frictions between regions, hurdle rates are considered and vary between 0 and 10 $/MWh.

(f) The network is suitable for use as a transportation network. Data from [42] for 2010 indicates that loop flows occur frequently (e.g., more than half of the time flows are from TVA to SOCO, SOCO to VACAR, and then from VACAR back to TVA), suggesting that Kirchhoff's Voltage Low (KVL) does not hold for this zonal model.

2.4.2 Input data and modeling of policies

The purpose of this case study is to explore and illustrate the benefits of co-optimization rather than to replicate the full EIPC study or come up with an actual transmission plan. Thus, I focus on one of the EIPC planning scenarios, the EIPC CO2+ scenario (also known as "Future 8 Sensitivity 7"). I choose this scenario because of its relatively high investments in transmission and renewable generation in the original EIPC study. A high assumed CO2 price is the key driver of those investments (Table 2-1).

Table 2-1: Indicative CO2 prices (source: EIPC [69])

Year	**2015**	**2020**	**2025**	**2030**
Carbon tax (2010$/tn)	26.83	38.1	62.39	139.74

In brief, some basic characteristics of the case study are:

1) Energy demand falls by 4% from 2011 to 2030 due to growth in energy efficiency and distributed generation.

2) A high amount of Demand Response (DR) (152 GW in 2030) is installed. That DR is given full credit in the planning reserve constraint and is dispatched as a pseudo-generator with a variable cost of 750 $/MWh.

3) Renewable portfolio standards are applied to eight aggregated zones, and 6 zones are used specifically for solar.

4) Generation capital costs are reduced annually to account for learning effects. They are also adjusted for regional differences and financing costs for various technologies.

Finally, I briefly discuss some key data assumptions to make interpretation of results easier. First, I keep the same horizon (2011–2030) as the original study so stakeholders can better assess the benefits of co-optimization. Second, I consider twelve types of generators *G* for new investments. These include combustion turbines, combined cycle (CC), hydro, pulverized coal, integrated gasification combined cycle (IGCC), IGCC with carbon capture and sequestration (IGCC_CCS), onshore/offshore wind, nuclear (Nuc), biomass, landfill gas, and photovoltaics. Third, all dollar values are in 2010$. A 5% real discount rate is used in present worth calculations in line with the original study and industry practice [90]. Lastly, three other policies modeled in the EIPC study are omitted here in order to simplify the model. These include renewable incentives, NOx and SO2 caps, and other EPA rules (such as once-through cooling restrictions) that may require plant retrofits.

2.5 MODEL

In this section, I provide the model formulation for proactive transmission planning under the assumptions outlined in Section 2.3. Assuming perfect competition, the objective function reduces to maximization of net market surplus or benefits. In addition, the assumption of inelastic demand reduces the nonlinear objective function under elastic demand to minimization of cost, which is a linear objective in the formulation provided here. Under the assumption of perfect competition, I prove in Section 2.5.2 that the multi-level proactive planning framework is equivalent to integrated resource planning, which can be solved as a single-level maximization of market surplus problem [27]. In Section 2.6, I explain in detail how alternative frameworks such as the reactive and iterative are simulated by modifying the formulation provided in Section 2.5.1.

2.5.1 Formulation

In summary, the model identifies a set of transmission and generation investments required to meet demand at least cost over a multi-year planning period. Specifically, the costs considered include investment expenses along with fuel, variable and fixed maintenance costs for generators, carbon taxes, Renewable Portfolio Standards Alternative Compliance Payments, and hurdle rates that apply to power trade between regions. The problem is formulated as a Mixed Integer Linear Problem (MILP) with decision variables for generation and transmission investments in each year from 2011 to 2030. Transmission investments are modeled as discrete, integer variables to consider the lumpiness in line additions, while all other variables are modeled as continuous. Transmission expansion is possible only for existing interfaces, consistent with the EIPC study. Dispatch is modeled for three seasonal load duration curves, defining a total of 20 periods per year, representing a range of load and renewable output conditions.

Investment decisions for 20 years are modelled, which is a typical long-term planning horizon. Because investments have benefits beyond year 20 and full overnight capital costs are included in the objective function for new infrastructure, there could be large "end effects" distortions in cost calculations and investment decisions if no years after year 20 are simulated [91]. Therefore, I adopt an end-effects correction approach similar to EGEAS [92]. Specifically, I model a 40-year extension period with stationary conditions identical to year 20, essentially assuming that the last year's capacity and dispatch are maintained in years 2031–2070. I also include annualized capital payments for any generation infrastructure that would exceed its lifetime over the 2031–2070 period, assuming that retired plants are replaced with similar facilities. This end effects treatment is captured in the second term of the objective function, shown in equation 2-1.

Nomenclature

Sets and Indices:

B	Time blocks, indexed by b
G	Generators, indexed g
GE	Candidate generators (subset of *G*), indexed ge
GI	Intermittent generators (subset of *G*), indexed gi
IR	Intermittency region (partition of *N*), indexed *ir*
L	Transmission corridors, indexed l . Each corridor has an arbitrarily defined forward and reverse flow direction.
N	Nodes/regions, indexed n
P	Planning reserve region (partition of *N*), indexed p
PS	Pumped storage (subset of *G*), indexed ps
R	RPS constraints region (partition of *N*), indexed r
S	Seasons (partition of b), indexed s
T	Years, indexed t and u
V	Transmission configurations at different voltage levels, indexed by v

Parameters:

ACP_r	Compliance payment in 2010$/MWh
$AIC_{g,n}$	Annualized capital payment in 2010$/MW
$CC_{g,n}$	Capacity credit
$CF_{g,b,n}$	Capacity factor
DR	Discount rate
FOM_g	Fixed operation & maintenance cost in 2010$/MW
FOR_g	Forced Outage Rate
$GI_{ge,n,t}$	Generation capital cost in 2010 $/MW
$GI_{l,v}$	Transmission capital cost of voltage v for interface l in 2010 $/unit
H_b	Duration of a block in hours
HR_l	Hurdle rate in 2010 $/MWh
IC	Initial capacity in MW with index g, n or l
$L_{b,t,n}$	Load in MW
$M_{g,n,t}$	Fraction of generation capacity in a region n that is past its lifetime in year t.
MVA_v	Capacity of transmission at voltage v in MW/unit
$PL_{t,p}$	Peak load in MW
$POR_{g,b}$	Planned Outage Rate
$RC_{g,n,r}$	Renewable credit
RM_p	Planning reserve margin
$RPS_{r,t}$	Renewable Portfolio Standard target
$SL_{n,s}$	Max energy by pumped storage in MWh
$UL_{ge,n}$	Resource potential in MW
$VC_{g,t,b,n}$	Variable cost of generator in 2010$/MWh
$\Phi_{n,l}$	Element of node-line incidence matrix

Variables:

$c_{g,t,n}$	Capacity in MW
$ch_{t,b,n}$	Charge of pumped storage in MW
$disc_{t,b,n}$	Discharge of pumped storage in MW
$f_{l,b,t}^{+}$	Power flow in the forward direction in MW
$f_{l,b,t}^{-}$	Power flow in the reverse direction in MW
$i_{r,t}$	Unmet RPS requirement in MWh
Inv_t	Investment costs in year *t* in 2010$
$o_{g,t,b,n}$	Output of generator in MW
Op_t	Operational cost at year *t* in 2010$
$\lambda_{l,b,t}^{+}$	Shadow price for constraint (7a) in $/MW/year
$\lambda_{l,b,t}^{-}$	Shadow price for constraint (7b) in $/MW/year
$w_{l,t,v}$	Number of interfaces added by year *t* (integer)
$x_{ge,n,t}$	Generation Investment at year *t* in MW

Mathematical Program

$$\min \sum_{t=1}^{20} \frac{Inv_t + OP_t}{(1+DR)^t} + \sum_{t=21}^{60} \frac{Op_{20} + \sum_{g,n} AIC_{g,n} * M_{g,n,t}}{(1+DR)^t} \qquad \text{Eq. 2-1}$$

$$Inv_t = \sum_{ge,n} GI_{ge,n,t} x_{ge,n,t} + \sum_{l,v} GI_{l,v} * (w_{l,t,v} - w_{l,t-1,v}) \qquad \forall\, t \qquad \text{Eq. 2-2}$$

$$Op_t = \sum_{b,g,n} H_b VC_{g,t,b,n} o_{g,t,b,n} + \sum_{g,n} FOM_g c_{g,t,n} + \sum_{b,l} H_b HR_l (f_{l,b,t}^{+} + f_{l,b,t}^{-}) + \sum_r ACP_r i_{r,t} \qquad \forall\, t \qquad \text{Eq. 2-3}$$

$$\sum_l \Phi_{n,l} (f_{l,b,t}^{+} - f_{l,b,t}^{-}) + \sum_g o_{g,t,b,n} + disc_{t,b,n} = L_{b,t,n} + \ ch_{t,b,n} \qquad \forall t, b, n \qquad \text{Eq. 2-4}$$

$$o_{g,t,b,n} \le \left(1 - FOR_g\right)\left(1 - POR_{g,b}\right) CF_{g,b,n} c_{g,t,n} \qquad \forall g, t, b, n \qquad \text{Eq. 2-5}$$

$$c_{g,t,n} \le c_{g,t-1,n} + x_{ge,n,t}, \qquad \forall g, t, n \qquad \text{Eq. 2-6}$$

$$c_{g,0,n} = IC_{g,n}$$

$$f_{l,b,t}^{+} \le IC_l^{+} + \sum_v MVA_v * w_{l,t,v} \qquad \forall l, b, t \qquad \text{Eq. 2-7a}$$

$$f_{l,b,t}^{-} \le IC_l^{-} + \sum_v MVA_v * w_{l,t,v} \qquad \forall l, b, t \qquad \text{Eq. 2-7b}$$

$$c_{ge,t,n} \leq UL_{ge,n} \quad , \quad \forall t, ge, n \qquad \text{Eq. 2-8}$$

$$\sum_{n \in P,g} CC_{g,n} c_{g,t,n} \geq (1 + RM_p) PL_{t,p} \quad \forall p, t \qquad \text{Eq. 2-9}$$

$$0.75 * \sum_{b \in S} ch_{t,b,n} H_b \geq \sum_{b \in S} disc_{t,b,n} H_b \quad \forall s, t, n \qquad \text{Eq. 2-10}$$

$$ch_{t,b,n} \leq c_{ps,t,n}, \quad disc_{t,b,n} \leq c_{ps,t,n} \quad \forall t, b, n \qquad \text{Eq. 2-11}$$

$$\sum_{b \in S} disc_{t,b,n} H_b \leq SL_{n,s} \quad \forall s, t, n \qquad \text{Eq. 2-12}$$

$$i_{r,t} + \sum_{b,g,n} H_b RC_{g,n,r} o_{g,t,b,n} \geq RPS_{r,t} * \sum_{b,n} H_b L_{b,t,n} \quad \forall t, r \qquad \text{Eq. 2-13}$$

$$\sum_{b,gi,n \in IR} H_b o_{g,t,b,n} \leq 0.35 * \sum_{b,n \in IR} H_b L_{b,t,n} \quad \forall t, ir \qquad \text{Eq. 2-14}$$

In addition, all variables are assumed to be non-negative, and the transmission planning variable $w_{l,t,v}$ is integer.

The constraints modeled include a load balance constraint for each zone and time period (Eq. 2-4), generator capacity constraints taking into account forced and planned outages along with output profiles for intermittent resources (Eq. 2-5), interface flow limits (Eq. 2-7), limits on resource construction (Eq. 2-8), planning reserve constraints (Eq. 2-9), storage operational constraints (Eqs. 2-10 to 2-12), and renewable policy constraints (Eqs. 2-13 and 2-14). Constraint (Eq. 2-6) allows units to retire in any year, which might be optimal if a unit is not dispatched often and its fixed Operational & Maintenance costs are high enough. For storage constraints, a 75% efficiency is assumed (Eq. 2-10). Since pumped storage's energy capability was not available, an upper bound constraint (Eq. 2-12) is imposed on its discharge based on EIPC study results [40]. A similar approach is followed for hydro units. Equation 2-13 models Renewable Portfolio Standards (RPS) and equation 2-14 imposes an upper bound on wind and solar generation in each intermittency region equal to 35% of annual load, which was considered by EIPC to be a plausible penetration level.

Additional constraints, which are mainly slight modifications of constraint (Eq. 2-8), are imposed to take into consideration licensing issues for nuclear, lead time issues (e.g., for all generators, except natural gas, no investment is considered the first 4 years), maximum amount of investment per transmission interface (set to 20,000 MW), and limits on regional concentrations of investments (e.g., wind capacity installed in the SPP region cannot be higher than 50% of the total EI wind capacity). Many of these constraints represent stakeholder judgments concerning the feasibility of different resource development patterns.

2.5.2 Proof of equivalence of proactive transmission planning under perfect competition to single-level integrated resource planning

In this section, I provide the mathematical proofs that show how a tri-level problem with the transmission planner at the top level, generation investment at the intermediate and system operation at the bottom level can be approximated with a single level optimization problem. In brief, I prove that the formulation I provide in Section 2.5.1 accurately models the tri-level problem of a proactive transmission planner in case the objective of the transmission planner is maximization of social welfare and the generation market is efficient and competitive. Note that this observation has already been made as a particular case of a general bi-level formulation for transmission planning in reference [93]. However, here I provide a simpler proof that does not require the full formulation of the multi-level problem.

Lemma 2.1: If Problems 2.1 and 2.2 are feasible, then the optimal solution of Problem 2.2 — a single-level optimization problem subject to the union of two sets of constraints (upper-level and lower-level constraints) — is an optimal solution for Problem 2.1 — a bi-level optimization problem in which the same constraints apply and the objective function of the upper-level problem is identical to the objective function of the single-level problem and equal to the sum of the lower-level objective function and a function of upper-level variables. Further, the value of the objective function of Problem 2.1 at its optimal solution is equal to the value of the objective function of Problem 2.2 at the optimal solution.

Stylized representation of the bi-level problem of Lemma 2.1:[2] *Problem 2.1:*

$$\min_{x_{ul}} (f(x_{ll}) + g(x_{ul}))$$

Subject to: $h(x_{ul}) = 0$

Lower level problem: $\min_{x_{ll}} f(x_{ll})$

Subject to: $a(x_{ll}) = 0$

$b(x_{ll}, x_{ul}) = 0$

Stylized representation of the single-level problem of Lemma 2.1: Problem 2.2

$$\min_{x_{ul}, x_{ll}} (f(x_{ll}) + g(x_{ul}))$$

Subject to: $h(x_{ul}) = 0$

$a(x_{ll}) = 0$

$b(x_{ll}, x_{ul}) = 0$

There are no restrictions on the function form of any of the objective function terms or functions in the constraints. It is assumed that the feasible region of Problem 2.2 is not empty (a feasible solution exists).

Proof: I prove the proposition by contradiction. Let an optimal solution of the single level Problem 2.2 be $y^* = f(x_{ll}^*) + g(x_{ul}^*)$. Assume that the bi-level Problem 2.1 has an optimal solution y'.

Assume, contrary to the proposition, that Problems 2.1 and 2.2 do not have the same value for the objective function at optimality, i.e., $y' \neq y^* \; (Statement\ 1)$. Note that $y' \geq$

[2] This is a special case of the general bi-level problem in which the upper level does not necessarily include f() in its objective; the general problem can be very difficult to solve [316].

y^* $(Statement\ 2)$ because the feasible region of Problem 2.1 is a subset of the feasible region of Problem 2.2. Because $y' \neq y^*$ (1) and $y' \geq y^*$ (2), it follows that $y' > y^*$ $(Statement\ 3)$.

Assume that a feasible solution of Problem 2.1 with the upper level variable at x_{ul}^* has value of the objective function y'' . Feasibility of this problem is guaranteed through feasibility of Problem 2.2. Let x_{ll}'' be the optimal solution of the lower level of Problem 2.1 in that case. From optimality of the lower level and given that x_{ll}^* is a feasible solution for the lower level problem it then follows that $f(x_{ll}'') \leq f(x_{ll}^*) \rightarrow f(x_{ll}'') + g(x_{ul}^*) \leq f(x_{ll}^*) + g(x_{ul}^*) \rightarrow y'' \leq y^*$ $(Statement\ 4)$.

Note that since y' is by assumption the optimal solution of Problem 2.1, it follows that $y' \leq y''$ $(Statement\ 5)$.

Based on statements 4 and 5, $y' \leq y^*$ $(Statement\ 6)$. Statement 6 contradicts statement 3. Therefore, the assumption that $y' \neq y^*$ must be incorrect. So, the two problems have the same objective function at optimality i.e., $y' = y^*$. Thus, since the optimal solution of the single level Problem 2.2 (x_{ll}^*, x_{ul}^*) is a feasible solution to Problem 2.1, it therefore also constitutes an optimal solution of the bi-level Problem 2.1. **QED.**

Proposition 2.1: Proactive transmission planning under perfect competition for generation investment and operation is equivalent to co-optimization of generation and transmission planning.

Proof: The proactive transmission planning problem can be formulated as a tri-level problem where at the upper level is the transmission operator, the intermediate level is the generator investor and at the lower level the ISO-operated market. The objective function at the lower level is defined as the operational costs of generators and payments for hurdle rates[3] because the operational market is perfectly competitive. In the middle level, assuming that generators pay for

[3] Note that I assume that hurdle rates reflect actual costs in the market e.g. transaction costs to coordinate operations among different entities and they are not simply a transfer payment between two parties.

the hurdle rates, the objective function is the sum of the lower level objective function added to the investment costs for generation expansion since a perfectly competitive environment for capacity additions is assumed. Finally, at the upper level the objective function is the sum of the middle level objective function and the costs for transmission investment. Therefore, it is obvious that by applying Lemma 2.1 twice, once at the lower and middle levels and a second time at the combined lower/middle and upper levels, the proactive planning framework is equivalent to co-optimization of generation and transmission planning. **QED.**

2.6 EXPERIMENTAL DESIGN: MODELING AND COMPARISON OF ALTERNATIVE PLANNING APPROACHES

The objective of this chapter as specified in Section 2.1 is two-fold. The first objective is the comparison of three alternative transmission planning frameworks. The second objective is the comparison of the effectiveness of three screening metrics, used and proposed for reduction of the set of candidate transmission investments. In Section 2.6.1, I explain how the model formulation presented in 2.5.1 is modified to simulate alternative planning frameworks. Then, in Section 2.6.2, I provide a detailed and precise description of the net benefits metric. In Section 2.6.3, the steps and formulas for calculation of screening metrics are presented. Finally, in Section 2.6.4, I discuss how the three planning frameworks are expected to perform relative to each other.

2.6.1 Formulation of alternative transmission planning procedures

2.6.1.a Reactive transmission planning

This planning approach attempts to model traditional practice. In Section 2.1, I define reactive transmission planning as transmission planning under a pre-defined scenario for the generation fleet. The definition is quite broad and might correspond to different methods for identifying the assumed generation mix. For example, approaches followed in the past by MISO and ERCOT are presented in the introduction and it is obvious that they are quite different.

In the application included here, I draft a generation mix scenario through optimization of generation investments given the existing transmission network. Then, transmission planner designs conceptual transmission plans by solving an optimization problem for the entire system given that generation mix. In brief, the transmission plan identified by the reactive planning approach corresponds to the second iteration of the iterative approach. First, generation capacity is optimized to create a generation build-out scenario under the existing grid, and then transmission is optimized subject to the generation scenario. Although the transmission planner can identify the transmission plan in two iterations, I run three iterations to estimate system costs, generation investment and operation of the reactive approach in order to account for generation investment's response to the transmission investment identified by the planner.

For iterations 1 and 3, I fix transmission investment decisions to zero and the level identified by iteration 2 within the model formulation of Section 2.5.1, respectively. For iteration 2, I fix generation investment decisions to the level identified by iteration 1 within the model formulation of Section 2.5.1. To conclude, in all three cases I solve the model of Section 2.5.1 with lower number of decision variables because a subset of investment decisions is already fixed at pre-determined levels.

2.6.1.b Iterative transmission planning

This planning approach is similar to the iterative planning approach used in [62]. The model of Section 2.5.1 is used iteratively, switching between generation-only and transmission-only investment modes. In the former mode, the transmission investment decisions are fixed at the levels decided at the previous iteration, and the only investments optimized are generation. Similarly, when the mode is transmission-investment only, generation capacity in each zone is fixed at the levels decided at the previous iteration. The first iteration is the generation investment mode, given the present grid. I stop iterating between the two modes when the objective function does not improve further.

2.6.2 Definition of metric for the benefits of transmission planning

I follow the definition of net transmission benefits presented in [49]. There, net benefits of transmission planning are quantified by subtracting (a) the total cost as estimated by the planning procedure under examination from (b) the total cost of a planning model that does not allow any transmission investment (which is the first iteration of the iterative planning approach). The strength of this metric is its ability to acknowledge that part of the objective function is highly affected by exogenous parameters such as the carbon tax, fuel prices, existing infrastructure etc. and is relatively immune to changes in the grid. Therefore, the value of transmission investments can be judged only through the improvement in the cost that the transmission planning might contribute, given the existing set of assumed parameters.

2.6.3 Definition of metrics to screen transmission candidates

ISOs usually calculate screening metrics by extracting flows and shadow prices based on extensive production cost simulations they run under a specific generation siting scenario. In the application presented in this chapter, I use the same definitions but obtain the flows and shadow prices from the planning model. In particular, I run the generation-only planning model (formulation of Section 2.5.1 with transmission investments fixed at zero). The model is a linear program because transmission investment is the only set of binary variables and now it is not a variable. Thus, shadow prices for the transmission flow limit constraints (Eq. 2-7) are provided by the solver. The flows are also recorded and used for calculation of the metric in (Eq. 2-15), below. Moreover, instead of the year-by-year calculations ISOs use, I calculate the metrics for the entire planning horizon considering all years at once. The metrics are defined as follows:

Total congestion cost (TCC) is defined as the product of hourly shadow price and hourly flow on the interface, summed over all hours of the year (in \$/year):

$$TCC_{t,l} = \sum_b (|\lambda^{+}_{l,b,t}|^{4} + |\lambda^{-}_{l,b,t}|) * (f^{+}_{l,b,t} + f^{-}_{l,b,t}) \quad \text{Eq. 2-15}$$

Total shadow price (TSP) is defined as the sum of hourly shadow prices for the interface (in $/MW/year).

$$TSP_{t,l} = \sum_b (|\lambda^{+}_{l,b,t}| + |\lambda^{-}_{l,b,t}|) \quad \text{Eq. 2-16}$$

Estimated Potential Benefit (EPB) is defined as the product of the hourly shadow price of the original model and the maximum overflow (flow over the capacity) that is recorded in a second run of the model if the congested interface is unconstrained (constraint (Eq. 2-7) is relaxed). In its practical application by MISO, congested interfaces are sorted into groups and one simulation per group is conducted in which (Eq. 2-7) is deactivated and the unconstrained flow (f^{un}) is recorded for all interfaces of the group.

$$EPB_{t,l} = \sum_b (|\lambda^{+}_{l,b,t}| + |\lambda^{-}_{l,b,t}|) * |f^{+,un}_{l,b,t} + f^{-,un}_{l,b,t} - IC_l| \quad \text{Eq. 2-17}$$

All three metrics consider the benefit of additional capacity through shadow prices or overflows, but they ignore the investment cost of the line. This omission could lead to retention of high value but very costly candidate interfaces, but exclusion of lower value interfaces that have a higher net benefit. Attempting to counter this weakness, I apply a charge to any overflow. I assume a charge that would be a lower bound to the fixed charge (in $/MWh) required to recover the investment cost. For that purpose, I calculate the discounted sum of hours included in the model (174,112 hours). Then, I assume that the interface will be used all 8760 hours at full capacity and divide the investment cost per MW of the least expensive configuration for each interface by ~2*10^5 hours.

[4]Note that in all calculations we assume that there is one hourly shadow price per time block *b* and its relationship with the shadow price for constraint (7) is $\lambda_{l.b.t} = H_b * hourly\ shadow\ price$.

2.6.4 Relationship among transmission planning approaches

Reference [12] extensively discussed proactive and reactive transmission planning and proved that the reactive approach, in general, achieves a worse or equal objective compared to the proactive approach. However, the iterative planning approach was not discussed in reference [12]. For this reason, I discuss in this section how the iterative transmission planning approach compares to the reactive and proactive planning approaches. In the following paragraphs, I demonstrate through an example that it is possible for the iterative approach to identify a solution different from the joint optimum that the co-optimization approach finds. Moreover, I explain in detail the reasons why the iterative approach as defined in Section 2.6.1.b will always find a solution with a better or equal objective compared to the reactive approach as defined in Section 2.6.1.a.

In the example, I assume a simple system consisting of two nodes. The candidate generators at nodes 1 and 2 have operational costs of 1 and 2 \$/MWh, respectively, and capital costs of 5 and 2 \$/MW. A transmission line can be built between the two nodes at a cost of \$1/MW. I assume that we optimize the system for 1 hour and the demand at nodes 1 and 2 are 3 and 4 MW, respectively. The two nodes are currently connected with a line that has capacity L_0. The co-optimization problem is described below:

$$\min_{x_1,x_2,z_1,z_2,l,y} 5 * z_1 + 2 * z_2 + x_1 + 2 * x_2 + l$$

Subject to

$$x_1 + y = 3$$

$$x_2 - y = 4$$

$$x_1 \leq z_1$$

$$x_2 \leq z_2$$

$$l + L_0 \geq y \geq -l - L_0$$

$$x_1, x_2, z_1, z_2, l \geq 0$$

$$0 < L_0 < 3$$

The co-optimization identifies optimum solution $(x_1, x_2, z_1, z_2, l, y) = (0,7,0,7,3 - L_0, 3)$ and the cost is $31 - L_0$. In the iterative scheme, the solution identified by first iteration (generation-only optimization subject to present grid L_0) is $(x_1, x_2, z_1, z_2, y) = (3 - L_0, 4 + L_0, 3 - L_0, 4 + L_0, L_0)$ and the cost is $34 - 2 * L_0$. Then, the transmission-only iteration subject to that generation plan identifies as optimal solution $(x_1, x_2, l, y) = (3 - L_0, 4 + L_0, L_0)$ and the cost is also $34 - 2 * L_0$. So, the iterative approach converged in two iterations (i.e., in this example the iterative and reactive solutions are identical). Because $L_0 < 3$, it follows that $L_0 < 34 - 31 \rightarrow 2 * L_0 - L_0 < 34 - 31 \rightarrow 31 - L_0 < 34 - 2 * L_0$. Thus, the cost of the solution where the iterative approach converged at is higher than the cost of the solution identified by the co-optimization problem. Therefore, this example demonstrates how the iterative approach does not necessarily converge to the joint optimum.

On the other hand, the iterative approach is always guaranteed to perform as well as or better than the reactive approach with the same starting point (the same initial generation plan). Recall from Section 2.6.1 that I have defined the reactive planning procedure as the iterative method with a maximum number of iterations set to 3 with the following definition of the iterations:

- the first iteration is the generation investment problem with fixed transmission (present grid);
- the second iteration the transmission investment with fixed generation; and
- the third iteration is again the generation investment.

Note that the iterative approach leads to a monotonically non-increasing series of objective function valuations because in every iteration the levels at which transmission or generation investment was fixed in the previous iteration are feasible. So, each subsequent iteration will not choose a set of investments that worsens the objective; it will either identify a new level of investments that leads to a lower objective function value than the previous iteration, or it can choose the level at which investments were fixed before and the objective function value will remain the same. Given that the series of objective function valuations is monotonically non-increasing, it follows that the iterative approach (when run to convergence) will result to a solution with lower or equal cost compared to the reactive approach.

2.7 RESULTS

The problem is modeled in AIMMS. The CPLEX 12.6 solver is used to solve the model with a MIP gap tolerance of 10^{-6} (expressed as a fraction of the objective function).

2.7.1 Benefits of proactive transmission planning for EI

As demonstrated in Section 2.6.4, the solution identified by co-optimization of generation and transmission planning cannot have higher cost than the solution identified by the iterative approach. In brief, this is because the latter has the same objective function but a smaller feasible region since some of the decision variables are fixed at each iteration (e.g., generation investments are fixed for the 2nd iteration) and might not converge to the joint optimum. Since reactive planning is equivalent to the iterative approach with the maximum number of iterations set at three, and since the cost cannot be worsen from iteration to iteration, reactive planning cannot have a lower cost than the iterative method.

Here, I quantify the extent to which co-optimization outperforms both methods (reactive and iterative). Co-optimization increases the net benefits identified by the transmission planning process by \$3.5bn compared to the iterative and reactive approaches (see Table 2-2). Note that in this case, the iterative and reactive approaches lead to identical solution since they identified the same transmission investment plan given that the iterative method converged in only 4 iterations. In particular, as part of iteration 3, generation investment changed slightly in response to the transmission investments made in iteration 2. This similarity of the iterative and the reactive approaches is not generally the case as proved in Section 2.6.4 and demonstrated in results obtained under sensitivity analysis.

The increase in net transmission benefits seems significant. The iterative approach captures only 29% of the net benefits that the transmission planning procedure could add to the system if co-optimization was employed.

Table 2-2: Transmission benefits and investment costs under base case

In $2010 million	**Reactive (3rd iteration)**	**Iterative (4th iteration)**	**Co-optimization**
Net Transmission benefits	1,451	1,451	4,973
Transmission investment cost	807	807	8,744

Examining the time granularity of net benefits throughout the horizon in Table 2-3, I observe that the cost savings of using the co-optimization over the iterative approach manifest late in the horizon (post 2025).

Table 2-3: Difference of transmission net benefits between co-optimization and iterative planning across the model horizon (in millions of $2010)

Time period	**Co-optimization-Iterative**
2011–15	8
2016–20	-23
2021–25	-173
2026–30	420
2031–70	3,289

The timing of the net benefits increase seems to coincide with the timing of generation and transmission investment differences between the two methods. As Table 2-4 and Table 2-5 indicate, co-optimization invests more in wind and transmission investment and less in natural gas, but this deviation in the plan relative to reactive planning is observed only late in the horizon (2026–2030). The concentration of investment deviations in the late 2020's (Table 2-4 and Table 2-5) is probably explained by the high carbon tax required to make wind competitive with combined cycle capacity, even in regions with high quality wind. For example, 2020 is the first year that wind has a lower levelized cost in 4 regions. The number of such regions reaches 6 in 2030

(Figure 2-1). I further test the hypothesis that carbon tax affects significantly the timing of savings in one of the sensitivity cases in Section 2.7.2.

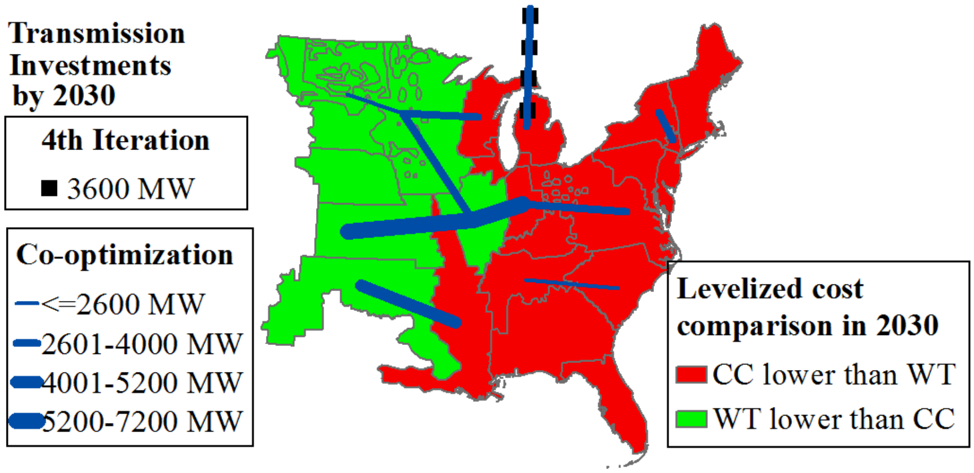

Figure 2-1: EI transmission investments by 2030 (MW)

Table 2-4: Generation investments in GW (Generation-only/Iterative/Co-optimization)

Generation Type	2011–15	2016–20	2021–25	2026–30
CC	16/16/15	63/57/59	19/22/18	43/45/35
CT	0	0	0	6/8/7
Nuclear, Hydro, IGCC_CCS	0	4/4/4	2/3/3	67/66/66
Wind	0	5/5/7	41/42/42	67/67/118
Other	0	5/5/5	4/4/4	4/4/3

Table 2-5: Transmission investments in GW-miles

Transmission investment (GW-miles)	2011–15	2016–20	2021–25	2026–30
Co-optimization		1,242		10,624
Iterative Planning		774		

Contrasting the two planning approaches, co-optimization invests more in wind and transmission lines (Table 2-4 and Table 2-5) increasing investment costs but saving operational costs (see Table 2-6). Co-optimization suggests investments in transmission that connects regions with wind capacity factors high enough to compete with conventional resources to high load regions that lack high quality wind resources. In that manner, co-optimization integrates approximately one-third more wind both in terms of capacity and energy (see Table 2-7). This generation mix change is significantly driven by the carbon tax cost savings (which make up \$51.5bn out of the \$907bn-\$818bn = \$89bn savings in extension period operational costs in Table 2-6).

Table 2-6: Objective function components

	Metric ($bn NPV in 2010$)	Co-optimization	Iterative (4th iteration)
Years: 2011–30	Generation Operation	1,583	1,592
	Generation Investment	692	633
	Transmission Operation (Hurdle Rates)	9	8
Years: 2031–70	Extension period annualized capital costs	500	473
	Extension period operational costs	818	907
Total	Transmission Investment	9	1
	Objective function	3,610.9	3,614.4

Table 2-7: EI Capacity/Generation mix in 2030, GW/TWh

Capacity Type	**Co-optimization**	**Iterative 4th**
CC	220/770	233/921
CT	49/7	45/7
Nuc, Hydro, IGCC_CCS	219/1501	219/1505
Wind	194/622	143/458
DR	152/1	152/1
Other	18/94	19/102

In Section 2.6.4, I demonstrated the conjectured relationship among the cost of the three approaches and demonstrated how the iterative approach has a cost that is higher than the co-optimization approach and lower than the generation-only approach. Here, I will explain the relationship by looking into the case study and provide some intuition on why the iterative approach converged before reaching the joint optimum.

In the first iteration, which invests in generation only, tight transmission constraints and the lack of a clear economic advantage for wind means that investment in gas-fired plants occurs even in regions with high quality wind. Wind integration is modest, and no curtailment is observed. Then the 2nd iteration identifies which transmission lines are justified by operational cost savings, given the generation build-out from the 1st iteration. The presence of gas generation and absence of wind curtailment leads the model to avoid new connections to regions with high quality wind. Thus, the iterative approach fails to recognize that operating cost savings can arise from simultaneously investing in remote wind and the interregional transmission needed to access it. In economic terms, those two investments are complementary, in that the presence of one increases the economic value of the other. Co-optimization is needed to capture this interdependency.

However, the iterative method does recognize operational savings due to regional fuel cost differences or/and differences in the marginal resource. Nevertheless, the former does not justify transmission investments here due to the wheeling charges exceeding fuel cost differences for the same type of resource. The latter, however, motivates the iterative method's only transmission investment, which is also identified by co-optimization. Ontario has spare low-cost capacity during most load periods. As a result, 3.6 GW of expansion is justified for one interface to facilitate export of its cheap capacity (Figure 2-1).

Finally, the amount of trade in the EI increases significantly under co-optimization compared to the iterative solution. This is expected since gas-fired plants can be developed in any region with fairly similar costs while high quality wind is found only at specific regions. To measure trade, I divide the EI into zones by combining regions that have zero hurdle rates between them, and then calculate flows among those zones. Co-optimization increases the sum of net trade between these zones by 150% (from 64 TWh to 152 TWh) in 2030.

2.7.2 Sensitivity analyses

I also quantify co-optimization's benefits for three sensitivity cases. All three sensitivities test the impact of different policies attempting to increase renewable penetration or mitigate carbon dioxide emissions. I choose to focus on those policies because they significantly affect renewable investments, which seem to be interlinked with transmission investments and subsequently affect the co-optimization benefits.

In the first sensitivity, I replace the carbon tax with an EI-wide renewable portfolio standard given that RPS mechanisms seem to be more popular than carbon tax. In the second, I extend through 2030 a production tax credit (PTC) of 22$/MWh of wind production for the first 10 years of a wind investment. In the third sensitivity, I enforce a uniform carbon tax of 140$/tn from 2015 onwards to examine if the timing of savings is affected.

For the first sensitivity, I enforce an EI-wide renewable energy target that is calculated to match the TWh of renewables generated by year in the base case co-optimization results, and I remove the carbon tax. Note that the results of the first sensitivity analysis depend on the flexibility allowed for trading renewable energy credits as shown in [94]. In the formulation employed here, enforcement at the EI-level assumes full flexibility for credit trading within EI. The iterative model now needs 10 iterations to converge.

Examining results obtained under this case, co-optimization benefits more than double compared to the base case. This is reasonable given that in the generation-only planning case, inefficient investments in renewables happen to comply with the renewable portfolio standard. Moreover, curtailments are much more frequent and responsible for part of the inefficiency. The presence of curtailments now motivates more transmission investments in the iterative approach. Thus, the iterative approach has a more similar pattern of transmission development with co-optimization and not the reactive case as in the base case. Moreover, the iterative approach is able to capture ~89% of the benefits that co-optimization might achieve. Whereas, the reactive approach only realized 46% of co-optimization's benefits in this case (Table 2-8). Although both iterative and co-optimization methods procure the same amount of renewable energy, the co-optimization approach builds more wind at the expense of biomass and wood. High quality of wind in specific regions compensates for the additional transmission investment needed to access them and makes those remote wind resources competitive to local renewables.

Table 2-8: Comparison of three planning approaches under sensitivity case with nationwide RPS

Transmission planning approach/iteration	**Reactive/3**	**Iterative/10**	**Co-optimization**
Transmission net benefits ($2010 million)	4,321	8,473	9,480
Transmission investment cost ($2010 million)	1,923	4,161	5,762
By 2030: Transmission Investment (GW-mile)	1,950	5,598	7,506

In the second sensitivity case, the PTC yields more wind investment in both approaches. However, the cost saved by co-optimization resembles that in the base case (see Section 2.7.1). Similar to the first sensitivity, the iterative approach is more similar to co-optimization and costs only $4.3bn more than the latter. However, the number of iterations required for convergence increases even further (4 in base case, 10 in first sensitivity, 24 now). The iterative now captures 84% of the co-optimization net benefits while reactive only obtains ~14%. Thus, a pronounced cost improvement resulting from using iterative rather than reactive planning (Table 2-9) is observed in both sensitivities.

Table 2-9: Comparison of three planning approaches under sensitivity case with production tax credit

Transmission planning approach/iteration	**Reactive/3**	**Iterative/24**	**Co-optimization**
Transmission net benefits ($2010 million)	3,826	23,391	27,721
Transmission investment cost ($2010 million)	1,877	13,782	24,680
By 2030: Transmission Investment (GW-mile)	1,554	19,161	33,896

I conduct the third sensitivity to test the impact of carbon tax on timing and magnitude of benefits. Specifically, I impose a 140$/ton carbon tax after 2015. The savings are observed earlier compared to the base case (post 2020 rather than post 2025). Further, it appears that tax affects significantly both the magnitude and timing of co-optimization benefits.

Table 2-10: Timing of net transmission benefits under sensitivity case with early implementation of high carbon tax

	Net transmission benefits (in $2010 million)	
	Co-optimization- Iterative	**Co-optimization- Iterative 3rd Sensitivity (High Carbon**
Time period	**Base case**	**Tax Earlier)**
2011–15	8	(283)
2016–20	(23)	(30)
2021–25	(173)	1,038
2026–30	420	1,971
2031–70	3,289	2,458

To conclude, the magnitude of co-optimization benefits is significantly affected by exogenous assumptions such as RPS (sensitivity 1) and carbon tax (base case, sensitivity 3). In general, under any single set of assumptions, co-optimization is the approach that yields the maximum net benefits. The reactive approach captures the lowest amount of potential transmission benefits (14–46% in cases simulated) among the three methods. Finally, the iterative approach realizes a higher fraction of co-optimization benefits, with a range of 14–89%, depending on the model formulation.

2.7.3 Reduced transmission candidate set

Computational time is a disadvantage of co-optimization. Here, co-optimization took 5–9 times as long to solve as the iterative approach, even though the latter involved solution of multiple model instances. So, I evaluate whether pre-screening of investments to reduce model size could improve solution times, and whether restricting the options considered decreases the benefits of co-optimization.

I pre-specify the number of candidates the reduced set should have to 10. Then, I identify the 10 most congested interfaces in the EI using the three metrics defined in 2.6.3. Thus, the set of candidate interfaces is greatly reduced from the original 47 interfaces. Using the three sets of interfaces identified by the metrics as the reduced sets of transmission candidates (noted S_R), I then co-optimize the EI system under base case assumptions three times, once for each metric.

Even though all metrics use the same shadow prices in their definition, the sets of interfaces they identify are very different because of the different roles of existing flows (in the case of metric TCC) and overflows (for EPB), as shown in Table 2-11. Only three interfaces appear in all three sets of 10 interfaces and one of them is the interface that expands under the iterative approach of the base case (Figure 2-1).

Table 2-11: Intersections of reduced sets of candidate interfaces

Set	Size	Set	Size
$S_{TCC} \cap S_{TSP}$	5	$S_{TSP} \cap S_{EPB}$	4
$S_{TCC} \cap S_{EPB}$	5	$S_{TSP} \cap S_{EPB} \cap S_{TCC}$	3

Pre-screening lines results in a smaller number of integer variables for new lines. The reduction in the number of binary variables results to reduction of the solution time by two-thirds for the co-optimization model, when using the same gap tolerance (10^{-6}). Unfortunately, however, by restricting which lines can be chosen by co-optimization, the benefits obtained from co-optimization are also reduced (see Table 2-12).

Table 2-12: Performance of restricted transmission planning models with screening metrics

Co-optimization with $\boldsymbol{S_R}$ based on:	TCC Metric	TSP Metric	EPB Metric	Full set of lines
Cost increase vs. full set of lines (\$bn)	1.8	1.6	0.6	0
Benefits increase vs. iterative (\$bn)	1.7	1.9	2.9	3.5
Time to solve (sec)	411	608	490	2081
No. of integer variables	480	384	480	1968

Note: The number of continuous variables is the same in each model (218,164). The LP Barrier method is used at each node of the Branch-and-Bound algorithm. The priority feature of integer variables for branching and full probing are adopted. These solution times are achieved on a desktop with Intel core processor i7-5930K at 3.50GHz and 32 GB Ram.

Cost savings achieved vary (Table 2-12) depending on the metric used. EPB outperforms the other two metrics: it captures the highest portion (82%) of co-optimization's cost savings without taking more time. The restricted model with top candidates based on EPB also incurs the least cost increase (+$0.6bn) compared to co-optimization with the full set of lines, while TCC and TSP incur an increase approximately three times as high. Given that the interface expanded by the iterative approach is part of all three reduced sets, the iterative approach is the same across all metrics.

Digging further into metrics' performance, I examine the number of interfaces at the intersection of two sets: 1) set O_F, defined as the set of interfaces expanding under co-optimization with the full set of lines and 2) set S_R. Then, the number of false positives is defined as the size of $S_R \cap (S_R \cap O_F)^C$ and the number of false negatives is equal to the size of the set $O_F \cap (S_R \cap O_F)^C$. Given that in this application, the sizes of S_R and O_F are identical, the numbers of false positives and negatives are equal (Table 2-13). I see that EPB also performs best (fewest false positives/negatives).

Table 2-13: Comparison of sets S_R and O_F

Reduction metric	**Size of $S_R \cap O_F$**	**False positives/negatives**
TCC	4	6
TSP	4	6
EPB	7	3

There are two reasons for the success of the EPB metric. First, the overflow analysis indicates which interfaces might experience the greatest increase in use if all interfaces are expanded simultaneously. In that manner, it identifies economically attractive multi-interface paths. Second, the overflow charge guides the flow and prevents some false positives. For example, in the case of two parallel paths with same shadow prices, EPB will favor the one with the lowest cost.

However, the success of EPB here does not depend on its ability to better approximate actual potential benefits (APB, defined above), contrary to the claim in [95]. Even if I identify the most promising interfaces using APB and co-optimize with this reduced set, I only get 77% of the full co-optimization savings because APB focuses on benefits from individual expansions, ignoring interactions among interfaces.

Examining the false positives of each S_R , I now consider the reasons for their inclusion. First, all three metrics employ shadow price information. Those prices are useful, but they do not quantify the extent (in GW) of expansion that would be beneficial, nor do they provide information on how those benefits would be affected by expanding other interfaces. In particular, there is a false positive interface identified by all three screening methods. Expansion of that interface is beneficial for a much lower number of MW than the size of a new line for that interface. Also, the TCC and TSP metrics include all interfaces connecting two adjacent regions with large price differences, while in practice it may be optimal to expand just the least costly interface. Finally, although the adjusted EPB does account for interface interactions, it could yield false positives because allowance of an overflow in one interface may cause overflows on other interfaces in series, not all of which may be optimal to expand.

Reviewing the false negatives, I see that all metrics tend to miss interfaces that consist of the next most limiting element on a multi-interface serial path. EPB seems to suffer the least because the simultaneous release of the flow limits might lead to significant overflow in the multi-interface path, prioritizing even lines with low shadow prices. However, in case of zero shadow prices, EPB would also estimate zero improvement and might miss an optimal series of lines to expand. To correct this, grouping techniques might be adopted [96]

2.8 CONCLUSIONS

I apply co-optimization, or "proactive transmission planning", to a 24-bus representation of the Eastern Interconnection, using a dataset for the entire EI developed in a past study including stakeholders. Co-optimization is the approach that theoretically allows the planner to maximize the value added by the transmission planning procedure. Comparing the value added by traditional planning approaches such as reactive (generation-first) planning and a model that iterates between generation and transmission expansion, I observe that those widely used methods capture only a portion of the maximum value (14–46% and 14–89%, respectively). When co-optimizing in the case study presented here, the transmission planner spends more on transmission since the planner anticipates that transmission investments will facilitate greater development of remote high-quality wind resources rendering more transmission additions economic. Integration of those resources leads to increasing trade between EI regions and system cost is reduced because the proactive planner recognizes the complementarity of transmission and remote generation investment.

However, model size and solution times are a challenge for practical implementation of co-optimization. I apply and evaluate congestion metrics as screening criteria to reduce the number of transmission options considered. I observe that two widely used congestion metrics have a high rate of failure, in terms of overlooking lines that would actually be expanded in a co-optimization with the full set. These metrics fail to achieve more than half of the cost savings of co-optimization with the full set. In contrast, a version of the estimated potential benefit (EPB) metric proposed by MISO performs better, capturing ~82% of the savings while reducing solution times by more than 75%.

Future work could test the benefits of co-optimization and the success of EPB as a screening criterion based upon more detailed representations of the EI network that include Kirchhoff's Voltage Laws. Furthermore, co-optimization benefits could also be quantified assuming strategic players rather than perfect competition. This would require use of large-scale multi-level optimization models.

CHAPTER 3
PLANNING POWER SYSTEMS IN FRAGILE AND CONFLICT-AFFECTED STATES

Novel approaches are necessary to accelerate provision of reliable electric power in fragile and conflict-affected countries. Existing approaches to planning power system investment tend to ignore conflict risk and its serious consequences. This chapter proposes a framework for identifying power system investment strategies in fragile and conflict-affected countries and applies it to South Sudan. Results show that investment strategies which consider the challenging conflict context may improve reliability of electricity service over the status-quo approach. The analysis suggests investing in a diverse resource mix for the electricity supply in the medium term and building a power system with redundancies or higher share of local resources in the long term.

3.1 INTRODUCTION

Sub-Saharan Africa (SSA) has been identified as the epicenter of the energy poverty challenge [32], with 588 million people lacking access to electricity as of 2016 [31]. Despite recent increases in the pace of electrification, the Sustainable Development Goal (SDG7) for universal energy access by 2030 [2] will not be met without intensified electrification efforts [97].

A challenge is that half of SSA countries have consistently ranked among the top 50 fragile countries in the world in the last decade [33]. Conditions in fragile countries may condemn conventional development plans to failure [34]. Conventional power system planning methods are also susceptible to failure. However, only a slim minority of peer-reviewed quantitative planning studies about SSA considers political factors [98], and almost all widely used energy planning models overlook socio-political aspects including political instability [17]. Therefore, new planning approaches are needed to identify actionable plans.

A relatively small number of papers has considered the impact of political instability on power system planning and operation [99], [100], [101]. However, as I will discuss in detail in Section 3.2.3, existing approaches are myopic in the way they simulate conflict. At least one of the following three weaknesses is observed in past studies. First, researchers focus on a single conflict effect, resulting in potentially biased recommendations. Second, status-quo approaches ignore the dynamic evolution of conflict and adopt uniform values for conflict-affected parameters over a multi-decadal horizon. In that case, implications of any future improvement or deterioration of conflict conditions for power system development are overlooked. In particular, the value of adaptive strategies is not recognized. Finally, previous articles propose methods without providing guidance on datasets and available models, which could be used in practical applications. In other words, practical difficulties are ignored, and planners would have to invest significant effort to draft an implementation plan for proposed methods.

This chapter aims to design and implement a practical framework that considers conflict-induced uncertainty over a multi-decadal time horizon, while accounting for multiple effects of conflict on power system investment and operation. The framework is designed to be readily applied to diverse situations around the globe, relying on qualitative analysis or statistical models for conflict uncertainty characterization and quantitative evidence of conflict impacts.

The rest of this chapter is structured as follows. Section 3.2 provides background information and reviews literature on fragility, power system vulnerability to conflict, and existing conflict-aware power system planning methods. Section 3.3 articulates the proposed framework and explains its components in detail. Section 3.4 presents key features of the case study and explains the implementation of each step for the case study. Section 3.5 illustrates the experimental design. Results for all cases chosen in Section 3.5 are provided in Section 3.6. The chapter ends with discussion on results (Section 3.7), conclusions, and potential extensions of the framework (Section 3.8).

3.2 BACKGROUND AND LITERATURE REVIEW

The United Nations and the World Bank Group have identified fragility, conflict and violence (FCV) as obstacles preventing the achievement of global development goals [102]. The Organization for Economic Cooperation and Development (OECD) defines fragility as "the combination of exposure to risk and insufficient coping capacity of the state, system and/or communities to manage, absorb or mitigate those risks. Fragility can lead to negative outcomes including violence, the breakdown of institutions, displacement, humanitarian crises or other emergencies" [103].

There has been a remarkable rise of conflict around the globe in the past decade [102]. Approximately 2 billion people live in countries now suffering from fragility, conflict and violence (FCV) [104]. By 2030, 46% of the global poor population is projected to live in FCV-affected states [104]. As a result, methodologies that measure and predict fragility and conflict have attracted growing interest as they can support decision makers to prepare for, intervene in, and cope with fragility and conflict [105]. Section 3.2.1 provides a synopsis of methods that measure and project FCV.

Access to reliable electricity possesses a unique position in the FCV agenda since it plays a role on all three phases of leading to, preventing, and coping with FCV conditions. In particular, discriminatory access to electricity might be perceived as an act of marginalization for certain populations within a state [106] and as a result act as a trigger for confrontation and conflict. If connectivity and infrastructure lead to economic development, which subsequently mitigates the FCV conditions, then improvement of electricity infrastructure also belongs to the prevention/peace-building agenda [34]. Finally, development and operation of power systems are not immune to FCV. Under FCV, normal procedures are frequently disrupted [107] and system resilience is necessary to cope with conflict and meet demand under adverse conditions. Currently, there is limited work on the role of electricity access as a predictor of conflict and its role on prevention. However, there is abundant historical evidence documenting the vulnerability of power system assets to conflict. In Section 3.2.2, I review past conflicts and create a comprehensive list of effects of conflict on power system assets. Lastly, in Section 3.2.3 I investigate how previous research articles have integrated conflict risks into power system models.

3.2.1 Measuring and projecting fragility and conflict

International agencies and donors have been developing and employing fragility indexes and conflict projection tools for decades. Recent advances in computational fields — e.g., in machine learning — have resulted in a new wave of quantitative conflict prediction tools [105], [108]. At the same time, qualitative frameworks are also evolving, and hybrid tools that use both qualitative and quantitative methods have been developed [109].

Similar categories of inputs are used for fragility measurement and conflict projection across tools. Authors of [110] employ three types of indicators: input, process, and output indicators. Input indicators refer to structural factors and the institutional framework in a country. Analysis of governance effectiveness and human development fall under this category. Process indicators mainly measure economic development and social welfare. Output indicators directly measure conflict episodes and incidents of unrest. Using a different classification system, reference [111] divides inputs into three classes: tensions, shocks and institutions. While institutions are similar to the input indicators used in [110], tensions and shocks are slightly different. Tensions capture ethnic or religious fractionalization and uneven distribution of wealth and resources within a country. Unlike structural factors which generally characterize chronic conditions, shocks refer to abrupt changes in trade or natural disasters. Overall, most methods that characterize a country's status assess multiple aspects: history of conflict, quality of governance, human rights, international relationships, population heterogeneity, economic development, and demographic or environmental stresses [112].

There exist qualitative, quantitative, and hybrid methods to translate input data into conflict projections [109]. Within qualitative methods, predictions might be devised based on structural analogies [113], structural frameworks [114] and alternative frameworks (e.g., Shell [115] and Delphi [116]). Quantitative methods range from regression models to machine learning approaches such as neural networks and random forests [109]. Modern software based on content analysis quantifies media coverage and, more recently, social media activity, which can be used as a conflict predictor [108]. Finally, hybrid methods rely on both quantitative measures and experts' perceptions of a situation [109].

Outputs vary significantly among tools. For instance, temporal and spatial resolution differs across quantitative tools [108], [109]. Definition of conflict also varies. Some tools define conflict based on the number of battle-related deaths and assign intensity levels accordingly [117]. Other tools choose to expand the definition of conflict to include the presence of peacekeeping operations and the displacement of the population [111]. In addition, tools might provide a qualitative [112], relative quantitative [118] or absolute quantitative measure of risk [119]. In the latter case of an absolute quantitative metric, tools might provide probabilities for onset and/or termination of conflict [108].

These tools are likely to become more useful in the future for several reasons. Recent advances in computational methods offer the possibility of improved accuracy of quantitative conflict predictions [108]. Moreover, quantitative methods are easily applied across the world; international or local agencies can use these numerical estimates to assess interventions and programs in any country [105]. However, researchers emphasize that the accuracy of quantitative predictions is constrained by epistemic and empirical uncertainty, which arise because of limited evidence and understanding of the complex phenomenon of conflict [108]. Moreover, quantitative methods are often criticized for being overly uniform, ignoring country-specific dynamics [109]. Thus, integration with relevant expert judgments is desirable.

The framework proposed in Section 3.3 requires planners to develop scenarios on the evolution of conflict but does not specify which conflict prediction tool to use. I would recommend selecting a conflict prediction tool that acknowledges the influence of conflict history on the likelihood of future conflict. In that way, planners can adapt their plan as more information on any specific conflict becomes available. Later, in Section 3.4, I provide detailed information and justification for the quantitative conflict prediction tool used in the case study.

3.2.2 Power system vulnerability to conflict

There is abundant evidence from around the globe indicating that power system components and processes are vulnerable to conflict. Attacks on transmission lines and natural gas pipelines are regularly reported in the press. However, vulnerability of power system components to conflict extends beyond attacks on energy infrastructure. To develop a comprehensive list of these power system vulnerabilities, I reviewed academic papers, databases listing attacks on power systems, damage assessment reports, reports and news articles describing power system operations in conflict zones, and reconstruction efforts in post-conflict environments.

Power system infrastructure constitutes a target for attacks that aim to disrupt power service. However, attacks take different forms. Bombing of transmission towers and substations occurred frequently during the extended civil conflict in Colombia [120]. Three Syrian cities [121], likewise, experienced attacks on 50% of substations and 10% of transmission towers between 2011 and 2017. There are numerous other examples of attacks upon transmission lines from around the world, e.g., during the 2011 crisis in Yemen [122] and the civil war in El Salvador [123]. Direct attacks on power plants occur less frequently [124], though incidents of hostage taking or occupation of power generation facilities are common. During the Liberian civil war, for instance, the main hydro plant for the country was wrecked [125]. Increased security for power plants during times of conflict might explain why fewer attacks have been recorded. For instance, several security measures were taken to safeguard the Hoover Dam during World War II [126]. However, the geographical extent of transmission and other infrastructure networks makes guaranteeing their security almost impossible.

Infrastructure systems are highly interdependent and thus attacks to other sectors have the potential to disrupt the power sector. Attacks on fuel supply lines are such an example. In Nigeria, attacks on natural gas pipelines disrupted the fuel supply to several natural gas power plants in 2015 [127]. Similarly, attacks on transportation infrastructure — e.g., railroads, ports, etc. — could disrupt fuel delivery and subsequently power system operations [128]. Cyberattacks targeting the communication system of electricity grids have recently emerged as a serious concern. In December 2015, hackers broke into the SCADA distribution management system of three Ukrainian energy distribution companies [129].

In addition, adhering to recommended maintenance schedules is challenging in conflict zones [107]. Irregular maintenance leads to higher malfunction rates. Chronic improper maintenance may necessitate significant refurbishment of equipment [130]. Repair times also increase in conflict zones for multiple reasons such as lack of spare parts and inaccessibility. During the Colombian conflict, the repair time for replacement of transmission towers varied greatly, with the shortest repair time one day and the longest 1,626 days [131].

Fuel shortages are also quite common during times of conflict. Shortages arise because of limited supplies, which in turn lead to increased prices. In South Sudan, existing diesel generators stayed idle because of the unavailability and unaffordability of oil [132]. Similarly, in Palestine, fuel shortages cause irregular electricity supply [133]. Limited supply is caused by multiple factors including attacks on fuel supply networks as mentioned above, import difficulties (which I discuss in more detail in the following paragraph), and loss of government control of natural resources.

For instance, in 2014 Syria ISIS (the Islamic State of Iraq and Syria) controlled oil and gas resources and the government of Syria allegedly purchased fuel for the Syrian electricity sector from the rebels[134].

Conflict crises profoundly affect the economy [135] and subsequently power system investment and operations. Gross Domestic Product (GDP) usually experiences slower (or even negative) growth compared to peaceful times [136]. The composition of the economy in terms of each sector's contribution to GDP is also distorted. The contribution of "war-invulnerable" and "war-vulnerable" sectors tend to increase and decrease, respectively [136]. Changes in growth and composition of GDP might result to changes in electricity demand.

Economic decisions by governments, private companies and rebel groups also change during times of conflict [135]. Government revenues tend to be lower because of lower taxable income and reduced trade with international partners, caused by sanctions or loss of control of export commodities. As a result, government deficits usually increase during times of conflict [135]. Moreover, governments usually change the budget allocation among sectors. The budget for defense and military operations usually increases at the expense of other government-sponsored activities including infrastructure development and maintenance [137]. Inflation, interest rates [99] and exchange rates are also affected by conflict [138] and in some cases shortages of hard currency have resulted in the devaluation of local currencies and the inability to import equipment and fuel [132]. Private companies and international organizations usually limit their economic activity in conflict zones and capital "flies away" [139], [140].

Conditions such as "capital flight" and difficulties in import of equipment are adverse for construction and might prolong construction times for power plants. Sabotage to construction sites might also lead to longer construction times. For example, in 1982 the African National Congress placed bombs at a site in South Africa, where construction of nuclear power plants was underway [141]. In Nigeria, kidnapping and killing of construction teams seriously impeded the construction of power plants [142]. Projects under development might be suspended until after the conflict is resolved. Development of a hydropower plant in Turkey was suspended in February 2016 because of violence in the vicinity of the power plant [143]. In Sierra Leone, construction of the Bumbuna Hydropower plant was 85% completed when conflict erupted in the country in 1992, but after suspension of construction for a decade, the project was finally completed in 2009 [144]. The Azito power plant at Ivory Coast is another case where conflict led to temporary suspension of power development plans. In that case, the Azito construction project consisted of multiple phases, starting in the first phase as a simple cycle gas plant with plans to convert it to a combined cycle in the second phase. However, the plant remained a simply cycle for more years than initially expected due to political crisis [145].

Finally, the negative impact of conflict on human capital translates into negative effects on power system operations and investment. Negative effects on human capital include lower numbers of skilled and unskilled workers along with population displacement. The former impedes construction and operations [146] and the latter changes the level and geographical distribution of electricity demand. For instance, Syrian refugees have increased the electricity demand in Lebanon [147].

3.2.3 Conflict risk in power system models

The above review has established that FCV conditions impact power system development and operations. So, it is surprising that widely used energy planning models do not take those conditions into account when they assess plans for power system development. An obvious reason is that that most of those models were created in developed countries [17] not torn by conflict in their recent past. I reviewed several articles analyzing conflict risks to power systems [148], [149], [150], [151], [152], [99], [100], [153], [101]. Based on their horizon, analyses can be classified as historical or forward-looking. Historical articles usually examine evolution of power system and attempt to explain how conflict conditions might have contributed to present status of the grid. For example, Bawakyillenuo [151] analyzes trajectories for PV deployment in three Sub-Saharan

African countries and observes that stability prevailed in two out of the three countries, which were able to attract more foreign investment and deploy more PV. Forward-looking studies, on the other hand, examine power system development plans looking into future and comment on the impact of conflict risk. In terms of type, such analyses are either quantitative or qualitative. Reference [98] observes that most qualitative analyses consider impacts of political factors on power systems while only a slim minority of quantitative models account for political factors. Power system planning models are forward-looking quantitative models. Thus, in this subsection, I discuss this type of models in detail.

Labordena et al. [99], for example, assess the potential for concentrated solar power in Sub-Saharan Africa. They consider conflict risk in a single manner: by using county-specific financing cost and strictly assume that no investment can happen in fragile states. Zerriffi et al. [100] reviewed effects on power systems in several past conflicts. They discussed a single conflict effect, i.e., the increase of repair time during conflict, which leads to longer unavailability of power system assets and prolonged outages. Simulating the reliability performance of two alternate designs of a test system — one with fewer and larger units than the other — they conclude that distributed generation systems provide reliability benefits during conflict.

Similar to Zerriffi et al. [100], Levin and Thomas [153] also start with two pre-determined power system development plans. They further test the performance of those plans through multiple simulations, where uncertain parameters are valued at levels drawn from a normal distribution. Within their simulations, they consider governance/political instability. They choose to model instability's impact on power systems through a single effect, which makes capital unavailable for development.

Trotter et al. [152] construct a metric for political risk. Then, they solve a least-cost power system planning problem imposing a constraint that does not allow the metric for political risk to exceed a maximum value set by the analyst. They solve this model multiple times for different levels of political risk. In other words, their approach is equivalent to the standard constraint method, which is used to solve multi-objective problems. In their approach, political instability is included as one of the six aspects comprising the composite metric for political risk. For the valuation of political instability, they multiply the "WGI Political Stability and Absence of Violence Index" of supplier countries by the amount of electricity imported from the supplier country. That way, reliance of a country on suppliers located in politically instable countries is noted and penalized. Their approach is characterized by at least three flaws. First, different aspects of political risk are weighted based on the number of references discussing that aspect. Second, the approach is deterministic using present values for political risk not allowing for adaptation of power system development plans. Third, the measure constructed for political risk recognizes risk based on "nationality" of a resource and not based on its vulnerability to conflict effects, which depends on multiple factors including location.

Bazilian and Chattopadhyay [101] contend that novel planning models that account for conflict-induced risks are necessary and list three options for incorporation of conflict uncertainty within the power system planning framework. They suggest that conflict-induced uncertainties could be reflected through adjusted inputs, simulation-based analysis of proposed plans or stochastic planning frameworks. Their proposed framework greatly inspired this chapter but is characterized by several limitations. First, they focus on planning model enhancements without providing a comprehensive framework for consideration of conflict effects on power systems and relevant guidance for data gathering and framework updates. Second, they do not provide an exhaustive list of conflict effects in their case study. Omission of conflict effects results in impractical planning recommendations. For example, their case study recommends increased investments in diesel generators, completely overlooking the reality of fuel shortages in conflict zones. Third, the authors briefly describe three approaches, but they decide to demonstrate only the first one. That approach ignores the dynamics of the conflict and simply assumes uniform differentiated parameter values for the entire planning horizon.

Based on the above review, I have established that there is a need for a framework that systematically and comprehensively considers conflict effects, acknowledges the dynamic evolution of conflict, and encourages the development of adaptive power system plans.

3.3 PROPOSED FRAMEWORK

The proposed scenario-based modeling framework can be used to address many urgent questions that governments, donors, investors or utilities face. Should development of a centralized grid be an immediate priority for a fragile country? Should investments in large projects be postponed until conflict risk is lower? Which types of resources best serve domestic demand? The proposed framework consists of five analytical steps summarized in Figure 3-1, which I further explain in the subsections of this section: characterization of power system vulnerabilities, development of scenarios on conflict evolution, scenario-based power system planning, uncertainty characterization, and sensitivity analysis.

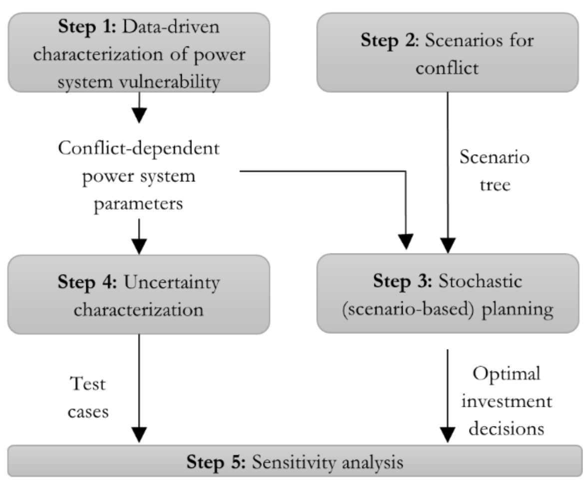

Figure 3-1: Schematic of the proposed scenario-based conflict-aware planning framework

3.3.1 Step 1: Characterization of power system vulnerabilities

Step 1 asks framework users to describe ways in which conflict affects the power system in both qualitative and quantitative terms. The list of interactions should be as comprehensive as possible. Omitting some interactions in the modeling framework will introduce biases favoring or disadvantaging certain investments. For example, past research [101] concluded that diesel generators can reduce outages in South Sudan during times of conflict, but this ignores the fact that diesel fuel shortages frequently occur in times of conflict. Figure 3-2 depicts the complex network of interactions that the review of past conflicts in Section 3.2.2 revealed.

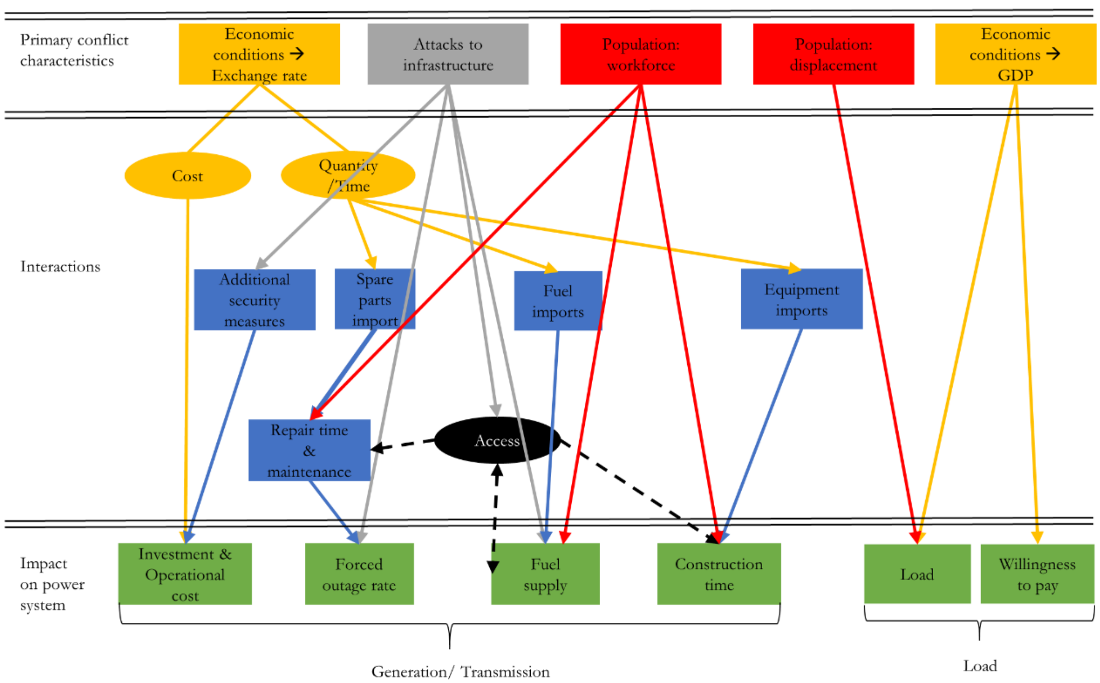

Figure 3-2: Schematic describing conflict's effects on power systems

The very existence of the complex and multi-dimensional interactions depicted in Figure 3-2 points to the intrinsic difficulty of modeling conflict's effects. Figure 3-2 should be used as a starting point in Step 1 to qualitatively describe conflict effects. Then, planners should customize it to make the framework representative of local conditions. For instance, if past evidence or information available to planners suggests that conflict leads to restricted access to capital, Figure 3-2 should expand to account for access to capital. Finally, planners should search for empirical research and data that could serve as an adequate basis for quantifying interactions. I provide a comprehensive list of sources I used to quantify interactions for the case study presented in this chapter in Section 3.4. Some sources might be useful in other conflict environments, too.

Following a hierarchical approach to describe conflict effects helps framework users to identify the primary characteristics of a conflict that impact power systems. In that manner, the framework facilitates generation and evaluation of actions planners could take to mitigate the impact of conflict on power systems. Following a hierarchical approach to develop Figure 3-2, I list in the upper level primary conflict characteristics. Then, in the middle level, I draw the mechanisms and procedures through which primary conflict characteristics affect power systems. Finally, the bottom level includes all conflict-affected power system planning parameters.

Figure 3-2 showcases the value of the hierarchical approach since planning parameters are affected by multiple phenomena. For instance, multiple factors contribute to the increase of forced outage rate under conflict. Deliberate attacks to power system assets render the assets idle for more time than usual. Moreover, improper maintenance during conflict leads to a higher malfunction rate as well. In addition, repair time might increase because efforts to restore the operation of power system assets might be challenged by unavailability of technicians, spare parts, equipment and inaccessibility to the sites of power system assets.

So, I list changes in economic conditions, demographics and attacks as primary conflict characteristics. Then, in the medium level, I describe the impact of upper-level stresses on efforts of power system agencies to import fuel and equipment, recruit personnel, access sites, guard assets and meet financial obligations. At the bottom level, I list conflict-affected parameters such as forced outage rate, cost, fuel supply, load, construction time. In the following paragraphs, I explain the mechanisms through which each primary conflict characteristic affects power system planning and operation.

Economic conditions are profoundly different in times of conflict (see Section 3.2.2 for a thorough discussion). In Figure 3-2, I include only two metrics (exchange rate and gross domestic product), but planners can expand the figure to include more metrics and/or use metrics that better represent the variables planners and governments control. Exchange rate is one macroeconomic metric frequently affected by conflict conditions [138]. Effects of exchange rate changes are widespread and alter the valuation of costs in local currency. It is important to note that financial obligations are often valued at an international currency and extreme exchange rate fluctuations significantly affect the ability to pay back loans for power system development. At the same time, the ability to import fuel, spare parts and equipment is affected. Import difficulties subsequently undermine the ability to repair power system components, build new assets and supply fuel. Gross domestic product is another metric that reflects the impact of conflict on economic development. Economic development is highly related to electricity demand growth and the willingness of consumers to pay for electricity services.

Deliberate attacks to infrastructure affect power system operation and development directly and indirectly. Directly when power system infrastructure is the target of the attacks. Indirectly when attacks target fuel supply or transportation infrastructure. Interdependency of infrastructure sectors allows disruptions on one sector to translate into disruptions for other sectors (here power) as explained earlier in Section 3.2.2.

Population dynamics are also quite challenging in conflict conditions. Involvement of population in violent activities limits personnel available to work on peaceful activities such as repair and construction of power system infrastructure. At the same time, population displacement is another sad reality in conflict zones. Displacement of population leads to change in geographical composition of population and subsequently load. If the displacement is permanent, then electricity demand projections should reflect population movements.

3.3.2 Step 2: Development of scenarios on conflict evolution

In the second step, planners should choose an approach to generate scenarios for conflict evolution. As discussed in Section 3.2.1, to develop scenarios and their associated probabilities (if necessary), planners may choose a qualitative, quantitative or hybrid approach [114]. Planners should first specify desirable attributes for scenarios. In that way, they can narrow their search for a method. For instance, time horizon is an attribute that planners should decide on under step 2. Usually, planning models assess investments in a multi-decadal horizon. Thus, only methods that can provide multi-decadal projections should be considered. In that manner, the set of alternative methods narrows as methods that provide intra-annual projections for next year do not meet the multi-decadal horizon requirement. Similarly, based on the review of conflict effects planners conducted in step 1, they can decide if they will model different levels of conflict intensity and which definition of conflict works best for them. Thus, planners should choose which states they want to consider. States reflect different degrees of political instability or conflict escalation. Another important consideration for planners here relates to the presence of signposts, i.e., information they can monitor or obtain as the future progresses and allows for adaptation of plans. In the case study, I use as a signpost the conflict history since it can be observed and is one of the predictors of future conflict. See Figure 3-3 for an example output of step 2. I explain in detail this scenario tree in Section 3.4.2.

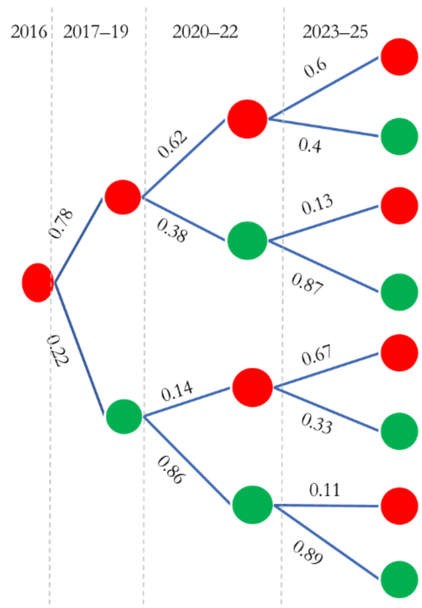

Figure 3-3: Example output of Step 2: Decision tree considered for the South Sudan case study.

3.3.3 Step 3: Scenario-based planning

In the third step, the framework employs a model that uses the scenario tree of step 2 and scenario-dependent values for conflict-affected parameters of step 1. To allow for learning and updated conflict projections as more information becomes available e.g., on conflict history, the model is formulated as a multi-stage mathematical program [154] with decision variables on investment and operations. To reflect investors' attitudes towards risk and account for available data, planners choose a model type (stochastic [154] or robust [155]). For example, a stochastic programming model that minimizes the probability-weighted present worth of costs can represent a competitive, risk-neutral investment environment, in which investment decisions are conditioned on the country's conflict history and are made knowing only the probabilities of the following states. On the other hand, alternative objective functions such as Conditional Value at Risk [154] or a risk-averse utility function might be more appropriate in case of risk-averse investors within a stochastic framework.

For any of these choices, the mathematical program should model the dynamics of conflict, account for timing between planning studies, and acknowledge that the planner can adapt investments based on conflict history. A stochastic programming model, such as the one applied in the case study, endogenously assesses the conflict risks and suggests the most efficient strategy — in terms of the objective function — to meet the projected demand. Moreover, the temporal, technological, and geographical resolution of the model allows planners to assess the relative vulnerability to conflict effects of investments pursued in different years, technologies, and locations. In particular, a model with adequate temporal, technological, and geographical resolution evaluates three generic courses of action. First, planners can wait for some of the conflict uncertainty to be resolved, deferring certain investments. Second, planners can diversify or change the technological/geographical composition of the investment plan. Third, planners can adjust capacity levels (e.g., install redundant capacity as backups). In general, a strategy (i.e., the set of scenario-dependent investment plans comprising the solution of the model) can include a single action or combinations. Later, in Section 3.6, it becomes obvious that recommended strategies often include instances of all three.

3.3.4 Step 4: Characterizing uncertainty

In step four, planners describe how uncertain the values used for conflict-dependent parameters in step 1 are. Planners can choose to describe uncertainty either through a set of possible values or a range to consider. In the case study of Section 3.4**,** I focus on extreme values for each conflict-affected parameter. In other words, I do a type of min-max sensitivity analysis. The minimum for each parameter is the value considered in the conflict-naïve model (which disregards the possibility of conflict) and the maximum (worst possible value) is based on past data or experience elsewhere.

3.3.5 Step 5: Sensitivity analysis

Sensitivity analysis (step 5) is needed because crucial information on conflict impacts is missing. This step investigates alternative recommendations suggested by model instances of step 3 that account for values of uncertain parameters determined in step 4. Results obtained under step 5 indicate the importance of each uncertain parameter, informing discussions on actions that might limit the impact of the uncertainty. Example of such an action is to adopt emergency response practices to reduce vulnerability or repair times.

3.4 CASE STUDY

The framework can be applied to any country. The case study offers a concrete example of a framework application and illustrates what sort of insights can be derived. I choose South Sudan for three reasons. First, two years after its independence in 2011, the country fell into a 5-year civil conflict. Divisions within the government that caused the civil conflict [156] have been at least temporarily resolved in August 2018 [157], [158]. Second, the country has the third lowest electrification rate in the world (9% in 2016 [159]). Electricity is almost entirely produced by local diesel generators (99 % of electricity came from oil sources in 2015 [160]). Thus, power grid development there is a green-field application, with no existing infrastructure constraining the design of the future power system. Third, the country has relatively large hydropower potential along the river Nile [161] and has previously encouraged investment in large-scale hydro projects that however did not materialize (see past preliminary agreements with investors for a 540 MW dam [162] and presentations by government officials [163]). I conjecture that one reason for this failure is the risk of conflict which was not considered in the planning phase of those projects. In the following subsections, I explain in detail how I applied each step of the framework.

3.4.1 Step 1: Implementation

Here, I consider effects of conflict on the power system through four planning parameters for which I was able to draw assumptions on their values under conflict conditions based on past data. However, the framework allows planners to model more conflict effects and a greater number of levels of intensity of conflict by expanding the set of conflict-affected parameters and conflict states, respectively. The geographical resolution for the status identification is the entire country. In other words, I do not allow for differentiated status of the conflict among regions within the country. This assumption might seem limiting since it is common for conflicts to be more intense in specific states or areas. On the other hand, even when one region of the country is in conflict, there might be power disruptions and conflict effects experienced in other parts of the country as well.

3.4.1.a Unavailability of the transmission network

Data from the Energy Infrastructure Attack Database (EIAD) [131] are used to quantify the impact of conflict on the transmission grid. EIAD has particularly good coverage of attacks to the Colombian power system for years 1995–2011. In the future, if more data become available, assumptions could rely on a broader analysis at a global level or within a set of countries with conflict dynamics similar to the country of interest.

Here, I calculate an average outage rate of ~41% for lines that connect more than 1000 MW of generation to the Colombian network over 1998–2002 (when the homicide rate was consistently increasing [164]). Therefore, I adopt a uniform assumption concerning the unavailability of the transmission network. All lines are assumed to be unavailable for half a year when the country is in conflict. This approach could be interpreted as a rebel group taking over the control room and the warehouse with spare parts for transmission lines for 6 months, not allowing energy to flow over the transmission system. Note though that the estimated outage rate varied a lot within the sample (see Table A-1) with some lines being almost completely down during the full five-year period and others experiencing only short outages. Multiple reasons might explain the observed differences but a model predicting the outage of a transmission line given its attributes (e.g., length, region, MW, etc.) is out of the scope of this chapter and could be the aim of future research. I consider alternative values for the outage rate in step 4.

3.4.1.b Fuel shortages

To estimate fuel availability in South Sudan, I base my assumptions on a recent report by the Sudd Institute [132]. That report provides historical availability of oil in South Sudan and outlines some options to increase availability in the future. In particular, the supply of oil for power generation during conflict occurring in the first stage is assumed to be equal to the supply of diesel in December 2015 (2.3 million liters). If the country experiences three years of peace between conflict events, I assume that the depots with total capacity of 100 million liters described in the report will be available and refilled once per year during times of conflict. Under peaceful conditions, I assume four levels for the supply of oil for power generation. When peace is restored in the country, the quantity of level 1 is supplied and then it takes 3 years of peace to move to a higher level:

- Level 1: The Juba storage facility can be refilled once per month and the whole quantity can be used for power generation. On top of that, imports of 40 million liters per month resume.
- Level 2: In addition to Level 1 options, depots with a total capacity of 100 million liters are available and refilled once a quarter, increasing the annual quantity available by 400 million liters.
- Level 3: Refinery producing 3,000 b/day [165] is added to the supply options of Level 2.
- Level 4: Refinery producing 50,000 b/day [165] is added to the supply options of Level 3.

In situations of fuel supply shortages, prices are higher than usual. To properly account for price increases, I would need a supply-demand model for the oil market in South Sudan. However, given the unavailability of such a model, I resort to a simple multiplier (2.0) that I apply every time the country is in conflict. My assumption seems to be in line with observed prices in Juba [166] (see Figure A-1).

3.4.1.c Exchange rate

Since the abandonment of the constant rate of 2.96 SSP/US $ on 15 Dec 2015 [167], the exchange rate has risen to 133 SSP/US$ in Dec 2017 [166]. Note that the aforementioned rate is the official/commercial exchange rate, which is much lower than the parallel exchange rate. Projecting the exchange rate in such an environment is highly challenging. So, for the purposes of this model, I adopt a simple assumption with two distinct levels for the real exchange rate based on IMF's World Economic Outlook projections [168]: 13.6 SSP/US$ when the country in conflict and 6 SSP/US$ when peaceful conditions prevail.

3.4.1.d Construction time

I assume that construction time in South Sudan is identical to construction time in the USA when the country is experiencing peace because the construction time for hydropower plants reported in a local report [169] is identical to the one assumed in the USA [170]. Because this assumption seems optimistic for developing countries [171], [172] , the initial construction time for hydropower plants is the one I consider when the country is in conflict. That assumption allows some time for recovery to normal operations in the post-conflict environment. The assumed time falls to the USA value post 2020 in case of continued peace. To predict the construction time under conflict, I applied the following logic. Units for which construction started in times of conflict under any of the first three stages will generate after: (a) Double the construction time of peace has passed; and (b) Consecutive years of peace equal to the construction time during peace have been experienced.

3.4.1.e Other conflict effects

As noted in the beginning of the section, I consider conflict-dependent values for four planning parameters. Here, I briefly discuss how two conflict effects I did not consider could affect the results and suggest ways for future applications to consider them.

(1) Damages. Damages vary significantly across conflicts and I could not develop a good estimate of their magnitude. This simplification is not expected to significantly affect the results for at least two reasons. First, damage on generation assets is minor as long as power plants are well guarded. Second, repair cost for transmission lines might further discourage remote generation but the operational disruption caused by outages has already significantly shifted the plan away from remote generation options illustrating this insight in our case study. In future applications, planners might want to simulate different scenarios of attacks to infrastructure and perform Monte Carlo Simulations in order to obtain estimate of damages.

(2) Load. Population displacement is frequently observed in a conflict [173]. For example, the 2nd biggest city in South Sudan (Malakal) has been evacuated multiple times during the last couple of years [174], [175]. Existing literature on the return of forcibly displaced population is scarce and focuses on factors that influence the desire and/or the decision to return [176]. Hence, population distribution post-conflict is highly uncertain. Here, given the focus of the study on urban centers, I assume that reintegration programs by the United Nations or other agencies will be successful and the population distribution will be the same as pre-conflict. In addition, I did not consider any link between the national GDP and load projections, assuming that the demand projection just covers basic population needs.

3.4.2 Step 2: Implementation

Here, I chose the model developed by Hegre et al. [119] to develop scenarios for conflict evolution (i.e., sequence of states). To the best of my knowledge, this is the only quantitative model I could use to derive multi-decadal conflict scenarios because it provides the probability of transition from conflict to peace, peace to conflict, peace to peace and conflict to conflict. Moreover, Hegre et al. [119] have documented their procedure in detail and provide supplementary information online, rendering replication of their model easy. Finally, its predictive skill, as judged by the AIC and Brier score, is acceptable. Future framework users should compare the relative advantages of Hegre et al.'s model to other alternatives.

I formulate the chosen model in Matlab using input data described in Appendix A.3. I generate 9,000 sequences of states for South Sudan spanning from 2017 to 2045. Each year the country can be in any of the following three states: minor conflict, major conflict, peace. For each sequence, I determine the status of the country during the first three stages (stage 1: 2017–2019, stage 2: 2020–2022, stage 3: 2023–2025). If the country is under minor or major conflict for two or three years belonging to a stage (2017–2019, 2020–2022, 2023–2025), the status of the relevant stage is conflict. I assign each of the 9,000 sequences to one of the eight scenarios of Figure 3-3 based on the conflict status during the first three stages. Upon assignment of each of the 9,000 sequences to a scenario, I calculate the probability of the scenario as the number of sequences assigned to the scenario divided by the total number of sequences, i.e., 9000. For years belonging to the fourth stage (i.e., 2026–2030, 2035, 2040, 2045), I calculate the probability of conflict for each year under each scenario as follows. First, I count the number of sequences that are assigned to the scenario and have minor/major conflict that year. Last, I divide this number by the total number of sequences that are assigned to the scenario.

3.4.3 Step 3: Implementation

I decide to use a multi-stage stochastic programming model, where the objective function is the expected value of costs. I use four stages, where each of the first three stages lasts three years and the fourth stage approximates 24 years. I choose three years as the duration of the first three stages to keep it short enough to benefit from recent history (if a stage is long, its very first years are probably of low predictive value for the status of the next period), but long enough to align with typical power sector planning cycles. That way, for instance, I let the planner choose between investments in the 4th year based on the conflict record of the first three years (stage 1). Then, on 7th year the planner can choose a strategy based on the conflict record of the first two stages, and finally in the 9th year the planner can choose a strategy based on the conflict record of the first three stages. Note that after year 9 I do not allow for further differentiation in strategies because the complexity of the model would not be justified by the limited value the additional options would provide to the immediate plan. However, I simulate operational impact of conflict and allow differentiation of operational decisions in the 4th stage. Second, given computational limitations and the limited data on how the extent of conflict effects might differentiate under different severities of conflict, I choose to model just one conflict state. The structure of the problem is illustrated through a decision tree in Figure 3-4 and described analytically in the mathematical formulation of Section 3.4.3.a.

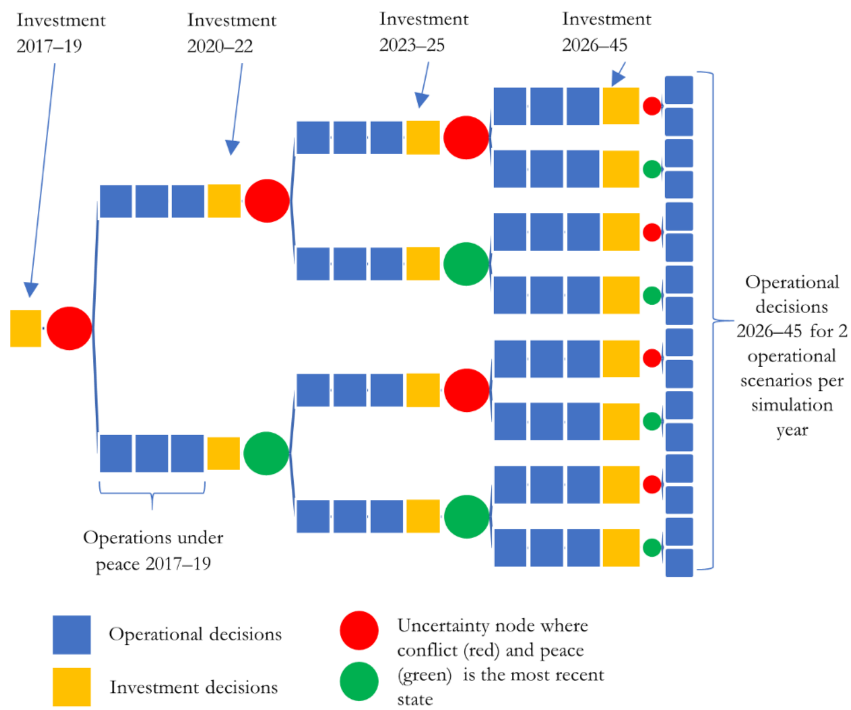

Figure 3-4: Decision tree that schematically describes the multi-stage stochastic program used in the case study

3.4.3.a Mathematical formulation

This subsection documents the equations of the mathematical program I use in this case study and explains the purpose of each equation. Note that in the formulation at the end of this subsection, green font is used for the conflict-affected parameters, i.e., the parameters that have different value depending on the state or the trajectory of conflict.

The model minimizes expected cost over all eight scenarios. Equation (3-1) calculates the expected (probability weighted) cost, which consists of annualized capital cost payments over the horizon (Eq. 3-2), operational costs (Eq. 3-3) and penalty for unserved energy (Eq. 3-4). VOLL is the penalty for unserved energy and a value of 800$/MWh is used in line with the estimated average willingness to pay by consumers in Juba [177]. In future applications, multiple levels of Value of Lost Load could be considered to reflect different types of load and the impact that disruption of their provision could have on the community. For example, hospitals have loads with high VOLL, which however are usually secured through on-site back-up generators. The model could readily be formulated to recognize this value and capability and curtail such loads only if all other loads are curtailed first. Fuel costs constitute a significant portion of the operational cost. To estimate fuel prices, I adopt a typical approach [16] which assumes that oil is sold at the international price in the capital, but a markup applies to other regions. The mark-up is assumed to be equal to the transportation cost from the capital. I estimate it assuming a truck traveling at 40 km/h, carrying 300 l per trip and consuming 12 l/hour. I slightly adjust some of the mark-ups based on historical data from the country.

I assess the economics of possible investment in batteries and three types of power generation: oil, hydropower and photovoltaic (PV). For oil, PV and batteries, the technology characterization is general because it does not specify exactly how those resources are deployed — as centralized grid installations or distributed among customers or microgrids. Meanwhile for hydropower, I consider five specific projects ranging from small-scale to large-scale hydropower plants (see Table A-4). In the formulation, the size of each hydropower project is noted as POT_g and the modularity of projects is represented through binary variables ($build\_hy$). Equation (3-5) ensures that the capacity available each year is increased by the investments completed and decreased by retirements compared to last year. Equation (3-6) retires generating units that exceed their operational life. Equation (3-7) limits unit output by its available capacity in each hour. Moreover, to accommodate maintenance outages, every unit's annual energy use is limited in (3-8). Fuel limits are enforced by (3-9) and transmission flows are bounded by (3-10).

Equation (3-11) is the energy balance for each node and hour. Some nodes just connect generators to the system (e.g., that is the case for hydropower plants) whereas 13 nodes are used to model 13 major cities in the country. Demand for those 13 cities are set at target levels from a past study [169]. One key assumption is that resources can always provide energy to any load located at the same node as the resource, even when the centralized network has been compromised. In other words, I ignore the operation of distribution system in my calculations. Hydropower generation is seasonal and thus, I limit hydro generation for two seasons (noted $\boldsymbol{P}$) in (Eq. 3-12). I approximately model battery storage in equations (3-13)–(3-15). For storage, I assume 75% round-trip efficiency, the capacity to store three hours of maximum output, and daily cycles for charging and discharging.

Here, I briefly discuss the temporal resolution of the model. I use k-means clustering to group the 8760 hours into 12 representative hours per year. I cluster the 8760 hours based on transmission line unavailability, load, and solar PV output. Clustering splits the 12 representative hours into two groups: 6 hours when the network is on and 6 hours when the network is off in times of conflict. Note that the network is always on when peace prevails in the country. Based on the profile of those two sets, they could also be interpreted as two representative days, consisting of six "hours" each and belonging to one season. This latter observation on the profile of the representative hours allowed me to enforce the storage and hydro seasonality constraints. Modelers can choose from several alternative temporal resolutions for operations within the planning model [178]. Recently proposed methods such as Tejada-Arango et al. [83] attempt to preserve chronological information in order to better simulate short-term constraints on operations; however, none of these recent methods is widely used yet. Generally, chronological representations require more variables and thus larger and less wieldy models. Thus, for this chapter I follow a simple clustering technique to choose a smaller sample of representative hours in order to keep a reasonable model size. In the future, however, planners could adopt a more sophisticated method and benefit from improved approximations of short-term operations.

Finally, equations (3-16)–(3-25) are non-anticipativity constraints that require any investment decision made prior to the resolution of uncertainty to be identical across scenarios with same information revealed.

Nomenclature

Sets and Indices

F	Fuels indexed by *f*
G	Generators indexed by *g*
I	Power system nodes indexed by *i*
L	Transmission lines indexed by *l*
S	Scenarios/trajectories for conflict, indexed by *s*, s'
$S1$	Scenarios/trajectories for conflict in the first stage, indexed by *s1*
$S2$	Scenarios/trajectories for conflict in the first two stages, indexed by *s2*
ST	States (i.e., peace, conflict), indexed by *st*
T	Representative hours of the year indexed by *t*
Y	Years indexed by *y*

Subsets

GHY	Hydropower plants (subset of G)
P	Seasons; partition of *T*, indexed by *p*
$Y1st$	Years (Y) belonging to 1^{st} stage
$Y2nd$	Years (Y) belonging to 2^{nd} stage
$Y3rd$	Years (Y) belonging to 3^{rd} stage
$Y4th$	Years (Y) following the 4^{th} stage

Decision variables

$build_{g,s,y}$	Generation investment in MW, construction starts at *y*
$cap_{g,s,y}$	Capacity in MW
$capex_s$	Present Value of annualized capital expenses over the horizon in scenario *s*
$cha_{g,s,st,t,y}$	Charge of storage *g* in MW
$gen_{f,g,s,st,t,y}$	Generation in MW at hour *t*
$opex_s$	Present Value of operational expenses over the horizon in scenario *s*
$penalty_s$	Present Value of penalty for unserved energy over the horizon in scenario s
$trans_{l,s,st,t,y}$	Power flow over line *l*
$ret_{g,s,y}$	Retirement of generator *g* in MW
$use_{i,s,st,t,y}$	Unserved energy at node *i* in MW

Binary decision variables

$build\_line_{l,s,y}$	Commit to build transmission line; construction starts at *y*
$build\_hy\_1_{g,y}$	Commit to develop hydropower; construction starts any year *y* belonging to stage 1
$build\_hy\_2_{g,y,s1 \in S}$	Commit to develop hydropower; construction starts any year *y* belonging to stage 2
$build\_hy\_3_{g,y,s2 \in S}$	Commit to develop hydropower; construction starts any year *y* belonging to stage 3
$build\_hy\_4_{g,y,s}$	Commit to develop hydropower; construction starts any year *y* belonging to stage 4

Parameters

$\Phi_{i,l}$	Element of node-line incidence matrix
$ANCAP_g$	Annualized capital cost for generator *g* in \$/MW
ACF_g	Maximum annual capacity factor for generator *g*
$CF_{g,t}$	Capacity factor for generator *g* at hour *t*
$CFHY_P$	Capacity factor for hydro during period *p*
D_t	Duration of representative hour *t* in hours
$Diesel_{s,st,y}$	Diesel available for power sector in MMBTU
$ER_{s,y}$	Exchange rate in 2014SSP to US\$
EX_{g,s,y,y_1}	1 for generators within their operational life; 0 otherwise
FOM_g	Fixed Operation and Maintenance costs in US\$
$FOR_{l,s,st,t,y}$	Forced outage rate
HR_g	Heat rate for generator *g* in MMBTU/MWh
$leadtime_{g,s,y}$	Construction time in years
$LOAD_{i,t,y}$	Electricity demand in MW
$Maps1s_{s,s1}$	1 if *s* has the same state in the first stage as s1; 0 otherwise
$Maps2s_{s,s2}$	1 if *s* has the same state in the first two stages as s2; 0 otherwise
$pf_{s,st,y}$	Probability of state *st*
POT_g	Potential for generator *g* in MW
r	Discount rate; assumed 10%
$VC_{f,g,s,st,y}$	Variable cost in \$/MWh
$VOLL$	Value of lost load in \$/MWh

Mathematical Program

$$\text{MINIMIZE} \sum_{s} p_s * (capex_s + opex_s + penalty_s) \qquad \text{Eq. 3-1}$$

$$capex_s = \sum_{g,y} \sum_{y1 \geq y+leadtime_{g,s,y}}^{y1<y+leadtime_{g,s,y}+life_g} \frac{(1+r_1)^{leadtime_{g,s,y}} * \sum_{st} pf_{s,st,y1} * ER_{st,y1} * ANCAP_g * build_{g,s,y}}{(1+r)^{y1-2017}} + \sum_{l,y} \sum_{y1 \geq y+leadtime_{l,,s,y}}^{1<y+leadtime_{l,,s,y}} \frac{(1+r_1)^{leadtime_{l,s,y}} * \sum_{st} pf_{s,st,y1} * ER_{st,y1} * ANCAP_l * build_{l,s,y}}{(1+r)^{y1-2017}} \qquad \text{Eq. 3-2}$$

$$opex_s = \sum_{y,st} \frac{pf_{s,st,y} * \boldsymbol{ER_{st,y}} * (\sum_g FOM_g * cap_{g,s,y} + \sum_{f,g,t} D_t * VC_{f,g,s,st,y} * gen_{f,g,s,st,t,y})}{(1+r)^{y-2017}} \qquad \text{Eq. 3-3}$$

$$penalty_s = \sum_{i,st,t,y} \frac{pf_{s,st,y} * D_t * VOLL * use_{i,s,st,t,y}}{(1+r)^{y-2017}} \qquad \text{Eq. 3-4}$$

$$cap_{g,s,y} = cap_{g,s,y-1|y>2017} + \sum_{y1|y1+leadtime_{g,s,y_1}=y} build_{g,s,y_1} - ret_{g,s,y} \qquad \forall(g,s,y) \qquad \text{Eq. 3-5}$$

$$cap_{g,s,y} \leq \sum_{y_1} EX_{g,s,y,y_1} * build_{g,s,y_1} \qquad \forall(g,s,y) \qquad \text{Eq. 3-6}$$

$$\sum_f gen_{f,g,s,st,t,y} \leq CF_{g,t} * cap_{g,s,y} \qquad \forall(g,s,st,t,y) \qquad \text{Eq. 3-7}$$

$$\sum_{f,t} D_t * gen_{f,g,s,st,t,y} \leq ACF_g * cap_{g,s,y} * 8760 \qquad \forall(g,s,st,y) \qquad \text{Eq. 3-8}$$

$$\sum_{g,t} D_t * gen_{f,g,s,st,t,y|f=diesel} * HR_g \leq Diesel_{s,st,y} \qquad \forall(s,st,y) \qquad \text{Eq. 3-9}$$

$$|trans_{l,s,st,t,y}| \leq FOR_{l,s,st,t,y} * \sum_{y_1+leadtime_{g,s,y_1} \leq y} build\_line_{l,s,y_1} * SIZE_l \qquad \forall(l,s,st,t,y) \qquad \text{Eq. 3-10}$$

$$\sum_{f,g \in I} gen_{f,g,s,st,t,y} - \sum_{g \in I} cha_{g,s,st,t,y} + \sum_l \Phi_{i,l} * trans_{l,s,st,t,y} + use_{i,s,st,t,y} = LOAD_{i,t,y} \qquad \forall(i,s,st,t,y) \qquad \text{Eq. 3-11}$$

$$\sum_{f,t \in P(t)} gen_{f,g,s,st,t,y} * D_t \leq CFHY_{g,p} * cap_{g,s,y} * \sum_{t \in P} D_t \qquad \forall(g \in GHY, p, s, st, y) \qquad \text{Eq. 3-12}$$

$$\sum_{t \in P} gen_{f=storage,g,s,st,t,y} * D_t \leq 0.75 * \sum_{t \in P} cha_{,i,s,st,t,y} * D_t \qquad \forall(g \in Storage, p, s, st, y) \qquad \text{Eq. 3-13}$$

$$\sum_{t \in P} cha_{g,s,st,t,y} * D_t \leq cap_{g,s,y} * \frac{4}{24} * \sum_{t \in P} D_t \qquad \forall(g \in Storage, p, s, st, y) \qquad \text{Eq. 3-14}$$

$$cha_{g,s,st,t,y} \leq cap_{g,s,y} \qquad \forall(g \in Storage, s, st, t, y) \qquad \text{Eq. 3-15}$$

$$build_{g,s,y} = build\_hy\_1_{g,y} * POT_g \qquad \forall(g \in GHY, s, y \in Y1ST) \qquad \text{Eq. 3-16}$$

$$build_{g,s,y2nd} = \sum_{s1} maps1s(s,s1) * build\_hy\_2_{g,y,s1} * POT_g \qquad \forall(g \in GHY, s, Y2nd) \qquad \text{Eq. 3-17}$$

$$build_{g,s,y} = \sum_{s2} maps2s(s,s2) * build\_hy\_3_{g,y,s2} * POT_g \qquad \forall(g \in GHY, s, Y3rd \qquad \text{Eq. 3-18}$$

$$build_{g,s,y} = build\_hy\_4_{g,y,s} * POT_g \;\; ghy, y4st, s \qquad \forall(g \in GHY, s, y \in Y4TH) \qquad \text{Eq. 3-19}$$

$$build\_line_{l,s,y} = build\_line_{l,s',y} \qquad \forall(l, s, s', y \in Y1ST) \qquad \text{Eq. 3-20}$$

$$build\_line_{l,s,y} = build\_line_{l,s',y} \qquad \forall(l, s \in maps1s(s,s1) = 1, s' \in maps1s(s',s1) = 1, s1, y \in Y2ND) \qquad \text{Eq. 3-21}$$

$$build\_line_{l,s,y} = build\_line_{l,s',y} \qquad \forall(l, s \in maps2s(s,s2) = 1, s' \in maps2s(s',s2) = 1, s2, y \in Y3RD) \qquad \text{Eq. 3-22}$$

$$build_{g,s,y} = build_{g,s',y} \qquad \forall(g \notin GHY, s, s', y \in Y1ST) \qquad \text{Eq. 3-23}$$

$$build_{g,s,y} = build_{g,s',y} \qquad \forall(g \notin GHY, s \in maps1s(s,s1) = 1, s' \in maps1s(s',s1) = 1, s1, y \in Y2ND) \qquad \text{Eq. 3-24}$$

$$build_{g,s,y} = build_{g,s',y} \qquad \forall(g \notin GHY, s \in maps2s(s,s2) = 1, s' \in maps2s(s',s2) = 1, s2, y \in Y3RD)) \qquad \text{Eq. 3-25}$$

Variables $build_{g,s,y}$, $cap_{g,s,y}$, $cha_{g,s,st,t,y}$, $gen_{f,g,s,st,t,y}$, $ret_{g,s,y}$, $use_{i,s,st,t,y}$ are positive.

3.4.4 Step 4: Implementation

The values for all conflict-affected parameters I use are uncertain. There are different ways to describe how uncertain the values used are. Here, I decide to use a min-max approach, where the minimum value for each uncertain factor is the value during peace.

For forced outage rate, I assume that 50% of the time transmission lines would be unavailable. However, according to data from the Colombian conflict some lines were unavailable during the entire year. So, the maximum value considered is 100%.

For exchange rate, I use the IMF projection for the base case analysis (13.6 SSP/$). However, the observed exchange rate in December 2017 was much higher (130 SSP/$) [166]. Thus, the maximum value of 130 SSP/$ is considered.

For construction time, I do not have detailed evidence. Whereas for fuel shortages, the impact on the results is already pronounced. So, for both of them I decide to not perform a sensitivity analysis. Moreover, this case study is not an actual planning study and the main purpose of the analysis is to shed some light on the mechanisms of conflict. As it will become obvious from the results, this objective is achieved by just looking only into two cases with extreme impact for forced outage rate and exchange rate in this case study.

3.4.5 Step 5: Implementation

The main purpose of this step is to estimate the sensitivity of recommended plans to uncertain assumptions. So, using the maximum values determined in Section 3.4.4 and the model of Section 3.4.3.a, I obtain additional investment strategies that I further analyze and provide additional insight on the impact of the uncertainties.

Moreover, I expand the scope of this step to include analysis of policy and financing constraints. According to practitioners and researchers working on electrification in Sub-Saharan Africa [179], policies and financing constraints might have significant impact on the development plans. Thus, I decide to explore how sensitive results obtained from my model are to both constraints.

3.5 EXPERIMENTAL DESIGN

This section aims to help the reader understand the set of model runs I performed and the rationale behind them. Overall, I solved the mathematical problem described in 3.4.3.a nine times under different specifications using CPEX 12.6 solvers within GAMS. The problem is a mixed integer program and the solution method I employ is branch and bound. I terminate the algorithm and record the best feasible solution when either adequate time had passed (75,600 sec) or the optimality gap is less than 0.5%.

Table 3-1 provides an overview of the model specifications for the nine strategies. Strategy 1 or alternatively called "conflict-naïve" resembles the status-quo approach traditionally followed by power system planners. The model instance used for strategy 1 assumes conflict-free values for the conflict-affected parameters, completely ignoring the conflict environment. Then, in strategies 2–5, I adjust values for conflict-affected parameters to reflect conflict conditions one at a time until all four conflict effects are simulated in strategy 5. In detail, strategy 2 considers the effect of increased transmission outages and then 3 adds fuel shortages, 4 adds exchange rate deterioration, and finally 5 adds increases in construction time, at which point all four effects are modelled.

Table 3-1: Specifications for model runs

	Conflict effects				Unserved demand		Financing constraint	
	Forced Outage	Fuel shortages	Exchange Rate	Construction time	Allowed through out the horizon	Fixed to zero after a certain year per scenario	No annual constrai nt	Annual require ment to break-even
1: "Conflict-naïve strategy"	+				+		+	
2: "Transmission outage-aware strategy"	+	+			+		+	
3: "Outage/shortage-aware strategy"	+	+	+		+		+	
4:Outage/shortage/ ER-aware strategy"	+	+	+		+		+	
5: "Conflict-aware strategy"	+	+	+	+	+		+	
6: "Maximum-FOR conflict-aware strategy"	+	+	+	+	+		+	
7: "Maximum-ER conflict-aware strategy"	+	+	+	+	+		+	
8: "Zero-unserved energy" strategy	+	+	+	+		+	+	
9: "Conflict-aware strategy with financing constraint"	+	+	+	+	+			+

To demonstrate the additional value a strategy that is conflict-aware (i.e., considers conflict effects to devise a power system plan) offers, I also solve a slightly different model from the one in Section 3.4.3.a. This modified model instance fixes the investment decisions at the levels obtained by the conflict-naïve strategy. Thus, investment decisions are no longer decision variables and the set of decision variables just includes operational decisions: output levels for generators, flows over transmission lines, and unserved demand at each representative hour of the model years in each scenario. I solve this modified model instance four times with direct correspondence to strategies 2–5 in order to estimate cost and performance of the conflict-naïve strategy under the influence of one, two, three, and four conflict effects. By construction of the model instances, strategies 2–5 will perform better in expected cost terms (i.e., have lower objective function) than their counterparts with investment decisions fixed because the feasible region of the former model instance is larger.

As part of the sensitivity analysis, to account for different level of conflict effects, I solve two additional model instances with maximum values for forced outage and exchange rate considered (see strategies 6 and 7). Finally, strategies 8 and 9 account for policy and financing constraints respectively. Strategy 8 assumes that the global community is committed to achieve universal electrification at the earliest time possible. I model this commitment by not allowing the unserved energy to be non-zero after a specific year in each scenario (see Table A-5). Note that the target demand in the model does not correspond to 100% electrification since it is focusing on urban centers and accounts for a smooth trajectory of electrification. Lastly, the model instance for strategy 9 includes an additional financing constraint. That constraint ensures that the annual revenues from electricity services are adequate to pay off any operational costs and loan paybacks for power plant construction. The constraint considers the maximum value for revenues, which is calculated by multiplying the willingness to pay (VOLL) by the amount of served energy.

3.6 RESULTS

In the following sub-sections, I discuss results obtained from all model instances solved under the same set of assumptions with respect to conflict effects, policy and financing constraints.

Results demonstrate which course(s) of action is recommended for planners in each case i.e., differentiation, adjustment, postponing. For each strategy, I discuss capacity additions and provide the levelized cost of electricity (LCOE) and unserved energy rate (USE).

$$LCOE_s = \frac{capex_s + opex_s}{\sum_y \frac{\sum_{t,i,st}(pf_{st} * (LOAD_{i,t,y} - use_{i,s,st,t,y}) * D_t)}{(1+r)^{y-2017}}} \quad \text{Eq. 3-26}$$

$$USE_s = \frac{penalty_s}{\sum_{i,st,t} pf_{st,y} * D_t * VOLL * LOAD_{i,t,y}} \quad \text{Eq. 3-27}$$

Note that in sections 3.6.2–3.6.5 — where I discuss results obtained from both model instances (conflict-naïve and conflict-aware framework) under one to four conflict effects — I choose to first discuss the impact of conflict effects on the performance of the conflict-naïve strategy and then explain how the conflict-aware strategy is different from the conflict-naïve strategy and in which ways this differentiation allows it to achieve better results.

3.6.1 Conflict-naïve strategy

The standard model assumes uninterrupted peace and recommends a plan with the following estimates: levelized cost of electricity (LCOE) of 942 2014SSP (South Sudanese Pound) per MWh and an unserved energy rate (USE) of 0.14%. In the short term (up to 2024) while hydropower capacity is under construction, the conflict-naïve plan relies mainly on oil (>75% of generation) to meet demand. In the medium term (up to 2035), large-scale hydropower becomes the major source of electricity (>80% of generation during 2024–2035). Finally, in the long term (2040–45), hydropower serves ~70% of the demand, while PV and oil provide the rest. Please see detailed results in Appendix Section A.6.

From a least-cost perspective, the conflict-naïve plan seems reasonable for two reasons. First, hydropower is a promising option with low estimated construction costs and satisfactory capacity factors. Second, the other options are less attractive because of high oil prices (due to the absence of local refineries), and incompatibility of night peaking demand with PV generation. However, the LCOE and USE estimated ignore the fact that the power system would have to operate during times of conflict and as it will become obvious in the following sub-sections the estimates obtained from the conflict-naïve framework grossly underestimate the values of those two metrics in case of conflict.

3.6.2 Transmission outages during conflict

During transmission outages, electricity from remote generation (especially hydro) and excess generation from different nodes does not reach load. Local generators, mostly oil, increase output to the extent possible to accommodate the loss of hydropower (see Table 3-2).

Table 3-2: 2025 Energy mix (GWh) when the conflict-naïve strategy is followed and transmission outages are simulated

Scenario	**Status**	**Oil**	**Hydro**	**PV**	**Energy served (GWh)**
Conflict-Conflict-Peace	Peace	0%	86%	14%	2,412
Conflict-Conflict-Conflict	Conflict	38%	47%	15%	2,317
Conflict-Peace-Peace	Peace	0%	86%	14%	2,412
Conflict-Peace-Conflict	Conflict	38%	47%	15%	2,317
Peace-Conflict-Peace	Peace	0%	86%	14%	2,412
Peace-Conflict-Conflict	Conflict	38%	47%	15%	2,317
Peace-Peace-Peace	Peace	0%	86%	14%	2,412
Peace-Peace-Conflict	Conflict	38%	47%	15%	2,317

On the other hand, strategy 2 installs more local capacity (oil, PV, storage) in the short term. Thus, even when the transmission network is unavailable, higher share of the demand can be met (see USE in Table 3-3). At the same time, strategy 2 adjusts hydropower capacity investments. Hydropower investments are still pursued early in the horizon, but they are in smaller units (300 MW). The largest hydropower project considered (which also happens to be the more economical in $/MWh) is not constructed until 2035. In the long term, oil capacity is at least four times as high as in the conflict-naïve plan. The additional oil capacity, which is redundant under peaceful conditions, allows the system to cope with the transmission outages during conflict. Overall, strategy 2 results in higher cost but lower unserved energy. Detailed information on strategy 2 are provided in Appendix Section A.7.

Table 3-3: Performance of strategies 1 and 2 under conflict with a single effect of transmission outages. Note that results for strategy 1 are reported right of "/" and results for strategy 2 are reported left of "/".

States in 2017–2019, 2020–2022, 2023–2025	LCOE (2014SSP/MWh)	USE (%)
Conflict-Conflict-Peace	1,035/995	0.4%/2.7%
Conflict-Conflict-Conflict	1,121/1,124	0.3%/5.5%
Conflict-Peace-Peace	1,043/1,004	0.4%/3.1%
Conflict-Peace-Conflict	1,126/1,120	0.4%/5.3%
Peace-Conflict-Peace	1,028/989	0.4%/2.4%
Peace-Conflict-Conflict	1,121/1,128	0.3%/5.5%
Peace-Peace-Peace	1,048/1,008	0.4%/3.3%
Peace-Peace-Conflict	1,113/1,118	0.4%/5.2%

3.6.3 Transmission outages and fuel shortages

Transmission outages do not allow remote generation to reach load and at the same time, fuel shortages significantly undermine oil's generation capability (local resource) during conflict.

Similar to strategy 2, strategy 3 recommends local investment. However, given the supply constraint oil generators face, strategy 3 recommends more PV and storage in the short term. In strategy 3, investments are differentiated according to the conflict trajectory realized. For example, in case the first stage is peaceful, there is a short-term shift from PV and storage towards oil capacity compared to scenarios in which conflict occurs in the first period.

Development of the hydropower potential is also different compared to the conflict-naïve plan. Planners are advised to wait until 2035 before including the largest hydropower plant (1.1 GW) in the mix. The long-term exploitation of the hydropower potential also depends on the conflict trajectory. In scenarios with conflict occurring in the third period, the long-term probability of conflict is relatively high, which discourages investments in remote large-scale hydropower, leaving some potential untapped. Under scenarios with untapped hydro, more PV is integrated leading to lower USE rates than the "conflict-naïve strategy". See detailed results supporting all the arguments made here in Appendix Section A.8.

Table 3-4: Performance of strategies 1 and 3 under conflict with two effects: transmission outages and fuel shortages

States in 2017–2019, 2020–2022, 2023–2025	LCOE (2014SSP/MWh)	USE (%)
Conflict-Conflict-Peace	1,119/931	6%/20%
Conflict-Conflict-Conflict	1,193/1,061	9%/31%
Conflict-Peace-Peace	1,116/979	6%/13%
Conflict-Peace-Conflict	1,232/1,125	6%/20%
Peace-Conflict-Peace	1,111/986	4%/9%
Peace-Conflict-Conflict	1,289/1,154	4%/17%
Peace-Peace-Peace	1,098/1,011	4%/5%
Peace-Peace-Conflict	1,195/1,139	5%/11%

3.6.4 Transmission outages, fuel shortages and exchange rate deterioration

Here, I assume that exchange rates deteriorate under conflict because the local currency depreciated during the most recent conflict in South Sudan [167]. Thus, I increase all cost components in line with the exchange rate except one: the willingness to pay for electricity. One consequence is that oil generation in all states except Central Equatoria becomes unaffordable during conflict, letting PV as the sole source of power at times the transmission grid is not operational.

Strategy 4 performs better than the conflict-naïve plan. However, the unserved energy rates estimated by strategy 4 are much higher than the ones achieved when one or two conflict effects are considered (see strategies 2 and 3). As described in Section 3.4.3.a, the objective function consists of penalties for unserved energy and costs to build and operate generators. The model solution is essentially an equilibrium where balance between those two opposing forces (penalty for unserved energy and cost for system construction & operation) is achieved. Here, a deterioration of exchange rate would increase capital and operational cost, but the penalty for unserved energy stays the same. Thus, higher levels of unserved energy result from conflict based on a shift in the balance of the two opposing forces away from costlier system construction and operating expenses.

Strategy 4 further adjusts hydropower investment to the trajectory, even in the short term. For example, if the first period is peaceful or violent, a larger (1,100 MW) or smaller (300 MW) hydropower plant investment is pursued respectively. In the long term, the capacity mix is similar to strategy 3 with some of the hydropower potential remaining untapped in case the third period experienced conflict. The PV and storage capacity of strategy 4 in 2025 is at least three times as high as the conflict-naïve strategy but lower than the amount installed in strategy 3. See detailed capacity mix over time in Appendix Section A.9.

Table 3-5: Performance of strategies 1 and 4 under conflict with three effects: transmission outages, fuel shortages, and exchange rate deterioration

States in 2017–2019, 2020–2022, 2023–2025	LCOE (2014SSP/MWh)	USE (%)
Conflict-Conflict-Peace	1,353/1,228	13%/21%
Conflict-Conflict-Conflict	1,900/1,877	19%/32%
Conflict-Peace-Peace	1,256/1,204	9%/13%
Conflict-Peace-Conflict	1,726/1,774	14%/22%
Peace-Conflict-Peace	1,287/1,213	7%/9%
Peace-Conflict-Conflict	1,944/1,858	14%/19%
Peace-Peace-Peace	1,222/1,161	5%/5%
Peace-Peace-Conflict	1,735/1,649	10%/13%

3.6.5 Four conflict effects considered: transmission outage, fuel shortage, exchange rate increase and construction time delays

Prolonged construction times during a conflict might delay commission of new generators, increasing the levels of unserved energy prior to commission of new units. If conflict continues through several stages, fulfillment of electricity demand seems impossible given disruption of PV supply chains, suspension of hydropower investment and fuel shortages. Under the conflict-aware framework, the average LCOE of the conflict-naïve plan varies between 1,161 and 2,213 SSP/MWh depending on the scenario for the first three stages, and USE levels are, at best, 5% and, at worst, reach 47% (Table 3-6). So, the 0.14% unserved energy rate projected by the conflict-naïve framework greatly underestimates the unserved energy rates that are likely to be realized, and its low value is explained by that framework's disregarding of conflict conditions.

Table 3-6: Performance of strategies 1 and 5 under conflict with four effects: transmission outages, fuel shortages, exchange rate deterioration, and construction delays

States in 2017–2019, 2020–2022, 2023–2025	LCOE (2014SSP/MWh)	USE (%)
Conflict-Conflict-Peace	1,504/1,349	27%/25%
Conflict-Conflict-Conflict	2,213/1,853	47%/42%
Conflict-Peace-Peace	1,395/1,258	16%/14%
Conflict-Peace-Conflict	1,981/1,833	31%/25%
Peace-Conflict-Peace	1,407/1,407	12%/10%
Peace-Conflict-Conflict	2,015/2,006	27%/22%
Peace-Peace-Peace	1,161/1,198	5%/4%
Peace-Peace-Conflict	1,768/1,687	20%/12%

The full conflict-aware strategy (i.e., strategy 5) cannot reduce unserved energy in case of consecutive years of conflict following the first conflict period but it can lessen the financial burden. Anticipating the possibility of delays, the strategy chooses to wait until the probability of conflict has approached its long-term value to decide on high financial commitments such as the ones associated with large hydropower development. For example, if the first period is peaceful, construction of 0.3GW hydropower starts in 2020. On the other hand, if the first three periods are violent or the second period is a brief truce period, hydropower doesn't become part of the energy mix until 2035. While postponing the investment in large-scale hydro, the plan recommends higher investment in local generation earlier in the horizon.

3.6.6 Four conflict effects with extreme forced outage rate

Here, network is assumed to be completely unavailable during times of conflict to simulate extreme disruption of centralized system operations. The unserved energy rates of strategy 1 significantly increase because the system can only rely on PV and limited oil generation (mainly in Juba) during times of conflict.

Strategy 6 accounting for the extreme vulnerability of transmission network to conflict, adjusts investments in remote hydropower. In particular, it invests in small hydropower (300 MW) in case the first period is peaceful; otherwise waits to see if the third period is peaceful. In the long term, hydropower potential is not exploited at the levels of the conflict-naïve plan in any of the scenarios considered. The 522 MW hydropower plant in Bedden is not pursued in any scenario. Overall, PV supported by storage meets higher share of the electricity demand. Detailed information on strategy 6 are provided in Appendix Section A.11.

3.6.7 Four conflict effects and extreme exchange rate increases

Here, I consider exchange rates at the highest level experienced in 2017. According to calculations by my model, the payments for loans valued at international currency become unaffordable under strategy 1, exceeding customers' WTP. At the same time, the high exchange rate renders oil unaffordable for electricity generation in the entire country.

Alternatively, strategy 7 invests up to 2035 predominantly on oil capacity given its low capital cost (despite risk of oil supply disruption) and decreased PV capacity to avoid risk of high interest rates. Because of the high capital expenses required for hydropower development, strategy 7 recommends none or one hydropower project in the long term. Therefore, significant share of the hydropower potential remains untapped. PV investment is significantly lower compared to strategy 5 because of the risk of high loan payments in times of conflict. See detailed information on strategy 7 in Appendix Section A.12.

3.6.8 Conflict-aware with policy constraints

The earliest year that zero unserved energy can be achieved varies among scenarios: from 2017 to 2027 (see Table A-5). The conflict-aware plan (strategy 5) experiences unserved energy in times of conflict across scenarios and years because of its reliance on the central grid and oil resources.

Alternatively, the focus of power development shifts from a balanced mix (strategy 5) to a mix heavily dominated by PV resources, supported by storage (strategy 8). Plans are very similar across scenarios with respect to the start time of construction, but the performance is different because of different timelines for construction across scenarios and exchange rates. Overall, strategy 8 recommends immediate commitment to low oil capacity (2017) and encourages large PV investments (2019) to meet the target demand as early as possible. See detailed capacity expansion plan in Appendix Section A.13.

3.6.9 Conflict-aware plan with financing constraint

Financing limitations are a practical constraint in most markets but are omitted by most planning models, which usually assume unlimited access to capital markets. Following the conflict-aware strategy (strategy 5),utilities cannot pay back their loans in case conflict resumes immediately after its resolution at the beginning of the planning horizon.

On the other hand, strategy 9 (i.e., the conflict-aware strategy with the financing constraint) differs from strategy 5 only in the short term (up to 2025). The short-term mix integrates less oil-fired capacity under scenarios where conflict precedes the investment accounting for the possibility of oil shortages and acute prices that might prevent operation of oil capacity. Instead, investments in PV are made earlier. The precise timing depends on conflict history. Details in the short-term capacity expansion plan suggested by strategy 9 are provided in Appendix Section A.14.

3.7 DISCUSSION

A key feature of the proposed framework is that it simulates the evolution of the conflict, which allows for dynamic adjustment of investment decisions based on conflict history. In particular, the probability of being in one state in a given stage depends on the state in the previous stage, with, for instance, peace following peace being more likely than peace following conflict. Investment commitments are therefore made knowing the past state, but not the following states. Thus, considering the likelihood of conflict, the extent of conflict impacts, and customers' Willingness to Pay (WTP), the model might shift the recommended strategy away from investments vulnerable to conflict effects, especially if conflict has already occurred which increases the posterior probability of conflict in the future.

In summary, alternative strategies 2–5 differ from the conflict-naïve plan in three ways. First, they invest in a more geographically diverse resource mix, integrating higher share of local resources (PV, Oil) in the medium term. The share of PV depends on the combination of conflict effects considered, being the highest when just outages and fuel shortages are considered. The share of oil resources, however, is the highest when only outages are considered and is significantly reduced when fuel shortages are taken into account.

The second difference is that planners sometimes decide to postpone or re-prioritize large hydropower investments. For example, strategies 2 and 3 choose a 300 MW hydropower plant as the first hydropower investment over the 1,100 MW hydro plant recommended by the conflict-naïve plan. Meanwhile, strategy 4 chooses the 300 MW or the 1,100 MW hydropower plant as the first hydropower investment in case the first period experiences conflict or is peaceful, respectively. Anticipating the possibility of delays, strategy 5 chooses to wait until the probability of conflict has approached its long-term value to decide on high financial commitments such as the ones associated with the largest hydropower plant (1,100 MW). Moreover, in contrast to the conflict-naïve plan, strategies 3–5 choose not to integrate a 522MW hydropower plant in long term if the third period has conflict.

The third way that alternative strategies differ from the conflict-naïve solution is that they sometimes include investments just for back-up. For example, strategy 2 includes back-up oil because fuel shortages are not accounted for and the redundant capacity helps the system cope with unavailability of the centralized system. Despite the improvements in unserved energy rates during conflict that the conflict-aware strategy achieves compared to the conflict-naïve strategy, the strategy's 5 rate for 2030 can still approach ~30% under conflict conditions (see Figure 3-5). Therefore, I also investigate how the optimal mix would change in case the planner aimed to have zero unserved energy as soon as possible for each scenario (see Section 3.6.8). In that case (strategy 8), expected costs are 56% higher than the conflict-aware strategy (strategy 5). This increase in supply costs greatly exceeds the assumed WTP for power. PV and storage are central in the power development strategy in that case, as PV and storage operations are assumed to be invulnerable to conflict, and that they only experience financial impacts. I also observe that strategy 5 decreases the amount of unserved energy in later years but not in the short term (up to 2025). So, if revenues depend on the served energy, they may be inadequate to pay back loans. Therefore, strategy 9 sets the upper bound for annual expenditure equal to the product of the demand fulfilled and the WTP. In that case, short-term investments in oil significantly drop because its ability to serve the load is affected by fuel shortages. In contrast, short-term installation of PV increases compared to a solution without this financing constraint, and that PV delivers energy as expected as soon as it is on-line, not being disrupted by transmission outages and fuel shortages.

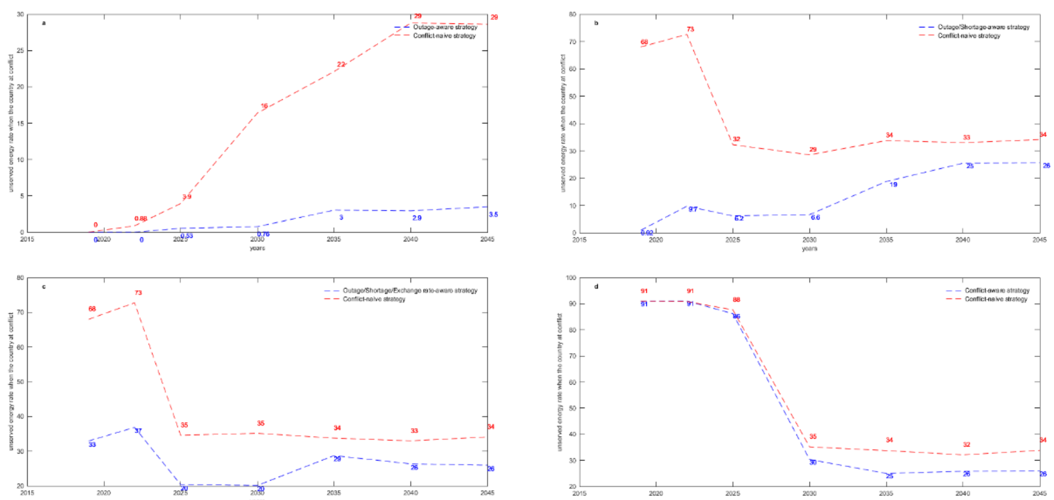

Figure 3-5: Unserved energy rate when the status is “conflict.” The four graphs present the levels of unserved energy as estimated by the conflict-aware model when one, two, three and four conflict effects are considered simultaneously for two strategies: strategy 1 and 2-5 respectively.

Lastly, each effect that I examine penalizes some technologies more than others. As a result, the conflict-aware model recommends a strategy the almost completely eliminates the most impacted technology from the short-term mix and suggests a relatively low amount of investment in it in the later stages. Thus, severe shortages penalize oil investments (see strategy 3); long transmission outages restrict hydro investment (see strategy 6); and acute exchange rates discourage capital-intensive investments such as storage, hydro, and PV (see strategy 7).

3.8 CONCLUSIONS AND FUTURE RESEARCH

To build a power system that better serves the population in a fragile and conflict-affected environment, there are at least three alternatives for power sector investment strategies. First, planners can wait to see how the conflict evolves before investing. Second, planners can pursue a more balanced and diverse portfolio of investments, integrating higher shares of technologies that are less vulnerable to conflict. Third, planners can strengthen the least-cost capacity mix with additional back-up resources.

The trade-off between power outages and cost determines which of the three options to pursue. For example, conflict-aware model's application to South Sudan considers the capital cost of hydropower and the effects of conflict-induced transmission outages on delivery of its generation and suggests wait-and-see for large hydropower investments. It also recommends diversifying generation mix in the medium term, with the optimal extent of geographical and technological diversity varying based on conflict history and thus the anticipated probability of future conflict. Finally, redundant oil-fired capacity is attractive if fuel supply is unlikely to be severely disrupted by conflict; otherwise, fuel shortages would render redundant capacity useless.

The current outlook for electrification of major cities in South Sudan seems pessimistic since all available electrification options are financially or operationally vulnerable. The plan recommended by the framework proposed in this chapter has higher net benefits than the "conflict-naïve plan" because the latter is biased towards certain technologies for which conflict-induced costs and deterioration of performance are high but disregarded in the conflict-naïve model. A centralized, predominantly hydropower system appears to be the most economical option for South Sudan under the assumption of continued peace; but the results in this chapter instead suggest postponing large-scale hydro projects until political conditions have stabilized.

Lastly, it is worth emphasizing that the value of recommendations provided by frameworks such as the one proposed here depends on the credibility of conflict simulations and the quality of input data. Potential advancements in conflict prediction and quantification of power system effects of conflict would improve the usefulness of the results. Collection of reliable data is often a challenge in developing countries, and characterizing societal risks is difficult everywhere. However, investments —and financial analyses of those investments— are necessary to achieve electrification. Despite data difficulties, investors and planners presently evaluate investments using models that ignore context-specific risks either because such models are unavailable or because planners prefer to avoid assumptions concerning the risks. However, planners already implicitly make such assumptions. When they ignore the risks, they essentially assume a risk-free environment and obtain overly optimistic plans. Our framework corrects this by considering the possibility of conflict, even if precise estimates of conflict risks cannot be justified. On the other hand, when planners exclude certain technologies and candidate sites, they implicitly assume, without analysis, that the excluded options are less beneficial to the system than the included options. In this situation, planners can use the framework to explore how alternative risk assumptions affect the net benefits of a wide range of alternatives without a priori excluding any options.

To conclude, the proposed framework can assist power system planners to adopt strategies that will be less vulnerable to the effects of conflict. Still, adoption of a particular planning approach cannot be a panacea. The technical contribution will likely not translate into benefits for service delivery unless many other steps are taken, including actively engaging with local agencies and researchers to improve the quality of data, and continuing to refine the prediction models and estimation of power system vulnerability to conflict. Finally, future research might support several framework extensions. For example, previous studies have investigated the impact of aid on conflict risk [180], [181] and discussed the necessity of public services for economic development and state building in a post-conflict environment [34], but the impact of power sector development on conflict risk remains unexamined. Thus, the proposed framework could be expanded to account for the impact of power sector development on conflict risk and thus its potential benefits to peace-building.

Besides incorporating an endogenous interaction between probability of conflict and electrification, there are several ways future applications of the framework could be more elaborate than this one. Several details are omitted from the model of the case study because the primary purpose of the chapter is to introduce the framework and the insights it can provide. The example of South Sudan is provided as a proof of concept for the proposed approach and is not as detailed and thorough as a comprehensive planning exercise for the country would be. In future applications of the proposed framework, the planning model could be expanded in order to: (1) consider more resources such as solar home systems; (2) estimate system reliability; (3) simulate systems operations with finer temporal resolutions including operational constraints; (4) consider costs of expanding the distribution network; and (5) expand the scope to a regional level with trade in the entire East African region.

CHAPTER 4

POWER SYSTEM PLANNING UNDER UNCERTAINTY: COMPARISON OF ROBUST DECISION MAKING AND STOCHASTIC PROGRAMMING

Computational advances along with the profound impact of uncertain factors on power system planning call for novel power system planning paradigms that endogenously handle long-run uncertainty. This chapter compares two distinct approaches for integration of uncertainty within a power system planning problem: Robust Decision Making and Stochastic Programming across three criteria: modeling capability, practical applicability, and contribution to decision making. The comparison is based on a case study of Bangladesh, where socio-economic and climate change uncertainties are integrated into power system planning. The vis-à-vis comparison demonstrates the reliance of both methods on approximations in large scale practical problem and illustrates how SP might be more practical, whereas RDM might provide more information on the decision context.

4.1 INTRODUCTION

Climate change is one of the two challenges in the global energy agenda of the 21st century according to former UN commissioner Ban Ki-Moon [13]. The power sector contributes to climate change through emissions of greenhouse gases [18], but is also vulnerable to climate change effects [19]. Policymakers have been designing and implementing mitigation policies for over 20 years — since the 1992 United Nations Earth Summit in Rio [182]. A breadth of literature has assessed the relative strengths and weaknesses of different mitigation policies [183]. Governments have implemented various programs around the globe. For example, the European Union, a coalition of Eastern States in the USA, and California have all implemented cap-and-trade schemes (EU Emissions Trading System [184], RGGI [185], and California's AB32 [186], respectively). While in the past the focus was on mitigation policies, nowadays there is an increasing interest in adaptation policies and plans [35], [187], [188]. Targeted initiatives such as the World Bank's Pilot Program on Climate Resilience [189] aim to improve adaptation knowledge & practice and incorporate principles on adaptation and resiliency into strategic planning for infrastructure.

As an essential component of a nation's infrastructure, power system planning has to adapt to a changing climate [190]. Traditionally, assessment of investments in the power sector assumes stationary climatic conditions [190]. Changes of climatic conditions cannot be predicted accurately because of imperfect knowledge and inherent uncertainty, and planning based on one set of climate assumptions may leave a power system vulnerable to disruption if other conditions emerge [191]. For example, nuclear power plants in France regularly shut down during heatwaves because of environmental restrictions on the temperature of cooling water they dispose to natural water bodies such as lakes, rivers etc. [192], [193], [194]. Thus, power system planning has to account for uncertain factors in order to recommend investments appropriate for a changing climate. The list of methods that assist decision making under uncertainty is long and includes, among other tools, methods such as real option analysis and robust decision making[37].

To the dismay of planners, there is limited guidance on consideration of future climate change into infrastructure planning — "*Utilities in the Partnership for Energy Sector Climate Resilience note that managers would welcome additional guidance, tools, and methodologies to help them move forward.*" [195] California Public Utility Commission (CA PUC) initiated a proceeding earlier in 2018 that aims to improve guidance on climate change adaptation for electric and gas utilities addressing questions such as "*How should climate scenarios, climate-relevant parameters, and resilience metrics be used in electric and gas utility planning and operations, and in Commission proceedings, to address climate adaptation in a consistent manner?"* [196]

So far, utilities and researchers choose methods without a careful comparison of methods according to a consistent set of criteria. For example, a recent research project on Western Electricity Coordinating Council (WECC) uses stochastic optimization [197], whereas CA PUC encouraged utilities to use a robust-decision-making framework in 2016 [198]. Recent past reviews [40], [43] agree that no method is superior to others and discuss strengths, weaknesses, and common problem types for each method. However, those reviews are not very helpful because they lack a consistent set of criteria and in some cases, they recommend multiple methods as equally suitable or specific methods based on incorrect characterization of methods' properties. Past reviews acknowledge that practical experience with a variety of methods provides additional insights for method selection, but do not systematically critique that experience. The need for a practical cross-comparison of methods that integrate uncertainty into power system planning problems was first identified in 1989 [42] and was reiterated more recently in the broader context of decision making under climate change uncertainty [41]. To the best of my knowledge, no cross-comparison of two widely applied methods — Robust Decision Making and Stochastic Programming — on a realistic case study has been attempted [42].

This chapter addresses the long-standing need for a cross-comparison of Robust Decision Making and Stochastic Programming on a practical problem. It applies both methods in order to recommend power system expansion plans in Bangladesh. I compare both methods across three criteria: modeling capability, practical applicability, and contribution to decision making [42]. Additionally, the case study contributes to the literature by analyzing the impact of floods on power plants. Power plant designers and insurance companies have considered effects of floods on power plants for decades in order to design power plants and insurance programs respectively. However, relevant information is scarce in the public domain.

The rest of this chapter is structured as follows. Section 4.2 provides background information on the two methods I implement on the case study. Section 4.3 reviews existing literature that compares the two methods and case studies on integration of climate change uncertainty within power system planning models. Section 4.4 discusses key features of the case study. The experimental design of the cross-comparison is provided in Section 4.5, followed by results in Section 4.6. Major conclusions are summarized in Section 4.7. Detailed information on data sources, assumptions and calculations are provided in Appendix B.

4.2 BACKGROUND

4.2.1 Background on Robust Decision Making

In this thesis, "Robust Decision Making (RDM)" refers to a decision analysis framework that the RAND Corporation developed in the 1990s [199].[5] There are four basic components in RDM, commonly organized within the "XLRM" framework [200]: X refers to the set of exogenous uncertainties, L refers to the set of strategies (the actions decisionmakers want to assess), R describes the relationships between input and outputs, and M refers to the set of performance measures.

Robust Decision Making is a multi-step framework that aims to identify vulnerabilities and trade-offs among strategies L [39]. RDM uses models (R) to estimate the performance (M) of

[5] In the general literature, the term robustness might refer to different concepts and multiple methods have been developed to identify robust solutions and decisions [317].

strategies (L) under all scenarios describing uncertainties (X). In other words, RDM conducts $R \times L \times X$ simulations and calculates the value of performance metrics (M) for each simulation. Then, RDM identifies vulnerable regions i.e., subset of simulations with poor values in performance metrics. Trade-offs become clear when the performance of different strategies is compared. Note that RDM is an exploratory method [200]; it assists decision makers to explore the landscape of uncertainty. RDM, as usually implemented, does not recommend a specific strategy and is not guaranteed to identify a robust strategy [201], as one may not exist. RDM has been applied both as an open and closed loop framework; in the former case the set of strategies L is defined ahead of time, whereas in the latter case results of previous iterations inform development of new strategies L, which are then tested in subsequent iterations [202]. In the following paragraphs, I discuss each step of RDM in more detail. Note that RDM does not prescribe a specific implementation for each step. Instead, analysts are called to decide on each step. The review below provides examples on implementation of each step based on previous applications. The steps are [202]:

1. Structure problem – specify X, R and M
2. Identify strategies to evaluate – specify L
3. Evaluate each candidate strategy across scenarios – estimate M for each strategy in L for every model in R under any scenario belonging to X
4. Characterize vulnerabilities
5. Identify additional new strategies to add in set L and go back to step 3.

Step 1: Structure problem. I describe this step in three sub-steps because three components of RDM are specified in this step.

Step 1a: Specify M. Decision makers, here power system planners, undertake the analysis because they want to ensure that the system of interest performs satisfactorily in the future. Performance is measured with one or multiple metrics. For example, in reference [203] two metrics are used: one for reliability and one for cost. Actual power planning studies can involve dozens of metrics and analysts have to consider several issues when they select and define metrics including but not limited to double counting and conceptual independence [204].

Once the metrics are defined, then analysts in consultation with stakeholders usually specify thresholds that distinguish satisfactory from unsatisfactory performance. For instance, reference [203] examines Lima's long term water resources plan, specifies a threshold for reliability (meeting 90% of the monthly demand 90% of the time), and sets a budget constraint for cost. Performance might also be assessed based on the relative distance (or "regret") from the performance of the alternative that has the very best value of that metric [202].

Step 1b: Specify R. Here, analysts have to specify how $X \, and \, L$ interact and affect the performance (M). R is usually a set of equations or models that analysts can simulate using a computer. For example, in reference [45] two tools are specified under R: one that simulates the water demand and supply and another than optimizes power system expansion.

Step 1c: Specify X. Analysts specify a set of scenarios that capture exogenous uncertain factors important — that each have the potential to change the recommended actions — for the problem at hand. Depending on the case study, the scenarios might describe uncertainties in future economics, technology, environmental policy etc. [200]. Under this step, analysts decide if they will generate their own scenarios or rely on past studies to design scenarios. For example, reference [45] uses temperature and precipitation projections under 121 scenarios produced by climate models.

Step 2: Identify strategies to evaluate. In practical cases, approaches to determine the set of preliminary strategies L vary: stakeholders might provide a set of preliminary strategies; deterministic problems might be solved to identify a perfect-foresight strategy per scenario [203]; and stochastic programming models with different probability distributions [205] might be solved to identify potentially robust decisions. For example, Inland Empire Utilities Agency (USA) decided to test against a large set of scenarios the performance of their status-quo strategy as well a couple of strategies that stakeholders had considered in the past but did not include in the official plan [202]. The status-quo strategy documented in regional infrastructure development master plans was also selected as the first strategy to test in [45]. In reference [203], analysts first calculated the perfect-foresight strategies and included in the set of preliminary strategies for further testing the strategies with the highest frequency. In another application, Lempert et al. [205] generated alternative strategies using stochastic programming with varying probability distributions.

Step 3. Evaluate each candidate strategy across scenarios. This step performs computer simulations of models describing the relationships (R) in an ensemble of $(L \times X)$. When the ensemble $(L \times X)$ is very large, sampling techniques are used and the simulations are performed only on a subset of the ensemble [39].

Step 4. Characterize vulnerabilities. Here, analysts aim to identify clusters of scenarios where each strategy performs poorly. Data mining algorithms such as the patient rule induction method (PRIM) are frequently employed [39]. In case of multiple criteria, analysts can assess performance of strategies by employing either trade-off curves [202] or aggregation rules that convert values of multiple metrics into a single score [206]. A rich literature has discussed trade-off analysis and aggregation metrics [204].

Step 5. Identify additional new strategies. Analysts, in consultation with stakeholders, may be called to propose further strategies for testing, especially if Step 4 has failed to find satisfactorily robust strategies. Vulnerable regions — identified under step 4 — inform the design of new strategies. Overall, analysts aim to propose new strategies that might be less vulnerable than strategies already tested. Strategy refinement can include adding adaptive strategies that use information available at a future point. Adaptive strategies have been part of RDM since the first paper that introduced the method [39]. There [39], “safety-valve” strategies are discussed where costs of policies are monitored and performance targets are adjusted accordingly. In reference [207], rule-based near-term energy strategies are tested for Israel. Adaptive strategies of [207] adopt rules that differentiate the suggested investment plans according to information on the levelized cost of electricity of different technologies and the level of a carbon cap.

The ultimate product of RDM is a multi-dimensional dataset with performance metrics (*M*) for multiple strategies (*L*) across all possible futures (*X*). Depending on the project, different visualizations of this multi-dimensional dataset are employed. Trade-off curves are frequently used where the cost of each strategy in *L* is in one axis and the performance values in the other axis/es [208]. Other trade-off curves might describe the trade-off between expected performance across the entire set of scenarios *X* and a subset of scenarios [39].

4.2.2 Background on Stochastic Programming

Dantzig [209] and Beale [210] studied linear programming under uncertainty and proved that a linear program with uncertain parameters — described through a discrete set of scenarios — on the right hand side of constraints can also be formulated as a linear program. This approach can also be applied to linear programs in which objective function parameters and left-hand-side constraint coefficients are also scenario dependent [210]. Any constrained optimization problem has three components: a set of decision variables l, an objective function $m(l)$, and a set of constraints $h(l)$.

$$\min_{l} m(l) \qquad \text{Eq. 4-1}$$

subject to $$h(l) = b \qquad \text{Eq. 4-2}$$

In the case of stochastic programming, some parameters are uncertain. For example, a random vector ξ might appear in the right-hand side b of constraints in equation 4.2. Moreover, the problem might consist of two stages: (a) 1st stage: when ξ is uncertain and a subset of decision variables (l_1) has to be determined before ξ is known; (b) 2nd stage: when ξ is known and corrective actions can be made i.e., specify values for second-stage decision variables ($l_{2,\mathrm{X}}$). Stochastic programs with more than two decision stages are also possible in which uncertainties are represented as an event tree such that not all uncertainties are resolved in the second stage. See below a simple formulation for a stochastic (two-stage) linear program:

$$\min_{l_1, l_{2,X}} C * l_1 + \sum_{X} p_X * D * l_{2,X} \quad \text{Eq. 4-3}$$

subject to

$$A * l_1 = B \quad \text{Eq. 4-4}$$

$$E * l_1 + G * l_{2,X} = \xi_X \quad \text{Eq. 4-5}$$

I make three observations about the formulation above:

1. The first-stage variables (l_1) and constraints (Eq. 4-4) are the same across all scenarios in X. Some decomposition algorithms such as progressive hedging [211] create scenario-dependent first-stage variables $l_{1,X}$ and impose a set of constraints to make sure that all first-stage variables have the same value across scenarios. That set of constraints is called the non-anticipativity restrictions.
2. The second-stage variables ($l_{2,X}$) are scenario-dependent and allow for corrective actions (Eq. 4-5).
3. The objective function (Eq. 4-3) consists of (a) the costs of first-stage variables and (b) the expected (probability-weighted) value of the cost associated with second-stage variables.

Implementation of stochastic programming is rarely presented as a series of steps, but here I define some basic steps in order to parallel the discussion on RDM in Section 4.2.1. These steps are:

1. Structure problem – specify X, l, m
2. Choose approximations if the full problem is intractable
3. Solve the (approximated) problem
4. Test the solution for the original problem
5. Conduct sensitivity/stability analysis

Step 1: Structure problem. Under this step, decision analysts formulate the problem at hand as a mathematical program. Thus, they make sure that all decisions are described in set L, the performance metrics decision makers care about are captured in the objective function m and the uncertainties are described through a set X. In case the expected performance is optimized, probabilities for scenarios in set X are required. I intentionally used the same notation as in Section 4.2.1 so it is clear that both methods structure the problem in similar way. The basic difference of stochastic programming and RDM in this step is that (a) SP requires probabilistic description for scenarios in set X and (b) the relationships (R) are described in SP via a mathematical program's objective, variables, and constraints.

Step 2: Choose approximations. The problem size increases with the number of discrete scenarios in set X. If the number of scenarios is very large, the problem might become intractable. This intractability problem is called "the curse of dimensionality". For instance, the stochastic program for the Bangladesh case presented later in this chapter would have ~40 million variables and ~40 million constraints if all 486 possible scenarios were to be included. To overcome the curse of dimensionality, researchers and practitioners solve an easier problem that approximates the original. Approximation techniques usually limit the problem horizon, ignore some variables, aggregate stages, sample scenarios and/or discretize time, states, decisions [212]. In the past decade, over ten research articles have proposed different techniques to select a reduced set of scenarios for power system planning [213] and operational problems [214].

Step 3: Solve the (approximated) problem. This step solves the problem in order to identify a strategy for the first-stage decision variables. Common algorithms to solve mathematical programs are used, such as mixed integer linear programming solvers in commercial packages. In case of overly large problems, decomposition algorithms and/or parallel computing are necessary [154]. Decomposition schemes frequently applied in power system problems include Bender's decomposition [215], progressive hedging [216], and stochastic dual dynamic programming [217].

Step 4: Test the solution for the original problem. This step requires analysts to build a "simulator" [212] for the original problem of step 1, ignoring any approximations chosen in step 2. The solution identified in step 3 is imposed on the simulator and the performance is recorded. Using the "simulator" as a testbed for solutions is crucial since the "simulator" estimates the actual performance of a solution. In a recent review, Powell and Meisel [212] observe that many studies skip this step, despite its importance. Note that if this step is skipped, there is a disconnection between the original problem analysts are trying to solve and the approximated problem, where the former is not being addressed unless a "simulator" is developed.

Step 5: Conduct sensitivity/stability analysis. This step is also frequently skipped in practical applications. This step aims to calculate bounds on the resulting errors of approximate solutions and/or estimate the sensitivity of the recommended solution to perturbations in the assumed scenario probabilities. Theoretical papers [218] discuss stability properties, but applications rarely provide bounds [219] on the resulting errors of approximate solutions.

The product of multiple-stage stochastic programming that is most useful to analysts is a recommended solution for first-stage variables and an estimate of the objective function value. Multiple-stage stochastic programming recommends a first-stage course of action anticipating the resolution of uncertainty in the second and later stages, when decision makers will have the opportunity to take corrective actions.

4.3 LITERATURE REVIEW: CLIMATE UNCERTAINTY IN POWER SYSTEM PLANNING

There is increasing concern about the effects of climate change on power system infrastructure [19]. In Section 4.3.1, I review articles that analyze the impact of climate change on power systems. The review summarizes approaches to represent climate change uncertainty in power system planning models and how researchers and practitioners justify their choice of uncertainty representation. In Section 4.3.2, I discuss articles that review methods for climate change adaptation decisions. There, I summarize conclusions by past reviews and any limitations pertaining to their analysis. This review of the practical experience with methods and relevant literature provides more detailed arguments than Section 4.1 and establishes the need for a cross-comparison of methods. The review also informs the choice of criteria that I will use to compare Robust Decision Making to Stochastic Programming.

4.3.1 Integration of climate change effects into power system models

Existing articles study climate change effects on power systems to various depths. At the very least, they estimate the impact of climate change on resource potential (e.g., renewable potential [220], [221], [222]) and operational parameters (e.g., capacity factors for thermal power plants based on cooling water availability [223]). Studies of intermediate depth estimate the impact of climate change on power system costs and reliability ([224], [225]). Lastly, at the greatest depth power system planning models propose investments accounting for the fact that new infrastructure will have to operate under uncertain climate conditions ([226], [197]). Table 4-1 summarizes information on 16 studies I reviewed. Note that studies investigating effects of extreme events are not included in this overview since they usually rely on simulation models, which have finer resolution than planning models.

Table 4-1: Summary of studies that model the impact of climate change trends on power systems

Study	Power system model/ Relevant power system parameter	Technology/ Phenomenon	If multiple scenarios, uncertainty handling	Actions and cost information
[220]	No power system model/ Wind capacity factor	Wind	One scenario	No action (Study of potential impacts)
[221]	No power system model/ Wind capacity factor	Wind	Scenario analysis for two scenarios	No action (Study of potential impacts)
[222]	No power system model/ Wind capacity factor	Wind	Scenario analysis of three scenarios	No action (Study of potential impacts)
[223]	No power system model / Usable daily capacity- seasonal capacity factor	Cooling needs of thermoelectric plants	Scenario analysis of two scenarios	No action (Study of potential impacts)
[227]	No power system model/ PV capacity factor	PV power production	Scenario analysis of two scenarios	No action (Study of potential impacts)
[228]	No power system model/ capacity factor	PV and CSP	One scenario	No action/cost modeled
[229]	No power system model/ Usable daily capacity- seasonal capacity factor	Hydro and thermal	Scenario analysis of two scenarios	What-if type of analysis for adaptation (change in cooling, efficiency) without cost
[230]	No power system model/ Available capacity	Steam turbines, Combustion turbines, PV, wind, hydro	Scenario analysis of six scenarios	No action (study of potential impacts)
[225]	Capacity expansion model/ Outage factor for gas and nuclear, demand	Temperature change	One scenario	Scenario-specific adaptation of the generation mix
[231]	Capacity expansion planning model/ (water constraint and supply curve added, cost, heat rate, water withdrawal rate)	Water availability	Scenario analysis of three scenarios	Scenario-specific assessment of two resiliency solutions: installation of efficient cooling technologies, use of alternative water resources
[232]	Energy supply optimization model/ (power sector: capacity factor for HY, efficiency for gas-thermal, demand)	Impact of temperature and precipitation on HY, gas-fired generation, and demand	Scenario analysis of two scenarios	Scenario-specific adaptation of the generation mix
[233]	Capacity expansion planning model	Impact of temperature on electricity demand	One scenario	Scenario-specific adaptation of the generation mix
[44]	Capacity expansion planning model/ (explicit modeling of streamflow balance)	Impact of temperature and streamflow changes on hydro and demand	Scenario-based stochastic planning	Adaptation of the generation mix
[45]	Coordination of two optimization models: one for irrigation and one for hydropower	Impact of climate change on 7 basins	Robust Decision Making with regret criterion	Adaptation options considered at the farmer level and power system
[224]	Capacity expansion planning model (ICF's IPM)	Impact of temperature on demand and thermal capacity and efficiency	Scenario analysis of four scenarios	Adaptation of the generation mix
[197]	Capacity expansion planning model (SWITCH for WECC)	Impact on load and hydropower	Scenario-based stochastic planning	Adaptation of the generation mix

Studies at the lowest depth usually estimate the impact of climate change on the resource potential of renewable generation such as wind ([220], [221], [222]) and solar ([227], [228]). The impact of rising temperatures and changes in precipitation patterns on availability of cooling water for thermal power plants is studied in [223]. Reference [230] studies the impact of changes in streamflow, stream temperature, air temperature, vapour pressure, wind speed and air density on the available capacity of power plants at the peak load hour in the WECC (Western Electricity Coordinating Council). Low-depth analysis translates climate change uncertainty into power system technical parameter uncertainty (e.g., MW capability or conversion efficiency), which can be then be further analyzed.

Studies of intermediate depth estimate the effects of climate change on power system costs and reliability. Those studies account for climate change effects by differentiating the values of certain parameters within power system planning models such as capacity, efficiency etc. among climate change scenarios. Most studies adopt a narrow scope for climate change modeling and focus on a single phenomenon or technology. For example, references [224] and [225] model the impact of changes in temperature patterns on demand (heating and cooling) and thermal power plants (capacity rating & efficiency).

Studies of intermediate depth usually employ scenario analysis. They solve multiple deterministic problems under different climate scenarios as if they had perfect foresight on future climate and analyze investment decisions and costs. For example, reference [224] solves a capacity planning model under three scenarios: with no, moderate, and severe climate change. Authors comment that under scenarios with moderate or severe climate change effects, the system cost is approximately the same: ~13–14% higher than the system cost without climate change. The capacity mixes though are different under the two climate change scenarios compared to the no change case. Results of such single scenario analyses provide useful information on the costs a sector would incur if planners could perfectly anticipate the effects of climate change. However, in reality decision makers do not have perfect foresight with respect to future climate change effects and need to decide on investments anticipating uncertain effects. That is exactly the reason why models of greater depth and complexity are necessary to assist decision makers in choosing a strategy that recognizes the ability to adapt later as the future unfolds.

Such highly sophisticated studies simultaneously consider multiple climate change scenarios in order to recommend adaptation plans. For instance, the authors of [44] assess hydropower investment in British Columbia using three climate change scenarios within a two-stage stochastic program, where investment decisions are made in the first stage and operational decisions at the second stage upon resolution of the uncertainty. Similarly, two-stage stochastic programming is used in [226] to identify a climate resilient power system plan for parts of the Eastern Interconnection. The authors of [45] though explore seven strategies for hydro development (with varying capacity, reservoir and efficiency levels) in seven basins across 121 futures within a robust decision making framework and identify a robust strategy for each basin using regret-based metrics.

The justification for selection of robust decision making or stochastic programming in the aforementioned examples is generally vague and ambiguous. Analysts do not compare all available methods across multiple criteria to select a method to follow. Instead, they provide some supporting arguments. For instance, the authors of [44] choose stochastic programming as an effective method "for proactively handling scenario-based uncertainties in large-scale system design problems." The authors of [226] use stochastic programming without providing any justification; they also use a minimization of maximum regret formulation in addition to stochastic programming and they mention in their introduction that "the objective is to select a compromise solution under discrete climate scenarios, avoiding the possible risk associated with a poor decision that is only optimal for one particular scenario or only the average climate change." Lastly, the authors of [45] justify their choice by arguing that climate change uncertainties "cannot be confidently characterized by any single probability distribution and may not be resolved soon."

According to [45], absence of probabilistic information favors RDM over stochastic programming. However, the authors of [45] contradict themselves since one of the criteria used to select the final strategy is "select the strategy with the lowest regret for 75% of the climate futures," which implies a probabilistic interpretation of the scenarios. Meanwhile, both papers that use stochastic programming ([44], [226]) lack any discussion on practical difficulties a power system planner would face on his attempt to draft scenarios and assign probabilities. The authors of [226] assign probabilities to scenarios for demonstration purposes and no comment is made on the availability of probabilities in practice. Reference [44] infers probabilities for climate change scenarios based on the frequency distribution associated with hydro-climate scenario ensembles.[6]

To conclude, past case studies offer ambiguous recommendations to analysts on method selection. The problems of the case studies are similar, but different methods are implemented based on contradictory rationales or rationales emphasizing different problem aspects. The examples discussed above suggest a lack of standard practice with respect to method selection. None of the studies used a set of criteria to guide their selection of method, contrary to what is proposed in reference [234]. So, in the next subsection I discuss which criteria past reviews have used to distinguish the two methods and any recommendations they provide.

4.3.2 How to choose a method for climate change uncertainty in power system planning

The choice of a decision analysis tool is a decision analysis problem itself. In practice, decision analysts compare available methods across a set of criteria, relevant for the problem, and decide on a method. For instance, Hobbs [234] suggested four criteria to aid selection of methods for environmental impact assessment: relevance to the purpose, ease of use, theoretical validity and whether methods differ significantly with respect to their recommendations.

[6] An ensemble of 23 downscaled climate projections for British Columbia was developed by the Pacific Climate Impacts Consortium.

In 1989, Crousillat [42] conducted the first review of methods that integrate uncertainty within the power system planning problem. He used three criteria, similar to the ones used by Hobbs [234]: modeling capability, practical applicability, and transparency and contribution to decision making. He compared stochastic optimization, risk-trade-off analysis, and option pricing across the three criteria and concluded that no method is superior to others. He recommended more case study applications that would shed light on the relative strengths and weaknesses of each method.

The increased interest in climate change adaptation problems has renewed interest in methodological reviews similar to the one by Crousillat [42]. Recent methodological reviews of methods that integrate uncertainty into adaptation problems build upon knowledge gained from applications in order to describe methodological features and provide recommendations. In this section, I discuss three recent reviews of uncertainty-based planning methods for climate change adaptation [41], [43], [40], and the only cross-comparison of methods within a case study [205] that I am aware of. The latter study though is quite simple assuming just a single uncertain factor at the right-hand side of a constraint. The methodological reviews cover multiple methods but none of them explicitly considers stochastic programming. Whereas the reviews might be useful for general adaptation problems, omission of stochastic programming limits their value for power system planning applications given the popularity of stochastic programming within the power system community [235], [236], [237] and the high level of familiarity that practitioners in the power system industry have with the tool.

All three reviews [41], [43], [40] discuss real option analysis (ROA), which can be viewed as a particular application of stochastic programming; in [34], stochastic programming is mentioned as one of the mathematical methods that implement ROA. So, in the following paragraphs I discuss key take-aways from the reviews that compare ROA and RDM, focusing on the similarities of ROA and SP and highlighting the differences where appropriate. For example, ROA assesses one project at a time while stochastic programming assesses many projects as a portfolio or integrated plan.

In general, past reviews discuss more methods than the two compared in this chapter. I focus on RDM and SP because of their frequent application and omit some other methods proposed such as portfolio analysis, safety margins and "climate-informed decision analysis". Portfolio analysis is a method originating in the finance literature that aims to diversify risk exposure and decides on a portfolio of investments using statistical measures such as the variance of costs. In the context of power system planning, multiple projects are evaluated at the same time within a mathematical program and objectives for diversification can be reflected through customized objective functions and constraints. Past applications have applied portfolio analysis in power system planning as a mathematical program with two objectives: the expected value and variance of costs [318], [319]. I omit precautionary approaches [204] because they address uncertainty outside of the power system planning problem. Precautionary approaches usually employ statistical methods in order to update parameters of deterministic power system problems. For example, safety margins on top of expected demand — also called reserves — are added to guarantee that the system will be able to serve demand within a range of forecast errors. Treatment of uncertainty with precautionary approaches does not always account for the trade-off between over-procuring and under-performing, resulting in potentially sub-optimal solutions. An example of approach that accounts for the trade-offs is the "over/under" approach [320] that employs probabilistic demand forecasts to determine the reserve margin for installed generation capacity that minimizes overall supply and disruption cost. Finally, I do not discuss separately "climate-informed decision analysis" because it shares similarities in its philosophy with robust decision making as both methods start by assessing the vulnerability of various strategies [44].

Neither the reviews [41], [43], [40] nor the cross-comparison [205] explicitly define criteria across which the methods are compared. In the following paragraphs, I summarize their observations on RDM and ROA using Crousillat's criteria [42].

Criterion I: modeling capability. This criterion refers to model's ability to capture the consequences of uncertainties on investment plans. Six questions below assist me in describing how the two methods handle different aspects of uncertainty and consequences.

1a) Evolution of uncertainty: Can both methods model dynamic uncertainties? According to [40], [41], [43], ROA can model dynamic uncertainty; it allows for learning that will lead to partial or complete resolution of uncertainty and explicitly accounts for the possibility to delay projects until additional information is available. All past reviews [40], [41], [43] though do not discuss adaptive (closed loop/state contingent) strategies within the robust decision making framework, potentially misleading practitioners that flexibility of plans and adaptation to future information is not a possibility within RDM.

1b) Probabilistic characterization of uncertainty: Do both methods need a probabilistic description of the uncertainty? Reference [43] argues that both stochastic programming and robust decision making use probabilities, but at different phases: at the first and last step of their implementation respectively. Reference [41] disagrees with that view and reports the requirement of probabilistic input data as a weakness for Real Option Analysis that favors application of Robust Decision Making in case of absence of probabilistic information, since that reference characterizes RDM as probability-independent. Both reviews are correct to some extent because the use of probabilistic distributions within RDM depends on the performance criteria employed. For instance, if a performance criterion is the expected value of a metric across scenarios, then a probabilistic description of scenarios is required. However, when criteria such as min-max regret are employed, there is no need for a probabilistic description within RDM. Note though that in case of min-max criteria, stochastic programming would not be the mathematical program of choice and robust optimization, which also does not require probabilities, could be applied[155].

1c) Probabilistic characterization of uncertainty: Can both methods model multiple views on the probabilistic characterization of uncertainty? RDM allows multiple probabilistic views of uncertainty [43]: it assesses the performance of strategies at hand under all different views and lets stakeholders build consensus and finalize their decision. Past reviews do not explain if ROA or stochastic programming can handle multiple probabilistic distributions. The cross-comparison in reference [205] highlights the ability of RDM to handle multiple probabilistic views as a feature that sets it apart from expected utility approaches such as stochastic programming, which instead use a single probabilistic description. Note though that implementation of stochastic programming in [205] is incomplete because there is no sensitivity analysis of the solution to assumed probabilities, even though that is recognized as a critical step in any application of stochastic programming with imperfect probabilistic information [218].

1d) Strategies: How does each method identify potential strategies? All reviews assume that decision makers already know a set of projects they want to assess. However, in case of power system planning, decision makers rely on mathematical programs to generate a set of strategies. Stochastic programming does not require a set of strategies as an input; it provides strategies as an output. RDM, though, does not generate strategies and relies on stakeholders or mathematical models for strategy generation. In the cross-comparison [205], multiple stochastic programs with different probabilistic distributions are used to define a set of alternative strategies. In that case, the generation of strategies in RDM is identical to the sensitivity analysis of the optimal stochastic solution to different probabilistic distributions.

1e) Project features: What types of project (size, horizon) each method can assess? RDM is recommended for evaluation of near-term investment with long horizon [41] in case of a rich portfolio of alternatives [43]. In contrast, ROA is recommended for large irreversible investments [43], [41]. The cross-comparison [205] argues that RDM is appropriate only in cases with a rich portfolio of alternatives because only in that case is there potential for differentiation among robust and optimal strategies. These recommendations should be perceived as heuristics, aiming to identify problems where the application of the method at hand might add more value.

1f) Type of benefits. Reference [40] does not recommend neither RDM nor ROA in case of non-monetary benefits. On the other hand, reference [41] requires monetary expression of benefits only for ROA and allows for quantitative benefits of any kind in RDM. The distinction based on type of quantitative benefits is irrelevant for this discussion as long as there is a quantitative definition or interpretation of the performance metrics.

Criterion II: Practical applicability. All reviews [40], [41], [43] agree that both ROA and RDM are resource-intensive: complex models have to be built; experts should be hired; and practitioners should receive training. In particular, reference [40] does not recommend either method for the appraisal of adaptation strategies in case of limited budget.

Criterion III: Transparency and contribution to decision making. This criterion compares methods with respect to their comprehensibility and friendliness to decision makers. Reviews [41] and [43] describe stakeholder involvement within RDM as both positive and negative. Positive because RDM forces stakeholders to reveal their preferences when they define performance metrics and assess trade-offs. That way, RDM might help stakeholders build consensus. Negative because RDM analysis is more subjective and lack of expertise and stakeholder biases might hurt the quality of the solutions. Review [43] mentions as an advantage of ROA for contribution to decision making the fact that its analysis fits well into the social cost-benefit analysis framework governments use to approve investments. Lastly, the cross-comparison [205] emphasizes as a strength of RDM the transparency it provides to stakeholders.

To conclude, existing overviews [40], [41], [43] and the only comparison of methods [205] each demonstrate at least one weakness and their recommendations and conclusions have limited value for power system planners. First, all reviews ignore stochastic programming, which is widely used in power system planning. Second, all reviews and the cross-comparison do not fully implement each method i.e., the possibility of considering adaptive strategies within Robust Decision Making or sensitivity analyses for stochastic programming are ignored. Third, overviews complicate the discussion through focus on less important capabilities i.e., the ability to model quantitative attributes. This chapter contributes to the literature by providing insights on all three criteria from a cross-comparison that is not limited by the aforementioned weaknesses as I later explain in the experimental design (Section 4.5).

4.4 CASE STUDY

The case country on which I conduct the cross-comparison is Bangladesh. Bangladesh, home to 161 million people, had 13,179 MW of electrical generating capacity in April 2017, about three-fourths of which operated on domestic gas extracted from onshore gas fields. Bangladesh has not achieved universal electrification and the consumption per capita is relatively low. Thus, growth rates of demand are expected to be high. Bangladesh constitutes an interesting case because its domestic gas reserves are depleting, demand growth is expected to be high, and the country is usually listed among the most vulnerable to climate change.

Although recent literature has discussed the vulnerability of Bangladeshi power system infrastructure to climate change [238], climate change effects are not considered in the planning analyses the Bangladeshi agencies employ. The least-cost planning analyses conducted in 2010 [239] by the consulting division of Tokyo Electric Power Company (TEPCO) suggested a shift in the generation mix from natural gas to coal. The shift reflected the declining amount of natural gas available domestically and the low price of coal (relative to imported liquefied natural gas (LNG)). Construction of coal power plants, though, sparked a heated debate for different reasons. One coal project is adjacent to the Sundarbans forest [240], an UNESCO heritage center. Similar environmental and human rights concerns were raised for the exploitation of domestic coal through open pit mines [241]. Moreover, most sites are located at areas vulnerable to flooding and the preliminary environmental assessments call for expensive hardening investment to elevate the power plants. The case of Matarbari is characteristic where construction of an artificial hill, 11 m high, is recommended [242].

The vulnerability of candidate coal investments to flooding risks motivated my interest in this case study. Besides uncertainty with respect to flooding, previous power system planning studies for Bangladesh identified additional uncertain factors [243]. In this modeling exercise, uncertainties in four socio-economic factors (demand growth, fuel price, supply of domestic and imported fuels) are explicitly represented through multiple discrete values. Demand growth is affected by the economic growth of the country. Fuel prices are influenced by the balance of global supply and demand and by policies related to renewable energy and trade. In Bangladesh, the supply of domestic coal is considered uncertain because of long delays in already announced coal mine development, public opposition to mine projects, and the absence of a current coal policy. Natural gas supply could be considered uncertain for similar reasons and because of uncertain available reserves. Projections for two climate variables (and associated power sector parameters) are used in this analysis: temperature (and cooling degree days) and flooding (derived from rainfall projections). The uncertainty associated with the projections related to climate variables can be broken down into: (a) climate model uncertainty, (b) processing model uncertainty, and (c) impact function uncertainty [244]. Here, I only capture the first type of uncertainty through consideration of projections from multiple climate models.

For the case study, I develop a power system planning model that assesses investments and retirements of power plants in Bangladesh for years 2016–2041. Investments and retirements are possible in any year within the horizon and operations are assessed using 28 representative hours for each year. The assessment accounts for operational and annualized investment costs. The transmission grid is ignored in this assessment. The model recommends investment for the entire horizon, but I assume that the planners will use this model only to decide on additions over the next 10 years since the power system plan will probably be updated within 5-10 years from now. Detailed information on the formulation of the model are provided in Appendix B.4.

In Section 4.4.1 below, I describe key components of the power system planning problem i.e., technologies, costs, sites, fuel supply. In Section 4.4.2, I discuss which factors of the power system planning problem are considered uncertain in this application and explain how their values are chosen. Finally, in Section 4.4.3 the results from a deterministic analysis under each scenario for the Bangladeshi power system planning problem are presented.

4.4.1 Bangladesh: Options for power system expansion

Natural gas power plants generated ~70% of Bangladesh's electricity in 2016, whereas oil and power imports accounted for ~27% of the supply in that year [245]. As domestic natural gas reserves are depleting [246], alternative sources of electricity are being considered [243] and the ones I assess in this chapter are the following[7]: (1) imported coal; (2) domestic coal; (3)domestic natural gas; (4) imported natural gas (Liquified Natural Gas); (5) interconnection with India to import hydropower from Bhutan or Nepal or electricity from India; (6) solar photovoltaic; and (7) biomass. In Table 4-2, I provide the capital cost and potential for all options except interconnection with India. For interconnection with India, I estimate transmission cost at 3,184$/MW/km and varying cost of energy depending on the origin (see Table 4-3).

Table 4-2: Capital cost and resource potential for candidate power plants in Bangladesh

Power plant	**Capital cost ($/kW)**	**Potential (GW)**
Domestic coal	2,032	30 (based on available land of 13,000 acres)
Imported coal	2,622	
Combined cycle (Natural gas)	1,342	180 (based on available land of 18,000 acres)
Simple cycle (Natural gas)	1,012	
PV	2,430	10
Biomass	3,000	0.3

Table 4-3: Cost of imported energy (Bangladesh)

Source for imported electricity	**Payment scheme**
Hydro from Nepal	$47/MWh
Hydro from Bhutan	500$/kW +37$/MWh
Power plants in India	Time-varying price (44 -223 $/MWh)

[7] Nuclear power has not been assessed in this chapter due to the very slow pace of progress observed for the Ruppur project [318]. Wind is also omitted because of low potential (600 MW) [314].

Note that capital costs for coal and natural gas power plants in this study vary per site to account for elevation of the grade level by a height equal to the inundation depth of a flood with 200 years return period. In previous work [47], I concluded that integration of site-specific detail is important for countries such as Bangladesh where compliance with flood protection standards increases the construction cost of power plants and varies among sites (see Table 4-4).

Table 4-4: Inundation depth for floods with return period 200 years and construction cost for flood protection at sites considered for power plants using imported coal

Location	Depth at rp = 200 years (m) [source: FATHOM]	Additional construction cost ($/kW)
Chandpur	0	-
Meghnaghat	0.1	7
Bheramara	0.1	7
Orion Dhaka	0.1	7
Mawa	0.2	14
Cox Bazaar	0.3	21
Zajira	0.5	36
Khulna South	1.2	85
Rampal	1.5	107
Payra	3.8	270
Matarbari	7.1	504
Chittagong	8.5	604

4.4.2 Bangladesh: Uncertain factors in power system planning

As mentioned earlier, multiple parameters used in Bangladesh power system planning are uncertain. In Table 4-5, I summarize the sources for uncertain values. Note that in some cases such as fuel prices, I use a subset of the full set of scenarios I had access to in order to keep the total number of scenarios tractable.

Table 4-5: Uncertain factors for power system planning in Bangladesh

Uncertain factor	Full set of scenarios	Source of data on uncertain factor	Scenarios modeled
Demand growth	3	(JICA and TEPCO [247])	3
Fuel prices	5	(JICA and TEPCO [247])F1–F4, [248]	F1, F3, [248]
Domestic coal availability	3	(JICA and TEPCO [247])	3
Natural gas availability	2	Based on (JICA and TEPCO [247])	2
Temperature/cooling degree days	17	http://climatewizard.ciat.cgiar.org/wbclimateanalysistool/	bcc-csm1-1, cesm1-bgc, mri-cgcm3
Flooding	3	FATHOM and [250]	3

For demand, I develop three scenarios with common forecasts up to 2025 (annual growth rate: 7.4-7.5%) and then later apply differentiated annual demand growth rates between 5% and 7%. For gas supply, I construct two scenarios (see Table B-5)**Error! Reference source not found.** : one in which no new domestic gas reserves or new infrastructure for LNG imports (apart from already planned infrastructure) is available and another in which all the sources mentioned in [247] are available. For domestic coal availability, I use the same scenarios as in [247] (see Table B-6**Error! Reference source not found.**).

For fuel prices, I use IEA's New Policies Scenario (F1) because it is presented as the most plausible scenario. I omit F2 (IEA's Current Policies Scenario) because IEA considered it "extremely unlikely". I include F3 (IEA's 450 Scenario) since it simulates a pathway consistent with goals for mitigation of climate change. Finally, instead of using IEA's Low Oil Price Scenario, I use World Bank Group's 2017 projections, which also predict low oil prices.

For temperature projections, I had access to downscaled results from 17 climate models. I translate the projections for cooling degree days into increases in MW electricity loads based upon an empirical equation estimated by [251]. Similarly, I convert projections for maximum temperature into generating capacity derates based upon a constant derate factor in % of maximum capacity per degree over the standard temperature at which the equipment is rated (see Appendix B4). I further analyze in this chapter only three of the seventeen scenarios. I choose those three scenarios using hierarchical clustering (see their projections in Table B-4**Error! Reference source not found.**).[8]

Finally, I consider three scenarios for flooding. Floods here affect power systems in two ways: (1) insurance costs, which are part of the Fixed Operation and Maintenance Costs and (2) outage rates, which limit the available output of the power plants. Note that both are considered in expected terms in this planning model. The expected value of damages increased by a premium is used to estimate the insurance cost and the expected outage days are used to decrease the availability factor.[9] For instance, the annual flood insurance cost at Chittagong increases the annualized capital cost by 1, 2, and 5%, respectively, in the three scenarios considered. Expected availability factors for all power plants are close to 1 (lowest 0.96) for all three scenarios considered.

4.4.3 Bangladesh: Scenario analysis of power system plans

I assume that all uncertain factors are probabilistically independent of each other, so that no combination of the six factors has zero probability. Thus, I consider all 486 = 3*3*3*2*3*3 scenarios that include all potential combinations of the six uncertain factors (Table 4-5). As an indication of whether uncertainty might be important, I first conduct a scenario analysis, i.e., I solve the deterministic problems under all scenarios as if I had perfect foresight. That is, for each scenario, I solve a power system expansion model formulated as a deterministic LP (see Appendix B.4) and record the near-term investment decisions (i.e., capacity additions up to 2025), which I designate as $build\_1^{st}$.

[8] The clustering takes as input 17 vectors (one for each climate model) and cluster them based on hierarchical clustering using a Chebychev distance metric to describe the distance between points within a cluster [319]. Then from each cluster the scenario with the minimum max distance from scenarios in the same cluster is chosen. Each vector has 2,912 elements: 2,184 (3*28*26) elements to describe the demand increase for three demand growth scenarios; 28 representative hours and 26 years within the horizon; and 728(28*26) elements that describe the temperature degrees over the standard temperature for all 28 representative hours over the entire horizon of 26 years.

[9] Note that the consideration of an expected outage factor for power plants has smoothen out the impact of floods over the entire horizon and the results do not capture the disruption an extreme flood would cause.

The average cost for the entire 26-year horizon across the 486 deterministic (perfect-foresight) solutions is ~100,913 million US$. The near-term (prior to 2025) investment for the entire country is ~24 GW (average across 486 deterministic solutions) and the average size of investment per candidate site, technology, and scenario is 447MW. For each candidate power plant, the near-term investments recommended by the 486 deterministic solutions are quite similar, differing less than 20 MW. However, the range is much larger for six candidate power generation options — which can be summarized in three groups based on the fuel used:

(i) additional investment in interconnections with India, which varies between 1 GW to 4 GW,

(ii) investment in power plants using imported coal at three sites (Rampal, Khulna and Zajira), which varies between 0.2 GW and 6.6 GW, and

(iii) investment in coal capacity using domestic coal at two sites (Barapukuria and Kharaspir), which ranges between 0.8 and 2.5 GW.

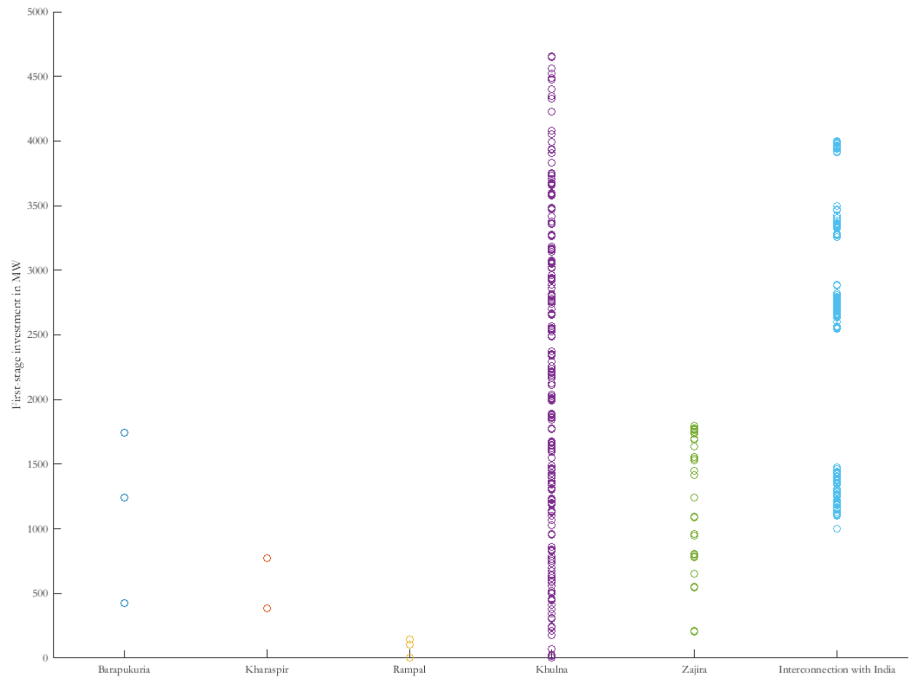

Figure 4-1: Range of first-stage investments for six candidate sites under 486 perfect-foresight plans

The ranges for those six candidate investments are large compared to the rest of the candidates which have a range less than 20 MW. Analyzing further the 486 perfect-foresight plans, there are three discrete levels for domestic coal (at Barapukuria and Kharaspir): 0.8, 1.6 and 2.5 GW. The selection of a level solely depends on the coal supply scenario. The 162 scenarios with low, base and high coal supply have 0.8, 1.6, and 2.5 GW of coal at Barapukuria and Kharaspir, respectively. This is reasonable because domestic coal is relatively inexpensive — only domestic gas is less expensive — and the least-cost plan would build domestic coal up to the available supply limit. Fuel price uncertainty explains the range of interconnection levels. Under the IEA New Policies, IEA 450 and, WB17 fuel scenarios, the interconnection with India is at 3.5–4 GW, 2.5–3.5 GW and 1–1.5 GW respectively. The fuel price scenarios above assume high, moderate, and low fuel prices, respectively. The interconnection to India, as currently modeled, provides access to nuclear and coal supply during base hours (~50% of the year). The lower the fuel prices of coal and LNG, the higher the incentive Bangladesh has to develop its own resources and optimally dispatch them throughout the year, instead of building transmission lines to interconnect with India and rely on those resources for part of the year when India does not use them for domestic demand. Finally, the observed range in levels of investment using imported coal cannot be explained by a single uncertain factor.

In brief, each of the multiple possible investment levels for the first stage (through 2025) is the ideal choice for one or more specific scenarios, but planners can only choose one investment level per candidate when defining a strategy. The large ranges of possible investments are the very reason that practitioners need a tool that aids decision making under uncertainty in order to select a specific near-term investment plan. Here, I use RDM and SP. I provide details on the implementation of both methods in the next section. Results for both tools are provided and compared in Section 4.6.

4.5 EXPERIMENTAL DESIGN

The general need for a cross-comparison of methods on a realistic example has been established based on a survey of the literature in Section 4.3. Here, I design the cross-comparison for the case study of Section 4.4. This chapter addresses gaps of past comparisons by including SP as an alternative and structuring the discussion on the comparison across the three criteria introduced by Crousillat [42]. In Section 4.2, it is obvious that analysts have a good deal of flexibility in designing an application of either RDP or SP to a particular case. My cross-comparison cannot cover the entire spectrum of choices for either method. Instead, I apply both methods using the same amount of information. I describe custom choices for each step of each method in Section 4.5.1, followed by a thorough discussion of choices for the second step in 4.5.2.

4.5.1 Step-by-step custom choices for RDM and SP in the case study

Step 1: Structure the problem

The first step is the same in both methods: "structure the problem". It is crucial for the design of the cross-comparison because it ensures that methods are compared in their ability to solve the same problem (criterion I: modeling capability). I describe my choices for step 1 using the "XLRM" framework (see Section 4.2.1).

Exogenous uncertainties (X): I use the same set of 486 scenarios for both methods and naively assume even probabilities for all scenarios. The probability of any particular scenario is the product of the marginal probabilities of the six uncertain factor values. More sophisticated assumptions (e.g., correlations among factors) could have been made, but were unnecessary for the purposes of this comparison of RDM and SP. Those probabilities are used to estimate the performance metric value as it will become clear in the paragraph below. Learning is assumed in both cases that allows planners to know with perfect certainty the values for uncertain factors past 2025 and during system operations (for example, loads and fuel prices are known when unit dispatch is decided). Note that complete resolution of uncertainties is not true in practice, as there will be residual uncertainty past 2025. However, the assumption reflects the fact that planners will have updated information with respect to the uncertainty in a later year. The assumption on learning affects the model formulation as I discuss later in *Relationships*.

Performance metrics (M): I employ the same performance metric (cost) in both methods and assume that the planner is risk-neutral, so that the objective can be minimization of expected (probability weighted) cost. No threshold is used to judge if the performance is satisfactory.

Strategies (L): Each strategy refers to a set of investment decisions up to 2025 because I assume that the planner aims to determine the investment decisions for the first 10 years of the horizon. In a later year, planners will use a method to decide on investments past 2025. That is why investments past 2025 are not included in the definition of strategies. Moreover, contrary to investments prior to 2025, which are scenario-independent, the investments after 2025 are assumed to be scenario-contingent because the uncertainty resolves in 2025 (see *Uncertainties (X)*). Operational decisions are not included in the definition of a strategy because they can be determined on shorter notice (minutes to days).

Relationships (R): In both methods, relationships refer to the model necessary for the vulnerability assessment. The vulnerability assessment aims to estimate the performance metric (*M*) for each strategy (*L*) across all scenarios (*X*). The strategy (*L*) specifies only a subset of the decision variables — investments prior to 2025 — with the remaining (recourse) decisions — investments past 2025 along with dispatch of generation throughout the horizon — being yet to be determined. Note that recourse decisions are in general scenario-dependent because uncertainties have been resolved by the time those decisions are made. Therefore, for each strategy (*L*) and scenario (*X*), a linear program is formulated that optimizes the system cost by choosing values of the recourse decision variables. The first-stage (prior to 2025) investments are no longer decision variables, but they are parameters fixed at the values determined by (*L*); by being fixed, their values limit the scope for adaptation. This optimal determination of second-stage investment decisions through a linear program in the vulnerability assessment allows for learning and determination of adaptive strategies in an identical way in both methods. This modeling choice sets my cross-comparison apart from past reviews that do not discuss how RDM can allow for development of adaptive strategies. Note that, at its heart, SP uses an additional mathematical program to recommend first-stage investments considering a reduced set of scenarios and imposing non-anticipativity on those investments (i.e., in the first stage, I can't condition the decisions on the scenario because the planner does not yet know which scenario will occur in the future).

Step 2: Identify strategies to evaluate (RDM) or Choose approximations if the full problem is intractable *(SP).*

Under step 2, I must choose strategy/ies under RDM and a subset of scenarios to include in SP. In other words, I must choose an approximate description of the continuum of strategies and the entire set of scenarios for RDM and SP, respectively. None of the two methods prescribe a specific approach for the approximation. So, I decide to use the same approach for both approximations relying on the investments recorded under the 486 perfect-foresight runs (see Section 4.4.3). I discuss in detail how I rely on this information to select a subset of seven scenarios for SP and seven distinct strategies for RDM in section 4.5.2.

Step 3 for SP: Solve the problem

In case of SP, under this step I solve a two-stage stochastic program considering only the subset of scenarios chosen under step 2. The decision tree provided in Figure 4-2 illustrates the formulation of the model for stochastic programming. Seven scenarios (presented in Table 4-7) are considered as part of the stochastic programming formulation.

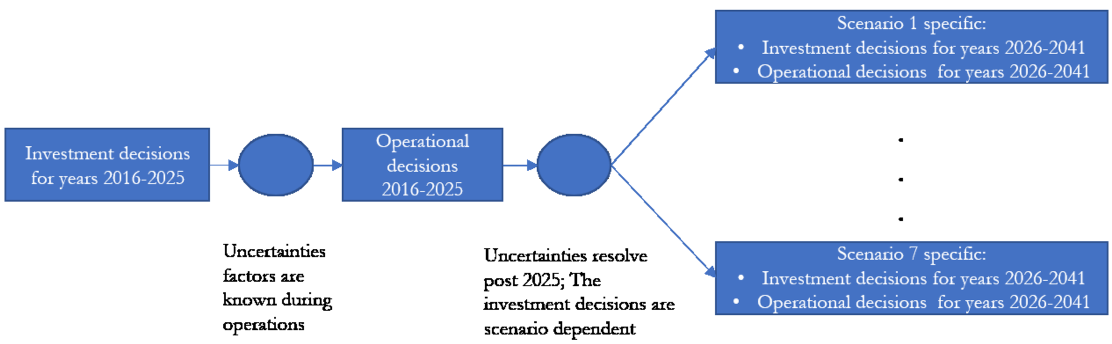

Figure 4-2: Decision tree for SP model

Step 4 for SP/Step 3 for RDM: Test the solution for the original problem/Evaluate strategy across scenarios. Steps 4 for SP and 3 for RDM use identical linear programs (described earlier in Relationships (*R*)) to assess the performance across scenarios. For SP, I impose first-stage investments at the levels identified by the stochastic program (solved with a subset of scenarios), and then optimize the second-stage investment and operational decisions using a linear program. Thus, one set of SP first-stage decisions are then imposed upon 486 linear programs, one per scenario, which are then solved for second-stage decisions that are optimal for that particular scenario. Analogously, for RDM, I consider the first-stage decisions for each of the 7 original RDM strategies and solve the linear program that optimizes second-stage investment and operational decisions. For each of

8*486 combinations of scenarios and strategies, I then record the value of the objective function and subtract from it the value of the objective function for the same scenario under the perfect-foresight run. The result of this subtraction is the "regret", i.e., the increase in cost because of deviation from the optimal strategy for the scenario. Thus, I have 486 regrets for the SP first-stage solution, and 7*486 regrets for the first-stage solutions from the 7 RDM strategies. Next, I calculate for each of these strategies (including the SP solution) the expected (probability-weighted) regret over all 486 scenarios. The expected regret ranks the eight strategies in the same exact way as expected cost, which is the performance metric I specified earlier in this section.

Note that in this implementation I skip Steps 4 and 5 of RDM and step 5 of SP. The reason for that choice is that in case of RDM, I did not have any stakeholders that would provide a definition of vulnerability or express their satisfaction or dismay with strategies already tested under RDM. For stochastic programming, I did not implement another iteration with a new subset of scenarios because the expected regret is already small relative to the expected cost.

Figure 4-3 summarizes in schematic form the comparison of the two methods. Note that both methods can be implemented in an iterative manner. For example, if the performance of the strategy identified by the stochastic programming method is unsatisfactory, a different subset of scenarios could be considered. That subset could have been suggested by a different scenario reduction method — there is rich literature concerning such heuristics in the past decade [213], [214]. Alternatively, the same heuristic could have been used with a larger subset of scenarios. Similarly, RDM could test the vulnerability of a different set of strategies. RDM does not prescribe how additional, new strategies could be formulated. However, it suggests that planners could leverage information on vulnerable regions of strategies already tested to draft new ones.

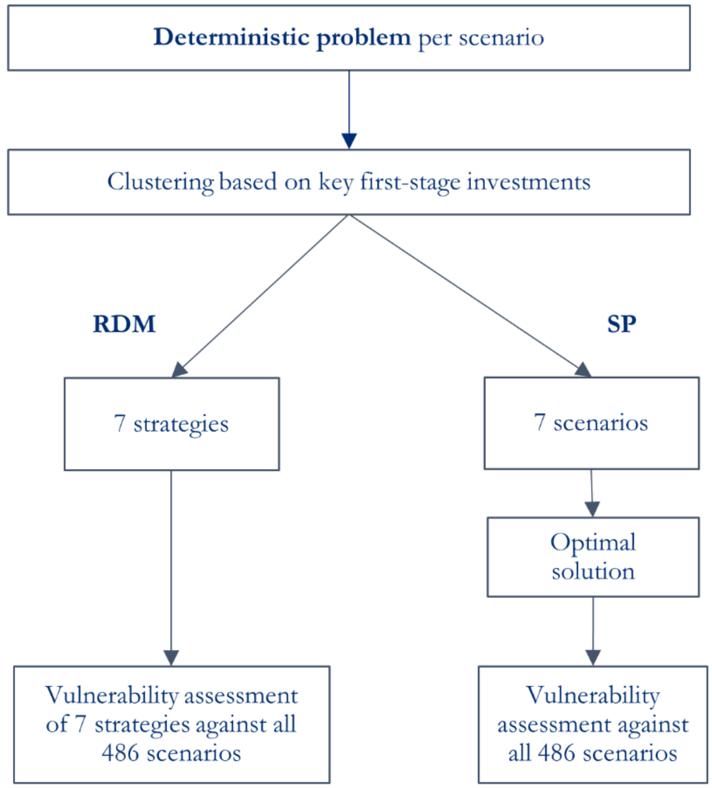

Figure 4-3: Schematic for RDM and SP implementation in the case study

4.5.2 Details on step 2: selection of scenarios for SP and strategies for RDM

In this section, I describe in detail how I used the results of the 486 deterministic runs with perfect foresight to identify candidate strategies for RDM and a subset of scenarios for SP. For stochastic programming, I select a subset of 7 scenarios with different assumptions on the values of uncertain factors. This is because a stochastic programming model with 486 scenarios simultaneously would have over 40 million variables and 40 million constraints, which I cannot solve. Meanwhile, for RDM, it is challenging to decide on a small number of candidate strategies in the power system planning problem, since it is practically impossible for the decision makers to enumerate all combinations of candidates and come up with a short list of candidate strategies.

Indeed, there are infinite number of candidate strategies, since the capacity decision variables are assumed to be continuous.

Here, I use the same approximation technique to identify scenarios for SP and strategies for RDM. Given that the objective of the problem is to identify first-stage investments, I decided to approximate the scenarios for SP and the strategies for RDM using an algorithm that clusters the 486 perfect-foresight cases of section 4.4.3 based on key first-stage investments. The method I followed is very similar to reference [252]. I define as key first-stage investments the ones that differ significantly among the 486 deterministic runs (see Section 4.4.3): interconnection with India, coal development at Barapukuria and Kharaspir (domestic coal) and coal development at Rampal, Khulna, Zajira (imported coal). For each scenario, I create a vector with six elements being the cumulative investment up to 2025 for each of the six candidates. Then, I employ the 486 vectors as an input into k-means clustering with Euclidean distance and identify seven clusters. The two last columns of Table 4-6 respectively contain the number of scenarios in each cluster and the mean value of investments for the six candidates under each cluster.

For each cluster, I construct a strategy to test under RDM and select a scenario to consider within the reduced stochastic programming model (see Figure 4-2). This is done as follows. For a given cluster, a single RDM strategy is defined as the investment levels for all candidate in years 2016–2025 (i.e., the first stage) averaged across all perfect-foresight solutions for scenarios belonging to that cluster. For stochastic programming, I select seven scenarios by choosing within each cluster the scenario with the minimum maximum Chebychev distance from all other scenarios in the cluster.[10] The probability of that scenario in the stochastic program is then set equal to the number of scenarios that belong to the cluster divided by the total number of scenarios (486). The RDM strategies are summarized in Table 4-6 and the scenarios for SP are given in Table 4-7.

[10] Select scenario s, which is the minimizer of the optimization problem with objective function $\min_{s \in cluster} \max_{s' \in cluster} |x_s - x_{s'}|_\infty$,where x is a 6 by 1 vector describing the total first-stage investments of six candidate power generation options (see Figure 4-1).

Table 4-6: Candidate strategies for RDM [47]

Scenarios clustered under this strategy (Names refer to the scenarios considered; coal and gas scenarios refer to supply)	**Near term strategy (investments up to 2025)**	**Number of future scenarios in the cluster**	**Capacity for which construction started before 2025 (GW) (Domestic coal, Imported coal, Interconnection)**
'High-base demand-NO WB17-High-base domestic coal-Gas unclear'	High domestic coal- Moderate imported coal- High interconnection	84	(2.1,3.9,3.4)
'Low-base demand-WB17-High-base domestic coal-Gas unclear'	High domestic coal- Low imported coal - Low interconnection	54	(2.2,2.6,1.1)
'Low-base demand-NO WB17-Low-base domestic coal-Gas unclear'	Low domestic coal - Moderate imported coal-High interconnection	75	(1.1,3.1,3.2)
'Demand unclear-WB17-Coal unclear-Gas unclear'	Moderate domestic coal- Moderate imported coal - Low interconnection	66	(1.5,4.2,1.1)
'Low demand-NO WB17-High-base domestic coal-Gas unclear'	High domestic coal - Low imported coal- High interconnection	93	(2.2,1.6,3.3)
'High demand-WB17-Low-base domestic coal-Gas unclear'	Low domestic coal - High imported coal - Low interconnection	42	(1.2,5.8,1.2)
'High demand-NO WB17-Low domestic coal-Low gas'	Low domestic coal - high imported coal - High interconnection	72	(1.0,5.3,3.6)

Table 4-7: Subset of scenarios considered for SP

Scenarios selected to represent the cluster	Probability (%)
High demand-IEA New Policies-Base coal-High gas	17%
Low demand-WB17-Base coal-High gas	11%
Low demand-IEA 450-Low coal-Low gas	15%
Base demand-WB17-Base coal-High gas	14%
Low demand-IEA New Policies-Base coal-High gas	19%
High demand-WB17-Base coal-Low gas	9%
High demand-IEA New Policies-Low coal-High gas	15%

The seven clusters adequately represent the full set of perfect-foresight strategies according to the comparison of mean (see Table 4-8) and range (see Table 4-10) between the original set of 486 strategies with perfect foresight and the set of 7 RDM strategies. However, the covariance matrixes of the two sets are more dissimilar (see Table 4-9). By definition, the mean of the first-stage investments is identical between the two sets (see Table 4-8).

Table 4-8: Mean value of first-stage investments for three candidate power plants

	Domestic Coal		Imported Coal			Interconnection
Strategies	Barapukuria	Kharaspir	Rampal	Khulna	Zajira	
7 RDM	1,136	516	1	1,876	1,737	2,631
486 with perfect foresight	1,136	516	1	1,876	1,737	2,631

Table 4-9: Covariance of first-stage investments within the set of 7 RDM strategies and within the set of 486 strategies with perfect foresight

		7 RDM strategies			
161,881	45,005	(297)	(326,341)	(25,363)	(6,525)
45,005	12,695	(106)	(96,270)	(7,617)	(1,823)
(297)	(106)	7	1,736	52	(1,201)
(326,341)	(96,270)	1,736	1,594,685	106,325	(213,744)
(25,363)	(7,617)	52	106,325	15,467	(39,311)
(6,525)	(1,823)	(1,201)	(213,744)	(39,311)	1,148,435
		486 strategies with perfect foresight			
294,939	78,495	(584)	(333,761)	(33,414)	(4,684)
78,495	33,402	(106)	(97,657)	(12,579)	(1,414)
(584)	(106)	111	2,283	52	(1,091)
(333,761)	(97,657)	2,283	1,842,086	118,080	(208,837)
(33,414)	(12,579)	52	118,080	54,844	(32,812)
(4,684)	(1,414)	(1,091)	(208,837)	(32,812)	1,292,109

Table 4-10: Min and max values of first-stage investments within the set of 7 RDM strategies and within the set of 486 strategies with perfect-foresight

			7 RDM strategies			
	Domestic Coal		Imported Coal			Interconnection
	Barapukuria	Kharaspir	Rampal	Khulna	Zajira	
Min	629	387	-	167	1,482	1,094
Max	1,575	645	9	3,989	1,800	3,555
			486 strategies with perfect foresight			
Min	426	387	-	-	205	1,000
Max	1,743	775	146	4,654	1,800	4,000

In column 1 of Table 4-6, I provide a brief description of the scenarios under each cluster. Descriptions of climate scenarios (flooding or temperature) are not provided in the description of the cluster, because there turned out to be little systematic difference between the clusters in those dimensions. Similarly, descriptions of gas supply are not provided in the description of six clusters. On the contrary, three factors (fuel prices, demand growth, and coal availability) vary strongly among the clusters. This might lead to the conclusion that the latter uncertainties might be more relevant to near-term investment decision than climate or gas supply. I will discuss further the relative impact of each uncertainty in results (Section 4.6.3.b).

4.5.2.a Discussion of RDM strategies

As described above, I employed clustering to identify initial strategies based on the 486 deterministic runs. Note though that a set of strategies like Table 4-6 could have also been provided directly by stakeholders with different beliefs about the future, as discussed in Section 4.2.1. For example:

- A stakeholder who considers plausible a future with high demand, low domestic coal supply, low gas supply and fuel prices in line with IEA scenarios (cluster 7) might logically propose relatively large short-term investments in both imported coal and interconnection.
- Alternatively, a stakeholder who considers plausible a future with low demand, high/base domestic coal, and prices in line with IEA scenarios (cluster 5) might favor a plan with small short-term investments in imported coal, large investments in domestic coal, and large investments in interconnection.

Similar descriptions, to the two provided above, reflecting stakeholder's view favoring a particular strategy can be provided for the remaining 5 strategies of Table 4-6. The advantage of the statistical approach I follow here is that it limits the reliance to stakeholders. As discussed earlier in Section 4.3.2, specification of inputs by stakeholders might make the analysis more subjective. On the other hand, limited interaction with stakeholders might prevent the analysts (me in this case) from properly structuring the problem making sure it addresses the needs of decision makers.

4.5.2.b Discussion on scenarios for SP

In the reduced SP of Figure 4-2, I used the input vector (assumptions regarding temperature, demand, fuel prices, coal/gas supply, flooding) of a specific scenario within the cluster and weight proportional to the number of original scenarios within the cluster, assuming equiprobable scenarios (see Table 4-7). Solving the reduced problem, the stochastic program recommends a strategy that invests 0.4, 0.4, 0, 1.4, 1.8, and 2.9 GW in domestic coal (Barapukuria, Kharaspir), imported coal (Rampal, Khulna, Zajira), and interconnection with India by 2025. The results for the vulnerability assessment for this strategy along with the 7 RDM strategies are discussed in the next section.

4.6 RESULTS

I compare the implementation and results from both methods (RDM, SP) across the three criteria by Crousillat [42] in Sections 4.6.1–4.6.3.

4.6.1 Criterion I (Modeling capability): Performance of RDM and SP on the case study

Crousillat [42] defined modeling capability as “the models' ability to capture the possible consequences of multiple uncertainties inherent to alternative investment plans.” As shown in the experimental design (Section 4.5), both methods capture the dynamics of the multi-faceted uncertainty and assess the vulnerability of recommended strategies across multiple scenarios.

Here, I examine modeling capability from a different angle, aiming to answer the following question “Did both methods identify a strategy that minimizes the expected regret — that was the target set in Section 4.5?” The results from the vulnerability assessment provide the answer to the question. In Table 4-11, I document the performance in terms of regret (expected, maximum, minimum) for the seven RDM strategies (see Section 4.5.2) and the strategy identified by the reduced stochastic program, i.e., the stochastic program with seven scenarios (see Figure 4-2).

Among all eight strategies of Table 4-11, the strategy identified by the SP (first row of Table 4-11) has the lowest expected regret. This strategy also happens to have the lowest worst (maximum) regret.

Table 4-11: Performance of strategies across all 486 scenarios (in millions of 2015 U.S. dollars)

Near-term strategy according to:	**Maximum regret**	**Minimum regret**	**Expected regret**
Stochastic model: Low domestic coal - Moderate imported coal-High interconnection	1,406	69	**555**
High domestic coal- Moderate imported coal- High interconnection	1,785	175	867
High domestic coal- Low imported coal - Low interconnection	3,727	92	1,476
Low domestic coal - Moderate imported coal-High interconnection	1,408	175	612
Moderate domestic coal- Moderate imported coal - Low interconnection	2,173	89	1,089
High domestic coal - Low imported coal-High interconnection	2,610	155	965
Low domestic coal - High imported coal - Low interconnection	3,274	118	1,262
Low domestic coal -high imported coal - High interconnection	2,702	174	833

This result might be expected because the SP identifies the strategy with the least expected regret by definition.[11] However, this is true only if all 486 scenarios could be simultaneously considered in the stochastic program, rather than just a subset of 7 scenarios. Here, the stochastic program has indeed identified the solution with the least expected regret among all eight strategies. Note that this is *not* saying that the overall least expected regret solution has been identified; that would require a SP that optimizes over all 486 scenarios. In Appendix Section B.6, I selected a subset of scenarios using a different method [214] and the SP recommended a strategy with even lower expected regret than the one presented in Table 4-11.

[11] The stochastic program minimizes the expected cost over all scenarios $\sum_s p_s * cost_s$. The average cost of the perfect foresight solutions is defined as $\sum_s p_s * cost\_perfect\_foresight_s$. The problem that minimizes the expected regret has as objective function $\sum_s p_s * (cost - cost\_perfect\_foresight_s)$ and because the average cost of the perfect foresight solution is a fixed term, the stochastic program is guaranteed to minimize the expected regret.

The best RDM strategy has $57M higher present worth of expected regret (about 10% higher than the SP solution). This result is *not* saying that SP will always identify a strategy with lower expected regret than any RDM strategies. In [47], where I compared SP and RDM on a similar problem, SP led to higher expected regret than the least-expected regret RDM solution.

Comparing the stochastic strategy with the least-expected-regret RDM strategy, I observe that the levels of investments are very similar; investments in domestic coal, imported coal, and interconnection differ by 260, 118, and 321 MW respectively. Moreover, the temporal profile within 2016–2025 is slightly different (see Table 4-12).

Table 4-12: First-stage investments in three "key" candidates by the two methods (MW)

		2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
	Barapukuria	123	62	277		62					163
RDM	Kharaspir							194	194		
cluster	Khulna									416	846
3	Interconnection			1,000	500	500	500	370	290	79	
	Zajira							89	949	704	57
	Barapukuria	149	194	45				39			
SP	Kharaspir							194	194		
solution	Khulna									625	755
	Interconnection			1,000	500	500	500	418			
	Zajira							675	540	585	

I compare the investment levels of the SP solution to the 486 perfect-foresight solutions reported in Section 4.4.3 to draw some insights on the trade-offs that the least-expected regret solution identified. First, the investment level for domestic coal is at the lowest level recorded in the 486 perfect-foresight solutions. In other words, the stochastic programming solution recommends postponement of domestic coal development until the uncertainty on the domestic coal policy resolves. If planners had built the domestic coal plants and they did not have access to fuel, Bangladesh would incur high financial loss because of the capital cost of the stranded assets. On the other hand, the SP suggests relatively high investment in interconnection with India at 3 GW (ranges from 1 to 4 GW in the set of 486 perfect-foresight solutions). The interconnection with India is at low capital cost and allows power system operators to adjust their imports according to future conditions. Lastly, the investment in imported coal development is moderate at 3.2 GW (ranges from 0.2 to 6.6 GW in the set of 486 perfect-foresight solutions). Almost all perfect-foresight solutions with high demand and majority of perfect-foresight solutions with base demand in Section 4.4.3 recommend higher (than 3.2 GW) investment in imported coal. SP appears to recommend moderate levels. That way, planners can avoid high capital costs of investment in coal power plants until uncertainties are resolved. Meanwhile, planners resort to imports of electricity or natural gas to meet varying levels of demand in the first stage and the early years of the second stage (see Appendix Note B.5).

To conclude the discussion on the first criterion (modeling capability), both methods can adequately assist planners to identify a strategy with the least expected regret. In the example presented above (Table 4-11), stochastic programming performs slightly better as judged by its ~9% lower expected regret compared to the RDM strategy with the lowest expected regret. However, this is not a general result. As I discuss in detail in Appendix Note B.6, the choice of subset of scenarios for stochastic programming matters and applying additional scenario reduction methods, I obtained SP solutions with higher and lower regret compared to the one reported in this chapter.

4.6.2 Criterion II (Practical applicability): Performance of RDM and SP on the case study

Practical applicability was a major criterion in this project. World Bank staff emphasized that the models should always be tractable on personal computers given the limited resources some agencies might have for planning. In Table 4-13, the computational time for analyses are provided along with the specifications of my personal computer.

Table 4-13: Computational time (clock-time) for RDM and SP

	RDM	SP
Step 2: approximations	~550 min to solve 486 deterministic problem. First-stage investments are variable.	
Step 2: clustering	92 sec to run k-means clustering and select RDM strategies and scenarios for SP	
Step 3 (SP)		~76 minutes to identify stochastic solution for SP with 7 scenarios
Step 3 (RDM)/Step 4 (SP)	~1,410 minutes	~180 minutes
Total time	~1,962 minutes	~808 minutes

Note: Those simulations were performed on a desktop with an Intel core processor i7-5930K at 3.50GHz and 32 GB Ram. For the vulnerability assessment (Step 3 (RDM)/Step 4 (SP)) I parallelized runs and solved ~4 models simultaneously.

The stochastic programming approach took significantly less time to complete: 76 minutes of clock-time to solve the reduced two-stage stochastic program for the candidate near-term investments, and 180 minutes to solve the 486 deterministic linear programs to assess the vulnerability of the stochastic strategy for near-term investments (Step 4 of SP). By comparison, the vulnerability assessment for all seven RDM strategies against 486 scenarios took approximately one day (~1,410 min). I designed the vulnerability assessment in such a way that 486 optimization problems are solved for each strategy. Note that those optimization problems have fewer decision variables compared to the full horizon planning problem because investments up to 2025 are fixed in the former model at the levels determined by each strategy. Therefore, solution of 486 optimization problems for the vulnerability assessment takes on average ~200 minutes, which is less than half the time it takes to solve the 486 perfect-foresight problems (550 minutes). Based on the information I decided to save for each solution, each vulnerability assessment results in a set of 486 files whose total size is~4 GB.

To conclude, the cross-comparison agrees with previous literature that both methods are resource-intensive. The computational time for RDM is significantly higher in this case because I tested all 7 RDM strategies that approximate the continuum of strategies. The computational time of both approaches would have been similar if 1-2 RDM strategies had been analyzed.

4.6.2.a Practical applicability: extension

The significant less time spent on SP with the reduced set of scenarios is the competitive advantage of SP in terms of practical applicability. RDM could potentially complete faster by limiting its scope to a small set of promising strategies. So, potential heuristics could use the reduced set of scenarios as a testbed for RDM strategies. That way, less promising RDM strategies —as judged by the reduced set of scenarios (seven here) —could be eliminated and the time-intensive vulnerability assessment would take less time.

Different heuristics could be used such as eliminating the bottom 50% of RDM strategies in terms of expected regret in the subset of seven scenarios. Then, I could conduct the full vulnerability analysis for all remaining RDM strategies (the ones that passed the first screening), rather than all representative strategies resulting from clustering. Of course, that would take less time because I would only have to conduct the vulnerability assessment for all RDM strategies across seven scenarios (7*7= 49 deterministic model runs) and the full assessment for just 50% (here 3) of RDM strategies ((486-7)*3=1437 deterministic model runs. That way, the runs done under the vulnerability assessment are reduced by ~58%.

In Table 4-14, I implement this idea. There, I provide the vulnerability assessment of all seven deterministic strategies across the subset of seven scenarios chosen by the method in Section 4.5.2. Here, the ranking of RDM strategies according to the reduced set of seven scenarios is almost identical with their true ranking across all 486 scenarios. In particular, the top 3 (in terms of lowest expected regret) and bottom 2 strategies among the 7 RDM strategies are correctly identified.

To conclude, the computational time RDM spends on the vulnerability assessment is the major bottleneck for its practical applicability. Development of heuristics or reliance on theoretical results that will help analysts define a small set of promising strategies might limit the computational burden. However, limiting the number of RDM strategies might limit benefits an abundant set of RDM strategies provide. I discuss those benefits in the next subsection.

Table 4-14: Performance of strategies across seven discrete scenarios considered by SP (value in millions of 2015 U.S. dollars) (Green cell indicates best value)

Near-term strategy	Maximum regret	Minimum regret	Expected regret [a]
Stochastic model: Low domestic coal - Moderate imported coal-High interconnection	840	193	416
High domestic coal- Moderate imported coal- High interconnection	1,532	317	990
High domestic coal- Low imported coal - Low interconnection	2,445	476	1,421
Low domestic coal - Moderate imported coal- High interconnection	921	328	480
Moderate domestic coal- Moderate imported coal - Low interconnection	1,618	89	1,008
High domestic coal - Low imported coal-High interconnection	1,507	394	932
Low domestic coal - High imported coal - Low interconnection	2,700	275	1,312
Low domestic coal -high imported coal - High interconnection	2,134	198	929

4.6.3 Criterion III (Transparency and contribution to decision making): performance of RDM and SP on the case study

Under this criterion "transparency and contribution to decision making", the two methods are compared in terms of how easily comprehensive their mechanics and results are. Ideally, "the consequences of differing judgmental inputs should be reviewed without excessive effort. " [42]

Here, I consider as "judgmental" inputs the scenarios and their probabilities. In Section 4.6.3.a, I start with an example where planners acquire updated information on some uncertainties and only a subset of the original set of scenarios is relevant. The consequences are two-fold: (a) the expected performance of strategies within a subset of scenarios or alternative probability weights changes (b) the previously recommended strategy might not be the best-performing anymore and planners should follow an alternative strategy. Then, in Section 4.6.3.b, I examine if any method provides an estimate for the value of perfect information.

4.6.3.a Example 1: Updated information on fuel prices

Assume that planners acquire reliable information on domestic coal supply and know with certainty that the scenario with high coal supply will be realized. In that case, only one of three coal supply scenarios (see Table 4-5) initially considered is valid and the set of scenarios now consists of 162 scenarios (486 initial scenarios divided by three fuel price scenarios).

Both methods can estimate within seconds the updated expected performance i.e., the expected regret of the eight strategies over the updated set of 162 scenarios. According to results in the second column of Table 4-15, the expected regret of the eight strategies increases or decreases compared to the regret calculated over the 486 scenarios (see Table 4-11). For the stochastic strategy, the expected regret increases.

The two methods though differ in their suggestions for alternative strategies, more appropriate for the updated set of scenarios. RDM recommends switch from strategy of row 4 to strategy of row 6 in Table 4-11, increasing the investment in domestic coal power plants and decreasing the investment in power plants using imported coal. On the contrary, stochastic programming has provided just one solution and cannot recommend an alternative course of action based on the already available results. A new stochastic program would have to be solved in order to assess if there is a better performing strategy. That new stochastic programming would either use the same set of seven scenarios with updated probability weights or re-clustering among the 162 scenarios would provide a new subset of scenarios.

Table 4-15: Performance of strategies across subset of scenarios (in millions of 2015 U.S. dollars) (Green solution indicates best strategy)

Near-term strategy according to:	Expected regret (across just 162 scenarios having high coal supply occurring)
Stochastic model: Low domestic coal - Moderate imported coal- High interconnection	774
High domestic coal- Moderate imported coal- High interconnection	595
High domestic coal- Low imported coal - Low interconnection	878
Low domestic coal - Moderate imported coal-High interconnection	766
Moderate domestic coal- Moderate imported coal - Low interconnection	1,074
High domestic coal - Low imported coal-High interconnection	**511**
Low domestic coal - High imported coal - Low interconnection	1,457
Low domestic coal -high imported coal - High interconnection	1,085

4.6.3.b Value of reliable information for each of the uncertainties

In case of uncertainty, planners are usually interested in learning how important each uncertainty is: which uncertain factor makes the biggest difference in solutions, and for which it would be most valuable to have additional information. The expected value of perfect information (EVPI) is a widely used metric for such an analysis. I mention here a few examples: the EVPI of natural gas cost and demand growth uncertainty for the US power sector is calculated in [236], the EVPI of uncertainty related to three policy instruments (carbon tax, carbon cap, renewable portfolio standards) for the US power sector is provided in [253], the EVPI of multiple uncertainties including carbon capture and storage development for the US electricity sector is reported in [254].

Given the insights EVPI provides, here I compare the two methods in their ability to provide estimates of the EVPI. In particular, I aim to estimate the value of perfect information [255] for one uncertainty at a time i.e., assuming that planners will acquire more reliable information for one uncertain factor but the others will remain uncertain. To calculate the EVPI in that case, I need to know the optimal strategy for the updated set of uncertain scenarios. For instance, I consider three coal supply scenarios in the original set of 486 scenarios. Assuming that I know with certainty which coal scenario will actually be realized, I would have to solve one stochastic program with 162 scenarios (each with the same coal supply) for each of the three coal supply scenarios. So, for the full set of uncertainties, I would have to solve 17 (3+3+3+3+2+3) stochastic programs and each program would have to consider 162 (=486/3) or 243 (=486/2) scenarios simultaneously. Each such stochastic program is impractically large to solve. Instead, I decide to investigate if any method provides approximate information on the EVPI.

Based on readily available information – without solving additional mathematical programs – SP provides an estimate of the EVPI if all uncertainties are simultaneously resolved. The EVPI for resolving all uncertainties is equal to the expected regret provided in Table 4-14. However, in line with observations made in Section 4.6.3.a, readily available information from the stochastic program I have solved in Section 4.5.2.b and the vulnerability assessment of the stochastic solution (see Section 4.6.1) cannot be used to estimate the value of perfect information for just a single uncertainty. In order to calculate the EVPI for each uncertain factor assuming that the remaining five factors will continue to be uncertain, I would need to solve 17 additional (as just calculated above) stochastic programs, each with a subset of scenarios drawn from the relevant set of scenarios (see above: 162 or 243). For instance, in order to estimate the EVPI for fuel price uncertainty, I would need to know the cost of the optimal investment plan for each of the three fuel price scenarios. Thus, I would have to solve three stochastic programs, one per fuel price scenario. In each of those three stochastic programs, all factors other than fuel price would still be uncertain and would be described through 162 scenarios (3(demand)*3(coal supply)*2(gas supply)* 3(temperature)* 3(flooding)). On the other hand, RDM can readily provide information on the expected cost improvement that planners would experience if they switch from the best-performing RDM strategy for the entire set of scenarios to the best RDM strategy for the subset of scenarios that are still relevant upon the acquisition of perfect information. The value of EVPI estimated based on RDM results would be accurate if the discrete set of strategies considered enumerates all possible strategies planners can follow. Given that this is not the case (only seven strategies are considered, not the infinite combinations), RDM thereby provides an approximate EVPI. Table 4-16 provides estimates of EVPI for all uncertainties considered in this chapter using the formula of equation 4.6:

$$\widetilde{EVPI}_{\xi} = \min_{x \in RDM\, strategies} E_{\xi,\xi'}(\,f(x,\omega)) - \,E_{\xi}(\min_{x \in RDM\, strategies} E_{\xi'}(f(x,\omega))) \quad \text{Eq. 4-6}$$

Equation 4-6 calculates the expected value of perfect information on one uncertain factor (ξ), while the remaining five factors remain uncertain and noted with ξ'. The set of scenarios Ω is the set of 486 scenarios. The expected values consider all 486 scenarios when both (ξ) and (ξ') are noted such as in the first term of equation 4-6. However, the inner expected value in the second term of equation 4-6 considers only a subset of the 486 scenarios, i.e., the scenarios that have the value for ξ specified in the outer expected value. The first term of equation 4-6 refers to the expected cost of the least-expected cost solution across all 486 scenarios (here the strategy in the 5th row of Table 4-6). The second term though is the expected value of multiple least-expected cost solutions, one for each scenario that describes uncertain factor ξ. An example for the case of coal supply uncertainty in provided in the footnote.[12]

[12] There are three scenarios on coal supply. To calculate the second term of equation 4-6, I identify the least expected cost solution among the 7 RDM strategies in three cases. First, I consider 162 scenarios where coal supply is low; in that case the RDM strategy of third row in Table 4-6 remains optimal and the expected regret is 550 million US$. The second case includes 162 scenarios where coal supply is medium and the least expected RDM strategy does not change; the updated expected regret is 519 million US$. Lastly, I look into a third case with 162 scenarios where coal supply is high and the RDM strategy of cluster 1 in Table 4-6 is optimal with regret 511 million US$. Therefore, the second term of equation 4.6 has expected cost (100,913 million US$+1/3*(550+519+511) million US$. The first term of equation 4-6 is (100,913+612) million US$. Thus, the result of the subtraction is 85 million US$ as reported in Table 4-16. Note that 100,913 is the expected cost of 486 perfect foresight plans mentioned in Section 4.4.3 and 612 million US$ is the expected regret of the least expected regret RDM strategy in Table 4-11.

Table 4-16: Approximation of expected value of perfect information in case the feasible set includes only the seven RDM strategies (in millions of 2015 U.S. dollars)

Uncertainty	**Approximate value of perfect information**
Temperature	0
Demand	149
Fuel prices	35
Coal policy/supply	85
Gas supply	45
Flooding	0

Results for the value of perfect information in Table 4-16 indicate that resolution of the uncertainties with respect to demand, fuel supply and prices would lead to tangible benefits. On the other hand, zero value of information is calculated for the remaining two uncertain factors. This information contributes to decision making because it aids planners to understand the relative importance of each uncertainty and guides planners' decisions on mitigation of each uncertainty. For example, the uncertainty of coal supply is majorly driven by the absence of a national coal policy. Results indicate that as long as there is uncertainty on domestic coal development, the recommended strategy moderately exploits that resource and foregoes any value that could be extracted in case of a policy that more aggressively exploits domestic coal potential.

Resolution of uncertainty in four factors (coal and gas supply, fuel prices and demand) would potentially lead to different 1st stage investments. In that case, the EVPI is positive because planners would have pursued different first-stage investment plans if they knew with certainty which scenario would realize. For instance, the SP solution recommends low development of domestic coal in the 1st stage. However, if planners knew with certainty that the domestic supply of coal will be high, they would have invested in more coal units early on (strategy of cluster 1 in Table 4-6). Demand growth appears to be the most impactful uncertainty according to EVPI. This is reasonable because uncertain demand growth makes determination of total investment challenging and the recommended plans are facing the risk of over or under-procuring. The SP solution here recommends under-procurement of baseload capacity such as imported coal for scenarios with high demand growth. If planners knew with certainty that scenarios with high demand growth would realize, they would have developed more power plants that use imported coal (switching to strategy of cluster 7 in Table 4-6).

Finally, the value of information on climate change is surprisingly zero and contradicts my motivating hypothesis that Bangladesh faces high uncertainty with respect to climate change. This surprising result is explained by (a) my relatively optimistic assumptions on climate change and its impact and (b) the relatively limited adaptation options included in this mathematical program. First, my assumptions on climate change and its impact are optimistic because I employ climate change projections for year 2025 (flooding) and 2016–2041 for temperature and cooling degree days. Note that the 5-day rainfall increases by 23% compared to historical levels in 2025 under the high climate change scenario, whereas it increases by 56% by the end of the century [249]. Second, I focus on a subset of climate change impacts on Bangladesh and potentially underestimate its impact. For instance, cyclones are not captured by FATHOM's model and their potential impact on the availability of transmission grid and fuel. Third, I investigate the flooding risk at each facility as statistically independent from each other facility because FATHOM — the company that provided the flooding risk projections — did not provide information on the geographical interdependencies of risk. That way, the disruption the grid experiences due to flooding is underestimated because simultaneous outages are not considered. Fourth, I use data from a single flooding model, developed by FATHOM. However, there are multiple flooding models in the literature, which can potentially produce different flooding projections under the same climate projections because of modeling differences. For instance, a cross-comparison of six global flooding models in [256] found significant differences between models' projections in river deltas. Fifth, the uncertainty resolves in the second stage (post 2025): that way planners prioritize investments in assets that are not expected to be affected by climate change and the plans can be adapted later.

Finally, in Table 4-17 I provide the estimates of the approximate EVPI in case the set of feasible strategies consists of the seven RDM strategies and the SP strategy. Note that in that case the first term of equation 4-6 is the expected cost of the SP strategy. Comparing the values of Tables 4-16 and 4-17, it is obvious that the approximate values of EVPI change. The relative importance of each uncertain factor — as determined by the ranking of each EVPI — is the same. However, the change of the value illustrates the fact that the values of EVPI calculated here are approximate.

Table 4-17: Approximation of expected value of perfect information in case the feasible set includes only the SP and seven RDM strategies (in millions of 2015 U.S. dollars)

Uncertainty	**Approximate value of perfect information**
Temperature	0
Demand	110
Fuel prices	0
Coal policy/supply	90
Gas supply	19
Flooding	0

Overall, these results are useful because they reveal actions planner could take to limit uncertainty and/or gaps in the consideration of uncertainty, e.g., with climate change.

4.7 CONCLUSIONS

Here, I summarize the major insights the cross-comparison of Robust Decision Making to Stochastic Programming offers across the three criteria suggested by Crousillat [42]: modeling capability, practical applicability, and contribution to decision making. Both methods can handle dynamic multi-factor uncertainties for power system planning and recommend adaptive strategies. In practical problems of large scale though, both methods rely on approximations. The quality of approximations determines the quality of the recommended solution. For stochastic programming applications where many scenarios might be plausible, the performance of stochastic programming is dependent on the quality of the scenario reduction or sampling method used. In power system planning problems where enumeration of all possible investment plans is impossible, performance of RDM is dependent on the set of strategies considered.

In terms of practical applicability, both methods are complex and resource-intensive. However, implementation of RDM seems more difficult as its execution time increases with the number of strategies. The number of runs the planner has to do is usually large, and parallelization of model runs might be needed to complete the task in a timely manner. For example, in this analysis the SP solution was identified within 80 minutes. In the contrary, it took on average ~200 minutes to conduct the vulnerability assessment for each strategy.

RDM usually provides more information on the performance of alternative strategies and in that way, it can help planners build a deeper understanding of the problem they face. RDM results can shed light on the relative importance of uncertainty, guiding corrective actions to eliminate or better define the uncertainty.

Overall, it seems that methods have complementary strengths and weaknesses. SP is more practical, whereas RDM provides a breadth of information to decision makers. Given the complementarities in strength and weaknesses of each method, as part of future research, it might worth to try different heuristics integrating aspects of both methods into a single method. As an example, I mention a heuristic that would have worked in this particular example. This heuristic relies on the reduced set of scenarios, identified for SP to screen promising strategies for further vulnerability analysis within RDM. Note however that there is no guarantee that the described heuristic would have been successful for another example.

The insights from the cross-comparison might have limited applicability for at least four reasons. First, only one planning problem is considered. It is possible that the structure of the problem might favor one method over another. For example, in this problem, first-stage investment decisions differed only for a few candidates across plausible scenarios; which may have made the selection of discrete strategies easy. Second, both methods are applied as "open-loop".

In other words, no additional strategies are tested for RDM after the vulnerability assessment and no sensitivity analysis of SP is conducted here. Third, no theoretical justification for the conclusions is provided that would guarantee applicability of the conclusions to other examples. Fourth, absence of stakeholders also limits the conclusions of the comparison since I miss any important differences on the way both methods facilitate stakeholder engagement.

Finally, the cross-comparison presented in this chapter is also limited by its focus on a single probabilistic performance metric — the expected value. In future applications, the scope of the cross-comparison could be expanded to include robust performance metrics such as min-max regret [45]. To optimize those metrics, robust optimization might be the method of choice instead of SP. For the case study presented in this chapter, robust optimization can be formulated as a linear program because the uncertainties are described through a finite, discrete set of scenarios. However, solving that linear program would be challenging for a typical personal computer given the large (over 40 million) number of constraints and variables, hence smaller problems (equivalent to or approximating the full problem) would have to be formulated. Note that robust optimization could also be used as a method to generate an initial strategy in step 2 of the RDM method (Section 4.2.1).

CHAPTER 5
CONCLUSIONS

5.1 SUMMARY

This thesis proposes and assesses three enhancements to power system planning models. The need for those enhancements is becoming increasingly pronounced under the 21st century challenges of energy access and climate change. Policymakers and decision makers rely on power system planning models to analyze policies and assess investments. Thus, any enhancements to power system planning models should be scrutinized to verify that they are practical and sufficiently represent uncertainties, techno-economic and other key factors. Chapters 2, 3, and 4 each assess one enhancement using a case study.

Chapter 2 assesses an enhancement to transmission planning for restructured electricity markets. The enhancement was proposed in the academic literature over a decade ago [12], but has not as of yet been put into practice. In brief, academics have suggested that transmission planners should be proactive and consider themselves Stackelberg leaders, i.e., in assessing transmission investments, models should anticipate that generators will optimize their investments and operations in response to changes in the grid configuration. In theory, the proactive approach improves planners' objective function compared to reactive approaches [12]. In [12], the proactive approach is formulated as a complex multi-level program, potentially discouraging its adoption by planners. Here, I prove that under assumptions of perfect competition the problem of the proactive planner can be formulated as a single-level co-optimization problem. Moreover, I estimate that transmission planners in the Eastern Interconnection, USA forego ~11–86% of the benefits resulting from transmission investments by adhering to traditional non-proactive practices for evaluation of transmission investments.

Chapter 3 proposes a conflict-aware power system planning framework for fragile and conflict-affected states. The analysis in Chapter 3 illustrates how traditional power system planning models that overlook conflict underestimate the cost and levels of unserved energy in conflict-affected regions. The conflict-aware framework of Chapter 3 highlights the fact that no technology or resource is immune to conflict effects. Chapter 3 demonstrates how conflict projections can inform power system planning through a multi-stage stochastic program. As time progresses, planners form updated projections on future conflict, and adaptive power system development strategies are suggested. The conflict-aware strategies differ from conventional approaches in that they suggest postponement, diversification, and/or adjustment of investments according to the trajectory of conflict. Testing the new framework on a case study of South Sudan, I demonstrate that the conflict-aware framework reduces power disruptions and/or the costs of power supply compared to conventional approaches.

Chapter 4 compares two methods that can recommend power plans that are more robust to long-term uncertainties compared to plans that are developed by models that consider only a "baseline" future. Uncertainty has been present and recognized in power system planning since the early days of the field [5]. However, climate change has renewed interest in the topic. Reviewing the literature in Chapter 4, I conclude that in current practice methods are chosen without justification, based on contradicting rationales or overly narrow characterization of methods. I compare two of the most popular methods — Stochastic Programming (SP) and Robust Decision Making (RDM) — using three criteria: modeling capability, practical applicability and contribution to decision making [42]. In the case study of power system planning in Bangladesh under climate, demand, and fuel uncertainties over the next 25 years, the two methods prove to be equally capable of capturing the nature and consequences of those uncertainties. However, the two methods have complementary strengths and weaknesses with regards to the two other criteria. In particular, SP is more practical and less demanding in computational time and power, whereas RDM provides rich information on the problem at hand that can help planners better understand the decision context. In the case study of this chapter, SP defines a plan that performs better than any RDM strategy in terms of expected costs when evaluated over approximately 500 scenarios, even though the SP model itself only included 7 scenarios due to the curse of dimensionality. However, this is not necessarily a general result, as the performance of SP over all possible futures depends on the ability of the selected subset to satisfactorily represent the original set of scenarios.

The enhancements proposed in this thesis are relevant for real-world power system planning studies. However, those enhancements are only a subset of the enhancements that power system planners should consider implementing as advances in software and hardware allow them to solve more complex models. This thesis focuses on enhancements that will improve the value of planning processes by better representing the context: the institutional framework in Chapter 2, in terms of the relationship of transmission and generation planning entities; civil conflict risk in Chapter 3; and exogenous long-term uncertainties in Chapter 4. In Sections 5.2–5.5 below, I elaborate on these limitations and identify promising research areas for power system planning models in general as well as for the specific topics that Chapters 2–4 address.

5.2 GENERAL LIMITATIONS AND FUTURE RESEARCH ON POWER SYSTEM PLANNING

I discuss limitations and areas for future research on power system planning in the following two subsections. The first highlights limitations and promising research directions rising from the emergence of new technologies. The second provides an overview of fundamental limitations of power system planning models and ongoing research to address them.

5.2.1 New technologies

Emergence of new technologies might make traditional approximations and assumptions followed in power system planning models obsolete. Enhanced temporal approximations will be necessary to simulate electricity generation by renewable resources; representation of elastic demand will become necessary if there are high amounts of "smart" loads and storage; and the scope and objective of planning might be totally redefined in a future scenario with high penetration of distributed resources.

The variable and uncertain nature of renewable generation is approximated crudely in traditional power system planning models [257]. For example, power system planning models usually include a capacity constraint, which ensures that sufficient capacity will be available for peak demand. Almost the entire rated capacity of conventional thermal power plants factors into that capacity constraint. However, the uncertain and variable nature of renewables makes the calculation of capacity credits for renewables less straightforward [258]. Renewables also increase the need for flexibility in power systems. This flexibility can be provided through storage and more cycling and ramping of conventional units. Currently, most power system planning models cannot value that flexibility because of temporal resolutions that do not respect the chronology of loads and generation, nor constraints arising from unit commitment. Thus, new methods that improve temporal resolution are being developed [83], [84], [259], [260].

Demand is modeled as inelastic in this thesis as well as in most power system planning models [6]. However, new technologies such as electric vehicles and smart appliances are projected to gain market share [261], [262]. Estimating the elasticity of demand as a result of those technologies and integrating updated descriptions of demand in power system planning models is another enhancement to consider.

Moreover, this thesis assumes that the role of transmission and power system planners remains the same, i.e., planners are responsible for cost-efficient, reliable operation of the grid. But this role is being questioned today. For example, declining costs of distributed generation combined with favorable regulation have led to growing adoption of community choice aggregation (CCA) programs in California [263]. Allocation of already incurred costs for customers that switched to CCA programs has initiated regulatory proceedings in California [264]. It is unclear what the role of planners will be if the grid becomes a last resort option. A recent report by the Electricity Advisory Committee [265] recommends additional research to avoid grid defection and discusses the possibility of risk sharing among customers through purchase of reliability plans.

5.2.2 Scope of power system planning

Power system planning models will be always limited by their narrow scope, their reliance on data, and their forward-looking character. Accounting for their limitations, their results can be useful for analysis of policies and strategies in the power sector. I discuss those three limitations in the following paragraphs.

Power system planning models — similar to the ones used in this thesis — usually solve single-sector partial-equilibrium problems, in that feedback effects upon power demands on the supply and prices of inputs for power production through other sectors of the economy are not considered [266]. Therefore, power system planning fails to see any economy-wide effects and substitutions. Context-specific risks such as the ones of Chapters 3 and 4 usually affect the entire economy and partial equilibria fail to capture the intersectoral adjustments such as electrification of the economy under climate change mitigation scenarios. In addition, power system modeling is blind to other infrastructure sectors. However, as Chapter 3 illustrates, the power sector highly depends on other sectors e.g. for fuel supply. Ongoing research on representation of infrastructure interdependencies [267] and development of links between computable generable equilibrium models that look into the entire economy and power system planning models [268] are helpful to address economy-wide feedbacks. .

Model results are as good as the quality of their inputs and assumptions. Access to good quality data is a challenge for any real-world power system planning study, but this challenge is far more pronounced in the developing world [17], where institutions and agencies might be in their infancy. Data might not be available e.g., on assessments of domestic resources, or the information may be in non-electronic form or scattered among various reports by different agencies and institutions.

As with any forward-looking model, power system planning models are bounded by epistemic uncertainty. In other words, models represent only relationships we are aware of. However, there are still unknown relationships and unknown unknowns. For instance, there is no empirical research on the effect of electrification on the probability of conflict. Moreover, the next technological breakthrough is in the sphere of unknown unknowns.

Despite all those limitations, the enhancements proposed here lead to improvement of power system planning as long as existing market flaws do not prevent their benefits from being realized. The limitations discussed above introduce uncertainty on the potential value planners can realize by implementing those enhancements.

In the remainder of this chapter, I elaborate on limitations and research directions for each chapter. Those limitations and directions are more project-specific compared to the general issues discussed above.

5.3 LIMITATIONS AND FUTURE RESEARCH ON TRANSMISSION PLANNING

There are at least four assumptions and limitations in Chapter 2 that could spur further research: (1) coordination of transmission planning across the entire Eastern Interconnection; (2) omission of reliability constraints and objectives; (3) compensation of transmission investments; and (4) approximate representation of the Eastern Interconnection power grid. I explain how future research could investigate the intersection between proactive transmission planning and each topic in the paragraphs below.

There are eight transmission planning regions recognized by FERC in the Eastern Interconnection (EI) [269] and many more agencies that a transmission developer would have to apply for approval to start the construction of a transmission line. Chapter 2 though takes the perspective of an EI-wide planner who assesses transmission investments optimizing the costs across the interconnection. In cases where side payments are possible, the framework of Chapter 2 could be equivalent to seamless coordination of transmission investments among planners. However, such coordination of planning procedures is not the case now [78]. As of September 2016, no regional transmission plan had selected an interregional project for cost allocation [56]. Future research and policies mainstreaming the coordination of planning and operation on issues such as cost allocation between regions would be beneficial as interregional coordination can smoothen renewable variability [270] and lead to lower system costs. While coordination between transmission planners remains imperfect, further research on models such as the ones proposed by Kasina [271] might be helpful to simulate the interactions between multiple strategic proactive transmission planners.

Transmission planning in this chapter considers only economic and policy objectives. Developing methods that evaluate transmission investments based on all three criteria (reliability, economic, and policy-related) is challenging because reliability is assessed based on non-linear models of power system operations. Research so far has integrated a subset of reliability constraints in the planning models such as N-1 contingency criteria [272]. MISO'S MVP [77] demonstrates the interest of planners in such a process since projects that might be suboptimal under any single criterion, might offer the best value when all three criteria are considered. Thus, future research on computational challenges and integration of reliability considerations would be beneficial.

Chapter 2 assumes that investments are compensated at a guaranteed rate of return, and investors would be incented to build the efficient investments identified by planning models. Furthermore, generators are assumed to be reacting to efficient locational marginal prices However, this is not the case everywhere [273] and different payment schemes might necessitate different formulations within the power system planning framework, for instance bi-level formulations that represent how generators and consumers react to inefficient transmission pricing. Financial Transmission Rights (FTR) are also available in most US markets and future research could investigate the impact of new transmission investments on FTR allocation along with financial incentives FTRs might provide for transmission investment [274].

The grid of the Eastern Interconnection is represented in Chapter 2 as a 24-node system. Better representation of the grid would allow future case studies to explicitly account for transmission grid constraints such as Kirchhoff's Voltage Law and simulate practices such as transmission switching [275]. Recognizing the actual constraints that networks impose as well as the flexibility provided by smart grid practices such as transmission switching would hopefully lead to better estimates of interregional trade and benefits of transmission expansion.

5.4 LIMITATIONS AND FUTURE RESEARCH ON CONFLICT-AWARE PLANNING

The conflict-aware framework of Chapter 3 would benefit from any advances in conflict prediction and systematical investigation of conflict effects on infrastructure. The analysis of Chapter 3 could be extended to include more sophisticated representation of conflict and account for technical feasibility of investment plans. I elaborate on those limitations and future research directions in the following paragraphs.

Databases such as the EIAD [131] are relatively new and provide information on a subset of effects of interest to power system planners (e.g., outage days), covering only a subset of historical events (e.g., attacks on infrastructure during the Liberian civil war are not included). At the same time, rich information including quantitative data on conflict effects on power systems are scattered in damage assessment reports, documents for reconstruction programs, and articles in the press. Hence, systematic collection and presentation of relevant information would facilitate further research.

In future applications, analysts could use finer resolution for conflict effects if conflict prediction methods provide it and represent the decision making process of attackers to the grid.

Finer resolution in three aspects might be beneficial: on the geographical extent because conflict effects tend to be more intense in certain regions of a country over others; temporal profiles because conflict effects are more meaningfully considered at a sub-annual granularity; and intensity of conflict because conflict effects are not constant (versus off/on, the assumption in Chapter 3). For instance, the conflict in South Sudan is more intense in some parts of the country and fuel prices have been fluctuating depending on the intensity of conflict. Such an extension of the model could be first tried out in an analysis that uses historical data on a conflict. Assessing the potential benefits of finer resolution in a historical case would only require updates on the resolution of the power system planning model and would indicate if the effort to create methods that predict conflict and its effect in finer resolution is worthwhile. The modeling framework could also be extended to include strategic rebels, relying on large literature on "opponent" type games in electricity networks primarily developed for terrorist and cyber-attacks. For instance, attackers might decide to target power system components that will cause the maximum disruption to the grid [276].

Analysis of Chapter 3 could be extended to include technical constraints. Here, I mention a couple of assumptions and results that make technical feasibility of recommended plans a high priority. Each city is assumed to be able to operate as both a standalone microgrid and as part of a national transmission grid at will. Results recommend electricity generation almost entirely by renewable resources and storage during some hours of the year. Finally, future studies in South Sudan should consider additional options such as trade with neighbors, investment in natural gas infrastructure, and other renewable resources.

5.5 LIMITATIONS AND FUTURE RESEARCH ON CLIMATE CHANGE ADAPTATION IN POWER SYSTEM PLANNING

The cross-comparison of Robust Decision Making and Stochastic Programming of Chapter 4 would greatly benefit by involvement of stakeholders. The conclusions of Chapter 4 would still be valid, but they would be enriched by adding stakeholder's perspective on all three criteria (modeling capability, practical applicability, contribution to decision making). Chapter 4's analysis and conclusions also suggest that further research on approximations used within the two methods, representation of climate change impact, uncertainty characterization of climate change projections, and climate change risk management would be beneficial. I elaborate on all four aspects in the following paragraphs.

Results of Chapter 4 highlighted the dependency of available methods on approximations of the scenario set or decisions. They also pointed out the complementarities between the two methods. So, future research on approximation heuristics such as scenario reduction methods and methods that measure the quality of those approximations e.g., through calculation of bounds would greatly help practitioners. Advances in parallelization methods would also reduce the computational burden for applications of RDM. Whereas, research proposing combination of both methods into a single framework to take advantage of the computational efficiency of SP and the transparency of RDM seems a promising area as well.

The analysis of climate change impact on the Bangladeshi power system could also be extended in several ways. Chapter 4 only examined the impact of flooding and increased temperature on power plants. However, other effects of climate change on power system infrastructure were ignored due to limited resources and information such as the availability of water for cooling needs of thermal power plants and the climate change effects on the transmission grid. Moreover, the analysis would benefit by advances in flooding models. As of now, global flooding models disagree on their projections in delta areas [277]. Adding information on geographical correlation of the flooding projections would also be beneficial for system analysis.

Any advances in climate change projections will obviously benefit adaptation modeling. More specifically though, decision making tools will benefit by additional characterization of the uncertainty. Additional research on the probabilistic interpretation of the projections would help. For instance, past research has suggested considering the genealogy of climate models to assign probabilities to projections [278] or assigning weights based on the "skill" of models to represent climate variables [279].

Finally, there is a fundamental question: How will the risk of climate change be managed and shared among countries, companies, and citizens? This thesis assumed that Bangladeshi power plants would be able to purchase insurance to cover flood-related damage. I did not specify under which program or financial tool the power plant owners would buy such an insurance product. COP23 in November 2017 organized a panel on frontiers of risk sharing [280], where a clearing house with information on risk transfer [281] was launched. Policymakers and decisionmakers will further discuss climate change risk mitigation and management in the coming years assessing options including but not limited to insurance products, sovereign catastrophe risk pools [282], and climate-resilient standards [283]. Assessment of climate risk management options and adaptation strategies under varying risk attitudes — departing from the risk neutral framework — at multiple scales (countries, companies, citizens) would probably provide useful insights for the forthcoming policy discussions.

APPENDIX A

FURTHER DETAILS ON CHAPTER 3

Appendix A provides detailed information on the quantitative analysis of Chapter 3. Sections A.1–A.5 document the assumptions regarding input data and Sections A.6–A.14 provide detailed results on strategies discussed in Sections 3.6.1–3.6.9. Sections A.1 and A.2 present detailed information on transmission outages during conflict in Colombia and fuel prices during conflict in Juba, respectively. Section A.3 lists the sources of input data for the conflict projection model. Section A.4 presents input assumptions for the power system planning model such as capital cost of candidate power plants. Section A.5. explains the enforcement of the policy constraint. Finally, Sections A.6–A.14 provide detailed results for Section 3.6.1–3.6.9, respectively and support arguments made in Chapter 3.

A.1 ASSUMPTIONS RELATED TO THE EFFECT OF CONFLICT ON TRANSMISSION OUTAGES

In order to develop realistic assumptions for the outage of transmission network during conflict, I analyze the Energy Infrastructure Attack Database (EIAD) [131] . EIAD has data on attacks from all over the world, but I decided to focus the analysis on Colombia because the database has particularly good coverage of it. As a benchmark, I calculate the outage rates observed during 1998–2002 because the armed-related deaths and homicide rate consistently increased over that period. I focus on lines which connect more than 1,000 MW of generation to the system acknowledging that the attacks might be targeting lines with higher disruption potential if the attackers are strategic and have limited resources.

Majority of the attacks to the transmission network in EIAD involved bombing of transmission towers. If at least one tower of the line is under repair, I assume that the line is not operational. I use the following information provided in EIAD to calculate the outage rate:

1. Name of transmission line for identification purposes.
2. Downtime.

If the name of the line is missing, I used geographical information to determine the line targeted by the attack. For downtime, the entries were both quantitative and qualitative. In the first case, I use them directly but in the latter case I employ the following assumption: (<1 week: 5 days, <1 month: 20 days, <3 months: 50 days, <6 months: 120 days, >6 months: 200 days).

Table A-1: Outage rates for transmission lines in Colombia connecting more than 1000 MW of generation capacity to the grid

	1998	1999	2000	2001	2002
TL Ancón Sur-S.Carlos 230 kV.	18%	100%	100%	96%	98%
TL Cerromatoso-San Carlos 500 kV.	95%	67%	100%	99%	100%
TL Chivor-Sochagota 230 kV.	0%	0%	0%	0%	28%
TL Chivor-Torca 230 kV.	6%	0%	0%	0%	0%
TL Esmeralda-S.Carlos 230 kV.	24%	100%	81%	100%	100%
TL Guatapé-San Carlos 230 kV.	0%	76%	14%	19%	40%
TL Guavio-Torca 230 kV.	0%	0%	0%	0%	17%
TL La Virginia-S.Carlos 500 kV.	40%	38%	100%	100%	100%
TL San Carlos-Torca 230 kV	0%	0%	0%	5%	0%

A.2 ASSUMPTIONS RELATED TO THE EFFECT OF CONFLICT ON FUEL PRICES

During conflict, fuel shortages are frequently observed. During shortages, limited fuel quantity is available, and the price is usually higher. Given the absence of a supply-demand model for the oil market in South Sudan, I used a multiplier to simulate price increases. To make sure that the chosen multiplier is realistic, I downloaded historical price data for petrol [166] in Juba over 2012–2017.

Acknowledging that in this case study I already account for two factors influencing the fuel price (i.e., the exchange rate and the international price of oil), I calculate the price I would expect to observe if the price was just affected by these two factors. Then, I divide the observed petrol price in Juba by the calculated/expected price and obtain a multiplier. I present the estimates for the multiplier in Figure A-1. The mean value of the multiplier during the first two and a half years is 0.92 (period: Dec 2012–July 2015) and for subsequent two and a half years the mean value is 3.6 (period: Aug 2015–Dec 2017). So, the value (2) I used in the case study seems realistic.

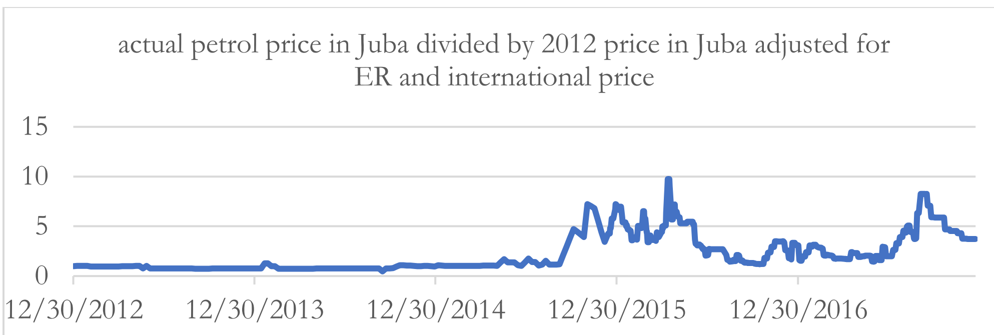

Figure A-1: Petrol price analysis in Juba

A.3 INPUT DATA FOR ESTIMATION OF PROBABILITY OF CONFLICT

I code the model by Hegre et al. [119] in Matlab, using the following inputs:

1. Population: the forecast provided under the medium variant scenario by the United Nations [284]
2. GDP: I use the GDP/capita for 2016 provided in [285]. For subsequent years, I vary GDP growth based on conflict history. In particular, I assume annual GDP growth of 0%, 0.5% and 2.5%, 5% if 0, 1, 2, 3 or more years of peace have been experienced since the last conflict, respectively. This assumption is similar to recent IMF

projections [286], where the 2018, 2019 and 2020 real GDP growths are 1.1%, 3.5%, and 6% respectively.

3. Education: I did not find projections of education statistics for South Sudan. Instead, I use projections [287] provided under Shared Socio-Economic Pathway 2 (SSP2) for Ethiopia because the 2015 education statistics reported for the two countries are similar [288].
4. Neighboring countries: I do not run a global model as in [119]. As a result, I do not have data on neighboring conflicts to use as inputs. Instead, I rely on conflict forecast estimated by [119] under SSP2. For each year in the planning horizon, I compare the forecasted probability of conflict against a random number drawn from the uniform distribution. If the number is higher or lower, I assume the neighboring country to be under conflict or in peace, respectively.
5. Coefficients: I draw 225 different sets of coefficients from a multi-variate normal distribution. Given the lack of estimate of random effects coefficients for South Sudan, I use the estimates for Central African Republic and draw 15 instances.

The probabilities for each of the eight scenarios used in the case study are presented in Table A-2. In Table A-3, I provide the probability of each state in years 2026–2029, 2030, 2035, 2040, 2045.

Table A-2: Probabilities for scenarios used in the case study

Scenario	**Probability**
Conflict-Conflict-Peace	0.19
Conflict-Conflict-Conflict	0.29
Conflict-Peace-Peace	0.26
Conflict-Peace-Conflict	0.04
Peace-Conflict-Peace	0.01
Peace-Conflict-Conflict	0.02
Peace-Peace-Peace	0.17
Peace-Peace-Conflict	0.02

Table A-3: Probability of conflict in years included in the model (past 2025) under all eight scenarios

Scenarios	2026	2027	2028	2029	2030	2035	2040	2045
Conflict-Conflict-Peace	0.10	0.13	0.15	0.17	0.17	0.20	0.21	0.20
Conflict-Conflict-Conflict	0.72	0.63	0.56	0.50	0.47	0.39	0.33	0.27
Conflict-Peace-Peace	0.12	0.16	0.18	0.20	0.21	0.23	0.23	0.23
Conflict-Peace-Conflict	0.71	0.62	0.56	0.50	0.46	0.34	0.31	0.28
Peace-Conflict-Peace	0.08	0.11	0.13	0.14	0.15	0.18	0.18	0.18
Peace-Conflict-Conflict	0.71	0.62	0.58	0.55	0.52	0.38	0.30	0.26
Peace-Peace-Peace	0.11	0.17	0.19	0.22	0.22	0.26	0.23	0.25
Peace-Peace-Conflict	0.68	0.62	0.56	0.49	0.48	0.31	0.29	0.29

A.4 ADDITIONAL INPUT DATA USED IN THE POWER SYSTEM PLANNING MODEL OF CHAPTER 3

I use the annual load projections for major cities provided under the base scenario in [169]. I assume a chronological profile for load based on the typical daily profile and the monthly peaks recorded in Kenya [289].

As power system candidates, I evaluate investments using:

- Assumptions for oil and hydropower plants provided in the same report as load projections [169]. See below in Table A-4, a list of candidate hydropower plants considered here.
- Capital costs for PV and storage are assumed to be 1,200$/kW and 1,700$/kW respectively, in line with recent quotes for South Sudan [290].
- Annual PV capacity factors provided by Global Solar Atlas [291].
- I assume that all PV in the country have the same hourly profile as the one found for Jimma in NREL PVWatts [292].
- For fuel prices, I use as starting price in 2014 the price provided in [169] and then apply the growth rate projected for crude oil price in [248].

Table A-4: Candidate hydropower plants

Candidate	Capacity (MW)	Annual capacity factor	Capital cost ($ mil/MW)
Lakki	300	45%	1.8
Bedden	522	45%	2.1
Shukoli	1100	49%	1.5
Wau_Dam	10.5	65%	10.8
Kinyeti	1.95	56%	7.6

A.5 POLICY CONSTRAINT

Here, I provide the earliest year unserved energy is not allowed to be positive per scenario. For scenarios starting with peace, the earliest year is the first year of the model horizon given that diesel generators can satisfy demand in times of peace.

Table A-5: Earliest year for elimination of unserved energy

Scenarios	Year
Conflict-Conflict-Conflict	2027
Conflict-Conflict-Peace	2023
Conflict-Peace-Conflict	2020
Conflict-Peace-Peace	2020
Peace-Conflict-Conflict	2017
Peace-Conflict-Peace	2017
Peace-Peace-Conflict	2017
Peace-Peace-Peace	2017

A.6 CONFLICT-NAÏVE STRATEGY (STRATEGY 1): DETAILED RESULTS

The conflict-naïve strategy is the solution to the optimization problem described in Section 3.4.3.a that considers peace prevailing for the entire planning horizon. The optimality gap at the solution reported here for the "conflict-naïve strategy" is 0.4968%. In Table A-6, I provide the cost composition and observe that majority of the cost is capital expenses (hereafter mentioned as Capex).

Table A-6: Cost composition of the conflict-naïve strategy under continued peaceful conditions

Category	**Cost (in million 2014 SSP)**
Capex	17,546
Dispatch	9,685
Fixed Operation and Maintenance Expenses (FOM)	819
Penalty for Unserved Energy	197
Total	28,247

In Table A-7, I provide the capacity mix under the conflict-naïve strategy. The solution recommends investment in the large hydropower plant (1.1 GW in Shukoli) as first priority given its favorable economics. Note that 2024 is the first year I let hydropower plants to be online in the model, accounting for some recovery time from the chronic conflict. In addition, Table A-8 presents the generation mix over the entire planning horizon.

Table A-7: 2017–2045 Capacity mix of the conflict-naive strategy assuming continued peace

Year	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
2017	176				176
2018	184		16	197	397
2019	201		16	213	429
2020	227		16	220	462
2021	246		16	222	484
2022	256		16	222	494
2023	256		16	222	494
2024	97	1,100	8	222	1,427
2025	97	1,100	8	222	1,427
2026	97	1,100	8	222	1,427
2027	97	1,100	8	222	1,427
2028	97	1,100	8	222	1,427
2029	97	1,100	8	222	1,427
2030	97	1,100	8	222	1,427
2035	146	1,100		296	1,542
2040	211	1,400		872	2,482
2045	287	1,922		1,430	3,639

Table A-8: 2017–2045 Generation mix of the conflict-naive strategy assuming continued peace

Year	Oil (GWh)	Hydro(GWh)	PV (GWh)
2017	1,096	-	-
2018	942	-	295
2019	1,056	-	321
2020	1,181	-	337
2021	1,325	-	350
2022	1,472	-	357
2023	1,612	-	357
2024	-	1,983	356
2025	-	2,218	343
2026	-	2,445	347
2027	-	2,697	352
2028	-	2,996	336
2029	-	3,283	350
2030	-	3,610	353
2035	582	4,733	439
2040	842	5,931	1,409
2045	1,167	7,997	2,307

A.7 TRANSMISSION OUTAGE-AWARE STRATEGY (STRATEGY 2): DETAILED RESULTS

The optimality gap of the solution reported here for the transmission outage-aware strategy is 5% and the objective function of the transmission outage-aware strategy is 9% lower compared to the objective function recorded when the conflict-naïve strategy is followed and the effects of conflict on transmission outages are simulated.

To demonstrate that the transmission outage-aware strategy (strategy 2) relies more on local capacity, I provide in Table A-9 the geographical distribution of energy generated for two indicative scenarios when the transmission outage-aware strategy (i.e., strategy 2) and the conflict-naïve strategy are followed. There, I observe a more balanced geographical distribution under the transmission outage-aware strategy. In particular, for both strategies the top node in terms of energy generated connects a hydropower plant to the transmission grid: Lakki (300 MW) under the transmission outage-aware strategy and Shukoli (1,100 MW) under the "conflict-naïve strategy". However, the transmission outage-aware strategy relies much less on the top generating node: under peaceful conditions 47% of the energy is generated at the top node (vs. 86% under the conflict-naïve strategy) and under conflict conditions 28% of the energy is generated at the top node (vs. 47% under the conflict-naïve strategy). Looking at the contribution of other nodes as well, it is clear that there is higher geographical diversification under the transmission outage-aware strategy.

Table A-9: Geographical distribution of energy generated in 2025 under two scenarios for two strategies: conflict-naïve and transmission outage-aware

	Conflict-Conflict-Conflict (status in 2025: conflict)		Peace-Peace-Peace (status in 2025: peace)	
Node	Transmission outage-aware strategy	Conflict-naïve strategy	Transmission outage-aware strategy	Conflict-naïve strategy
Aweil	4%	3%	3%	2%
Benitu	2%	2%	2%	1%
Bor	3%	3%	1%	0%
Juba	17%	13%	13%	0%
Kapoeta	1%	1%	1%	0%
Kuacjok	3%	2%	2%	1%
Lakki	**28%**	0%	**47%**	0%
Malakal	16%	14%	10%	6%
Maridi	4%	2%	4%	0%
Rumbeck	3%	2%	1%	1%
Shukoli	0%	**47%**	0%	**86%**
Torit	2%	1%	2%	0%
Wau	6%	5%	4%	2%
Yambio	4%	2%	4%	1%
Yei	7%	3%	7%	0%
Electricity demand met (GWh)	2,405	2,317	2,412	2,412

In Table A-10 to Table A-14 , I provide the capacity mix for years 2025, 2030, 2035, 2040 and 2045 for the transmission outage-aware strategy (strategy 2). For example, contrasting Table A-7 to Table A-14, it is obvious that there is redundant oil capacity under the transmission outage-aware strategy since the oil capacity is significantly higher in Table A-14 while capacity for hydro and PV is almost identical for both strategies (transmission outage-aware strategy and conflict-naïve strategy). In addition, the higher contribution of oil generation to the energy mix during times of conflict compared to times of peace in 2045 can be observed in Table A-15.

Table A-10: 2025 Capacity mix recommended by the transmission outage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	280	300	97	594	1,271
Conflict-Conflict-Peace	280	300	97	594	1,271
Conflict-Peace-Conflict	255	300	97	593	1,245
Conflict-Peace-Peace	255	300	97	593	1,245
Peace-Conflict-Conflict	281	300	97	593	1,270
Peace-Conflict-Peace	281	300	97	593	1,270
Peace-Peace-Conflict	252	300	96	592	1,240
Peace-Peace-Peace	252	300	96	592	1,240

Table A-11: 2030 Capacity mix recommended by the transmission outage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	467	300	97	870	1,734
Conflict-Conflict-Peace	411	300	97	847	1,656
Conflict-Peace-Conflict	447	300	112	876	1,736
Conflict-Peace-Peace	433	300	97	842	1,672
Peace-Conflict-Conflict	475	300	97	869	1,741
Peace-Conflict-Peace	391	300	97	846	1,634
Peace-Peace-Conflict	468	300	96	855	1,719
Peace-Peace-Peace	433	300	96	847	1,676

Table A-12: 2035 Capacity mix recommended by the transmission outage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	601	1,400	2	870	2,874
Conflict-Conflict-Peace	528	1,400	2	847	2,778
Conflict-Peace-Conflict	617	1,400	27	920	2,964
Conflict-Peace-Peace	533	1,400	2	842	2,777
Peace-Conflict-Conflict	601	1,400	2	869	2,873
Peace-Conflict-Peace	519	1,400	2	846	2,767
Peace-Peace-Conflict	584	1,400	1	855	2,840
Peace-Peace-Peace	576	1,400	1	847	2,824

Table A-13: 2040 Capacity mix recommended by the transmission outage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	887	1,400		883	3,170
Conflict-Conflict-Peace	816	1,400		884	3,100
Conflict-Peace-Conflict	879	1,400	25	882	3,187
Conflict-Peace-Peace	822	1,400		883	3,105
Peace-Conflict-Conflict	874	1,400		883	3,157
Peace-Conflict-Peace	793	1,400		884	3,077
Peace-Peace-Conflict	876	1,400		882	3,159
Peace-Peace-Peace	822	1,400		883	3,106

Table A-14: 2045 Capacity mix recommended by the transmission outage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	1,153	1,922		1,444	4,518
Conflict-Conflict-Peace	1,102	1,922		1,446	4,469
Conflict-Peace-Conflict	1,190	1,922	10	1,450	4,572
Conflict-Peace-Peace	1,118	1,922		1,444	4,483
Peace-Conflict-Conflict	1,141	1,922		1,445	4,509
Peace-Conflict-Peace	1,089	1,922		1,446	4,456
Peace-Peace-Conflict	1,189	1,922		1,441	4,552
Peace-Peace-Peace	1,134	1,922		1,444	4,500

Table A-15: 2045 Energy mix under all eight scenarios when the transmission outage-aware strategy is followed

Scenarios	Status	Oil	Hydro	PV	Energy served (GWh)
Conflict-Conflict-Peace	conflict	35%	44%	21%	10,424
Conflict-Conflict-Peace	peace	10%	70%	20%	10,843
Conflict-Conflict-Conflict	conflict	35%	44%	21%	10,486
Conflict-Conflict-Conflict	peace	10%	70%	20%	10,843
Conflict-Peace-Peace	conflict	35%	44%	21%	10,444
Conflict-Peace-Peace	peace	10%	70%	20%	10,843
Conflict-Peace-Conflict	conflict	36%	43%	21%	10,531
Conflict-Peace-Conflict	peace	10%	70%	20%	10,843
Peace-Conflict-Peace	conflict	35%	44%	21%	10,395
Peace-Conflict-Peace	peace	10%	70%	20%	10,843
Peace-Conflict-Conflict	conflict	35%	44%	21%	10,476
Peace-Conflict-Conflict	peace	10%	70%	20%	10,843
Peace-Peace-Peace	conflict	35%	44%	21%	10,465
Peace-Peace-Peace	peace	10%	70%	20%	10,843
Peace-Peace-Conflict	conflict	36%	43%	21%	10,525
Peace-Peace-Conflict	peace	10%	70%	20%	10,843

A.8 TRANSMISSION OUTAGE/SHORTAGE-AWARE STRATEGY (STRATEGY 3): DETAILED RESULTS

The optimality gap of the solution reported here for the outage/shortage-aware strategy is 5% and the objective function of the outage/shortage-aware strategy is 19% lower compared to the objective function recorded when the conflict–naïve strategy is followed and the effects of conflict on transmission outages and fuel supply are considered.

Here, I provide the capacity mix over time (Table A-16 to Table A-20). Comparing the first four rows (i.e., scenarios with violent first period) to the last four rows (i.e., scenarios with peaceful first period) of Table A-16, I observe different technological composition with more PV and storage in the former group and more oil in the latter group. Comparing the generation mix reported for conflict-naïve (strategy 1) and outage/shortage-aware strategy (strategy 3) in 2045 (see Table A-21), readers can confirm that there is limited room for additional generation by all technologies in times of conflict compared to their generation under peaceful conditions. More importantly, hydropower and oil produce lower amounts of energy given the unavailability of transmission network and fuel shortages. However, the outage/shortage-aware strategy demonstrates lower unserved energy rates due to higher integration of PV, whose operation is not affected by the two conflict effects modeled here.

Table A-16: 2025 Capacity mix recommended by the outage/shortage-aware strategy

Scenarios	**Oil (MW)**	**Hydro (MW)**	**Storage (MW)**	**PV (MW)**	**Total Capacity (MW)**
Conflict-Conflict-Conflict	83	300	673	1,323	2,380
Conflict-Conflict-Peace	82	300	673	1,323	2,379
Conflict-Peace-Conflict	99	300	630	1,210	2,238
Conflict-Peace-Peace	97	300	630	1,210	2,236
Peace-Conflict-Conflict	135	300	568	1,141	2,144
Peace-Conflict-Peace	132	300	568	1,141	2,140
Peace-Peace-Conflict	118	300	553	1,072	2,043
Peace-Peace-Peace	114	300	553	1,072	2,039

Table A-17: 2030 Capacity mix recommended by the outage/shortage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	176	300	688	1,635	2,798
Conflict-Conflict-Peace	150	300	673	1,536	2,659
Conflict-Peace-Conflict	197	300	664	1,617	2,779
Conflict-Peace-Peace	173	300	630	1,548	2,651
Peace-Conflict-Conflict	205	300	702	1,660	2,867
Peace-Conflict-Peace	160	300	568	1,494	2,522
Peace-Peace-Conflict	179	300	566	1,528	2,573
Peace-Peace-Peace	167	300	553	1,487	2,508

Table A-18: 2035 Capacity mix recommended by the outage/shortage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	198	1,400	92	1,635	3,324
Conflict-Conflict-Peace	182	1,400	77	1,536	3,195
Conflict-Peace-Conflict	159	1,400	281	1,779	3,619
Conflict-Peace-Peace	194	1,400	33	1,548	3,176
Peace-Conflict-Conflict	208	300	913	2,315	3,735
Peace-Conflict-Peace	192	1,400	15	1,494	3,101
Peace-Peace-Conflict	196	1,400	12	1,528	3,136
Peace-Peace-Peace	197	1,400		1,487	3,084

Table A-19: 2040 Capacity mix recommended by the outage/shortage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	175	1,400	15	1,561	3,151
Conflict-Conflict-Peace	178	1,400		1,537	3,115
Conflict-Peace-Conflict	182	1,400	247	1,952	3,782
Conflict-Peace-Peace	175	1,400		1,537	3,113
Peace-Conflict-Conflict	153	1,400	792	1,975	4,320
Peace-Conflict-Peace	161	1,400		1,478	3,039
Peace-Peace-Conflict	173	1,400	12	1,558	3,143
Peace-Peace-Peace	174	1,400		1,537	3,111

Table A-20: 2045 Capacity mix recommended by the outage/shortage-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	268	1,400	450	2,957	5,075
Conflict-Conflict-Peace	172	1,922	33	2,202	4,329
Conflict-Peace-Conflict	267	1,400	449	2,959	5,076
Conflict-Peace-Peace	172	1,922	33	2,202	4,329
Peace-Conflict-Conflict	189	1,400	764	3,266	5,619
Peace-Conflict-Peace	172	1,922	32	2,200	4,326
Peace-Peace-Conflict	269	1,400	450	2,957	5,076
Peace-Peace-Peace	172	1,922	33	2,202	4,329

Table A-21: 2045 Generation mix (in GWh) per scenario, status and fuel under conflict-naïve and outage/shortage-aware strategy when two conflict effects (transmission outages and fuel shortages) are modeled

		Conflict-naïve strategy		Outage/shortage-aware strategy	
Scenarios	Fuel	Status: conflict	Status: peace	Status: conflict	Status: peace
Conflict-Conflict-Peace	Oil	572	1,167	572	554
Conflict-Conflict-Peace	Hydro	4,718	7,997	4,718	7,997
Conflict-Conflict-Peace	PV	2,195	2,307	3,102	3,181
Conflict-Conflict-Conflict	Oil	572	1,167	572	842
Conflict-Conflict-Conflict	Hydro	4,718	7,997	3,499	5,931
Conflict-Conflict-Conflict	PV	2,195	2,307	4,675	4,688
Conflict-Peace-Peace	Oil	572	1,167	572	555
Conflict-Peace-Peace	Hydro	4,718	7,997	4,718	7,997
Conflict-Peace-Peace	PV	2,195	2,307	3,102	3,181
Conflict-Peace-Conflict	Oil	572	1,167	572	840
Conflict-Peace-Conflict	Hydro	4,718	7,997	3,499	5,931
Conflict-Peace-Conflict	PV	2,195	2,307	4,660	4,680
Peace-Conflict-Peace	Oil	572	1,167	572	557
Peace-Conflict-Peace	Hydro	4,718	7,997	4,718	7,997
Peace-Conflict-Peace	PV	2,195	2,307	3,099	3,178
Peace-Conflict-Conflict	Oil	572	1,167	572	611
Peace-Conflict-Conflict	Hydro	4,718	7,997	3,499	5,931
Peace-Conflict-Conflict	PV	2,195	2,307	5,008	5,074
Peace-Peace-Peace	Oil	572	1,167	572	555
Peace-Peace-Peace	Hydro	4,718	7,997	4,718	7,997
Peace-Peace-Peace	PV	2,195	2,307	3,102	3,181
Peace-Peace-Conflict	Oil	572	1,167	572	844
Peace-Peace-Conflict	Hydro	4,718	7,997	3,499	5,931
Peace-Peace-Conflict	PV	2,195	2,307	4,675	4,688

A.9 TRANSMISSION OUTAGE/SHORTAGE/EXCHANGE RATE-AWARE STRATEGY (STRATEGY 4): DETAILED RESULTS

Here (in Table A-22 to Table A-26), I provide the capacity mix of the outage/shortage/ER-aware strategy (strategy 4) overtime. The optimality gap of the solution reported here for the outage/shortage/ER-aware strategy is 6% and the objective function of the outage/shortage/ER-aware strategy is 8% lower compared to the objective function recorded when the conflict–naïve strategy is followed and the effects of conflict on transmission outages, fuel supply and exchange rate are considered.

Table A-22: 2025 Capacity mix recommended by the outage/shortage/ER-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	100	300	271	861	1,533
Conflict-Conflict-Peace	103	300	271	861	1,536
Conflict-Peace-Conflict	124	300	241	766	1,432
Conflict-Peace-Peace	125	300	241	766	1,432
Peace-Conflict-Conflict	75	1,100	194	643	2,012
Peace-Conflict-Peace	78	1,100	170	643	1,990
Peace-Peace-Conflict	79	1,100	183	643	2,005
Peace-Peace-Peace	79	1,100	173	643	1,994

Table A-23: 2030 Capacity mix recommended by the outage/shortage/ER-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	161	300	400	1,336	2,197
Conflict-Conflict-Peace	196	300	271	1,151	1,919
Conflict-Peace-Conflict	183	300	312	1,226	2,021
Conflict-Peace-Peace	203	300	241	1,125	1,869
Peace-Conflict-Conflict	75	1,100	170	909	2,255
Peace-Conflict-Peace	78	1,100	141	643	1,961
Peace-Peace-Conflict	79	1,100	164	783	2,125
Peace-Peace-Peace	79	1,100	119	643	1,941

Table A-24: 2035 Capacity mix recommended by the outage/shortage/ER-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	367	300	280	1,629	2,576
Conflict-Conflict-Peace	131	1,400	45	1,151	2,727
Conflict-Peace-Conflict	207	1,400	86	1,232	2,925
Conflict-Peace-Peace	124	1,400	15	1,125	2,664
Peace-Conflict-Conflict	60	1,100		1,021	2,181
Peace-Conflict-Peace	62	1,100		806	1,968
Peace-Peace-Conflict	63	1,100		1,021	2,184
Peace-Peace-Peace	63	1,100		1,021	2,184

Table A-25: 2040 Capacity mix recommended by the outage/shortage/ER-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	272	1,400	230	1,906	3,808
Conflict-Conflict-Peace	96	1,400		1,537	3,033
Conflict-Peace-Conflict	130	1,400	71	1,654	3,254
Conflict-Peace-Peace	96	1,400		1,537	3,033
Peace-Conflict-Conflict	210	1,100	64	1,639	3,013
Peace-Conflict-Peace	227	1,100		1,584	2,911
Peace-Peace-Conflict	210	1,100	64	1,639	3,013
Peace-Peace-Peace	99	1,400		1,516	3,014

Table A-26: 2045 Capacity mix recommended by the outage/shortage/ER-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	272	1,400	428	2,982	5,082
Conflict-Conflict-Peace	176	1,922		2,135	4,233
Conflict-Peace-Conflict	267	1,400	448	2,954	5,069
Conflict-Peace-Peace	175	1,922		2,150	4,247
Peace-Conflict-Conflict	269	1,400	446	2,952	5,068
Peace-Conflict-Peace	179	1,922		2,115	4,216
Peace-Peace-Conflict	270	1,400	448	2,955	5,073
Peace-Peace-Peace	175	1,922		2,150	4,247

A.10 CONFLICT-AWARE STRATEGY (STRATEGY 5): DETAILED RESULTS

The conflict-aware strategy is the solution to the optimization problem described in Section 3.4.3.a that considers conflict-dependent values for all four planning parameters. The optimality gap at the solution reported here for the conflict-aware strategy is 1.78%. To achieve a smaller gap, I could either let the model run for more hours or experiment with different settings and formulations. Please note that improving the gap would result in a solution with lower or equal cost to the one I identified here. However, for the purposes of this analysis, I consider the gap acceptable because the conflict-aware strategy identified has an objective function that is lower by 8.7% compared to the conflict-naïve strategy. The conflict-aware strategy has lower penalty costs for unserved energy across all scenarios (compare results in Table A-27 and Table A-28).

Table A-27: Cost composition of the conflict-naive strategy under all eight scenarios

Cost per scenario (in million 2014 SSP)	**Capex**	**Dispatch**	**FOM**	**Penalty for Unserved Energy**	**Total Cost**
Conflict-Conflict-Peace	21,781	9,795	951	39,328	71,855
Conflict-Conflict-Conflict	26,320	7,393	1,081	67,699	102,492
Conflict-Peace-Peace	21,864	11,951	936	23,552	58,303
Conflict-Peace-Conflict	25,586	14,258	1,065	44,029	84,937
Peace-Conflict-Peace	21,198	14,854	939	16,946	53,937
Peace-Conflict-Conflict	26,244	16,580	1,134	38,451	82,409
Peace-Peace-Peace	21,065	10,835	962	7,347	40,208
Peace-Peace-Conflict	24,525	16,422	1,002	29,263	71,212

Table A-28: Cost composition of the conflict-aware strategy under all eight scenarios

Cost per scenario (in million 2014 SSP)	**Capex**	**Dispatch**	**FOM**	**Penalty for Unserved Energy**	**Total Cost**
Conflict-Conflict-Peace	17,596	11,664	1,079	35,249	65,589
Conflict-Conflict-Conflict	22,098	8,726	1,358	59,791	91,973
Conflict-Peace-Peace	19,140	11,913	1,022	20,747	52,821
Conflict-Peace-Conflict	23,956	15,690	1,352	35,814	76,812
Peace-Conflict-Peace	20,191	16,698	1,039	13,736	51,664
Peace-Conflict-Conflict	27,780	17,599	1,340	31,391	78,110
Peace-Peace-Peace	20,201	12,986	1,034	6,027	40,248
Peace-Peace-Conflict	26,682	16,237	1,324	17,292	61,535

In Table A-29 to Table A-33, I provide the capacity mix recommended by the conflict-aware strategy under each of the eight scenarios.

Table A-29: 2025 Capacity mix recommended by the conflict-aware strategy

Scenario	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	332				332
Conflict-Conflict-Peace	332			276	608
Conflict-Peace-Conflict	326		10	269	604
Conflict-Peace-Peace	326		10	328	663
Peace-Conflict-Conflict	280		73	183	536
Peace-Conflict-Peace	280		73	596	949
Peace-Peace-Conflict	239		117	596	951
Peace-Peace-Peace	166	300	117	616	1,199

Table A-30: 2030 Capacity mix recommended by the conflict-aware strategy

Scenario	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	354		343	1,276	1,972
Conflict-Conflict-Peace	161	1,100	25	692	1,978
Conflict-Peace-Conflict	352		344	1,280	1,976
Conflict-Peace-Peace	129	1,100	10	328	1,567
Peace-Conflict-Conflict	200	300	246	1,156	1,903
Peace-Conflict-Peace	241	300	105	931	1,577
Peace-Peace-Conflict	199	300	254	1,167	1,920
Peace-Peace-Peace	237	300	119	965	1,621

Table A-31: 2035 Capacity mix recommended by the conflict-aware strategy

Scenario	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	116	1,100	343	1,276	2,834
Conflict-Conflict-Peace	145	1,100	25	908	2,179
Conflict-Peace-Conflict	123	1,100	336	1,280	2,839
Conflict-Peace-Peace	113	1,100	10	920	2,143
Peace-Conflict-Conflict	113	1,400	173	1,156	2,842
Peace-Conflict-Peace	130	1,400	32	931	2,493
Peace-Peace-Conflict	122	1,400	153	1,167	2,842
Peace-Peace-Peace	139	1,400	21	965	2,525

Table A-32: 2040 Capacity mix recommended by the conflict-aware strategy

Scenario	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	118	1,100	343	2,083	3,645
Conflict-Conflict-Peace	219	1,100	25	1,605	2,949
Conflict-Peace-Conflict	121	1,100	335	2,074	3,630
Conflict-Peace-Peace	226	1,100		1,584	2,911
Peace-Conflict-Conflict	44	1,400	173	1,818	3,435
Peace-Conflict-Peace	104	1,400	30	1,432	2,965
Peace-Peace-Conflict	57	1,400	138	1,761	3,356
Peace-Peace-Peace	95	1,400	3	1,542	3,039

Table A-33: 2045 Capacity mix recommended by the conflict-aware strategy

Scenario	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	269	1,400	447	2,953	5,069
Conflict-Conflict-Peace	175	1,922		2,150	4,247
Conflict-Peace-Conflict	269	1,400	448	2,954	5,072
Conflict-Peace-Peace	175	1,922		2,150	4,247
Peace-Conflict-Conflict	269	1,400	446	2,952	5,067
Peace-Conflict-Peace	175	1,922		2,144	4,241
Peace-Peace-Conflict	269	1,400	448	2,955	5,072
Peace-Peace-Peace	175	1,922		2,150	4,247

A.11 CONFLICT-AWARE STRATEGY WITH EXTREME TRANSMISSION OUTAGE (STRATEGY 6): DETAILED RESULTS

For the maximum-FOR sensitivity (strategy 6), I assume outage rate of 100% during times of conflict, which was the maximum value recorded for the benchmark lines (see Table A-1). The optimality gap for the maximum-FOR conflict-aware strategy reported here is 0.94%. In Table A-34 to Table A-38, I provide the capacity mix obtained.

Table A-34: 2025 Capacity mix of the maximum-FOR conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	296				296
Conflict-Conflict-Peace	296			355	651
Conflict-Peace-Conflict	274		176	355	805
Conflict-Peace-Peace	274		176	745	1,195
Peace-Conflict-Conflict	257		71	172	501
Peace-Conflict-Peace	257		71	601	929
Peace-Peace-Conflict	235		130	601	966
Peace-Peace-Peace	164	300	130	627	1,221

Table A-35: 2030 Capacity mix of the maximum-FOR conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	305		720	1,702	2,726
Conflict-Conflict-Peace	242	300	289	1,199	2,031
Conflict-Peace-Conflict	286		651	1,625	2,562
Conflict-Peace-Peace	210	300	275	1,185	1,970
Peace-Conflict-Conflict	210	300	567	1,527	2,604
Peace-Conflict-Peace	214	300	244	1,171	1,929
Peace-Peace-Conflict	208	300	578	1,540	2,626
Peace-Peace-Peace	204	300	276	1,184	1,964

Table A-36: 2035 Capacity mix of the maximum-FOR conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	426		842	2,230	3,498
Conflict-Conflict-Peace	363	300	300	1,653	2,616
Conflict-Peace-Conflict	272	300	663	2,027	3,261
Conflict-Peace-Peace	347	300	359	1,703	2,709
Peace-Conflict-Conflict	292	300	583	1,935	3,110
Peace-Conflict-Peace	374	300	257	1,640	2,571
Peace-Peace-Conflict	294	300	569	1,920	3,083
Peace-Peace-Peace	344	300	377	1,712	2,733

Table A-37: 2040 Capacity mix of the maximum-FOR conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	131	1,100	842	2,735	4,808
Conflict-Conflict-Peace	152	1,400	300	2,013	3,865
Conflict-Peace-Conflict	128	1,400	486	2,319	4,333
Conflict-Peace-Peace	167	1,400	182	1,884	3,633
Peace-Conflict-Conflict	131	1,400	527	2,379	4,437
Peace-Conflict-Peace	200	1,400	201	1,884	3,685
Peace-Peace-Conflict	134	1,400	455	2,283	4,272
Peace-Peace-Peace	192	1,400	262	2,012	3,866

Table A-38: 2045 Capacity mix of the maximum-FOR conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	273	1,400	395	3,080	5,149
Conflict-Conflict-Peace	274	1,400	397	3,041	5,112
Conflict-Peace-Conflict	244	1,400	544	3,110	5,297
Conflict-Peace-Peace	274	1,400	400	3,037	5,111
Peace-Conflict-Conflict	275	1,400	400	3,037	5,112
Peace-Conflict-Peace	269	1,400	444	2,969	5,082
Peace-Peace-Conflict	241	1,400	552	3,124	5,317
Peace-Peace-Peace	274	1,400	400	3,037	5,111

A.12 CONFLICT-AWARE STRATEGY WITH EXTREME EXCHANGE RATE (STRATEGY 7): DETAILED RESULTS

For the maximum-ER sensitivity (strategy 7), I assume an exchange rate of 130 SSP/$, which is in line with the 2017 end of the year exchange rate. The optimality gap for the maximum-ER conflict-aware strategy reported here is 0.5%. In Table A-39 to Table A-43, I provide the capacity mix.

Table A-39: 2025 Capacity mix of the maximum-ER conflict-aware strategy

Scenarios	Oil (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	16		16
Conflict-Conflict-Peace	16		16
Conflict-Peace-Conflict	343		343
Conflict-Peace-Peace	343	17	360
Peace-Conflict-Conflict	253		253
Peace-Conflict-Peace	253	15	267
Peace-Peace-Conflict	346	15	360
Peace-Peace-Peace	346	29	375

Table A-40: 2030 Capacity mix of the maximum-ER conflict-aware strategy

Scenarios	Oil (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	385		385
Conflict-Conflict-Peace	505	64	568
Conflict-Peace-Conflict	463	17	480
Conflict-Peace-Peace	515	18	533
Peace-Conflict-Conflict	305	15	319
Peace-Conflict-Peace	557	113	671
Peace-Peace-Conflict	454	29	482
Peace-Peace-Peace	510	29	539

Table A-41: 2035 Capacity mix of the maximum-ER conflict-aware strategy

Scenarios	Oil (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	596		596
Conflict-Conflict-Peace	782	64	846
Conflict-Peace-Conflict	738	17	755
Conflict-Peace-Peace	744	21	765
Peace-Conflict-Conflict	738	15	753
Peace-Conflict-Peace	754	143	897
Peace-Peace-Conflict	736	29	765
Peace-Peace-Peace	713	54	767

Table A-42: 2040 Capacity mix of the maximum-ER conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	771		175	945
Conflict-Conflict-Peace	1,064		71	1,135
Conflict-Peace-Conflict	1,056		17	1,074
Conflict-Peace-Peace	1,051		78	1,129
Peace-Conflict-Conflict	1,069		15	1,083
Peace-Conflict-Peace	477	1,100	143	1,720
Peace-Peace-Conflict	1,067		29	1,096
Peace-Peace-Peace	565	1,100	54	1,718

Table A-43: 2045 Capacity mix of the maximum-ER conflict-aware strategy

Scenarios	Oil (MW)	Hydro (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	785	1,100	465	2,350
Conflict-Conflict-Peace	1,629		86	1,715
Conflict-Peace-Conflict	952	1,100	17	2,069
Conflict-Peace-Peace	898	1,100	60	2,058
Peace-Conflict-Conflict	1,524		15	1,538
Peace-Conflict-Peace	925	1,100	129	2,153
Peace-Peace-Conflict	1,492		21	1,513
Peace-Peace-Peace	919	1,100	25	2,044

A.13 CONFLICT-AWARE STRATEGY WITH EARLY ELECTRIFICATION (STRATEGY 8): DETAILED RESULTS

In this sensitivity, I add several constraints which do not allow the unserved energy to be positive after a particular year for each scenario. I refer to this strategy as zero-unserved energy strategy (strategy 8) and the optimality gap for the solution reported here is 1.2%.

Table A-44: Cost composition of the "zero-unserved energy" strategy

Category	Cost (in million 2014 SSP)
Capex	41,835
Dispatch	8,137
FOM	1,724
Penalty for Unserved Energy	24,179
Total	75,875

Table A-45: 2025 Capacity mix of the "zero-unserved energy" strategy

Scenarios	Oil (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	295	92		387
Conflict-Conflict-Peace	295	92	1,524	1,911
Conflict-Peace-Conflict	176	725	1,524	2,425
Conflict-Peace-Peace	182	725	1,524	2,431
Peace-Conflict-Conflict	135	825	1,524	2,484
Peace-Conflict-Peace	135	825	1,524	2,484
Peace-Peace-Conflict	154	733	1,524	2,411
Peace-Peace-Peace	182	733	1,524	2,439

Table A-46: 2030 Capacity mix of the "zero-unserved energy" strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	187		1,548	2,640	4,375
Conflict-Conflict-Peace	195	300	1,246	2,274	4,014
Conflict-Peace-Conflict	177		1,339	2,418	3,934
Conflict-Peace-Peace	222	300	961	1,947	3,430
Peace-Conflict-Conflict	166		1,330	2,408	3,904
Peace-Conflict-Peace	157	300	1,205	2,208	3,869
Peace-Peace-Conflict	166		1,330	2,408	3,904
Peace-Peace-Peace	220	300	962	1,945	3,427

Table A-47: 2035 Capacity mix of the "zero-unserved energy" strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	180	311	1,793	3,177	5,460
Conflict-Conflict-Peace	226	311	1,620	3,088	5,244
Conflict-Peace-Conflict	218	311	1,627	3,095	5,250
Conflict-Peace-Peace	220	311	1,620	3,086	5,236
Peace-Conflict-Conflict	223	300	1,667	3,151	5,342
Peace-Conflict-Peace	220	311	1,617	3,079	5,226
Peace-Peace-Conflict	223	311	1,622	3,089	5,244
Peace-Peace-Peace	220	311	1,620	3,086	5,236

Table A-48: 2040 Capacity mix of the "zero-unserved energy" strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	221	311	2,769	4,949	8,249
Conflict-Conflict-Peace	221	311	2,769	4,949	8,249
Conflict-Peace-Conflict	218	311	2,782	4,963	8,274
Conflict-Peace-Peace	218	311	2,781	4,963	8,273
Peace-Conflict-Conflict	219	311	2,779	4,960	8,268
Peace-Conflict-Peace	223	311	2,757	4,932	8,223
Peace-Peace-Conflict	218	311	2,782	4,963	8,274
Peace-Peace-Peace	218	311	2,782	4,963	8,273

Table A-49: 2045 Capacity mix of the "zero-unserved energy" strategy

Scenarios	Oil (MW)	Hydro (MW)	Storage (MW)	PV (MW)	Total Capacity (MW)
Conflict-Conflict-Conflict	228	311	4,235	7,336	12,110
Conflict-Conflict-Peace	228	311	4,235	7,336	12,110
Conflict-Peace-Conflict	228	311	4,235	7,336	12,110
Conflict-Peace-Peace	228	311	4,235	7,336	12,110
Peace-Conflict-Conflict	228	311	4,235	7,336	12,110
Peace-Conflict-Peace	229	311	4,227	7,320	12,086
Peace-Peace-Conflict	228	311	4,235	7,336	12,110
Peace-Peace-Peace	228	311	4,235	7,336	12,110

A.14 CONFLICT-AWARE STRATEGY WITH FINANCING CONSTRAINTS (STRATEGY 9): DETAILED RESULTS

Adding a constraint that does not allow the annual expenses to exceed the maximum amount of revenue that the utility can collect based on the amount of energy served at the same year and the customer's WTP does not significantly change the capacity mix after 2025. However, the timing of the investments changes early in the horizon (before 2025). As figures in Table A-50 to Table A-52 indicate, the plan with the financing constraint recommends lower investment in oil units early on and higher investment on PV and storage compared to the plan without the financing constraint. The optimality gap for the solution reported here is 1.7%.

Table A-50: 2019 Capacity mix recommended by the conflict-aware model with and without financing constraint

	With financing constraint		Without financing constraint	
Scenarios	**Oil (MW)**	**PV (MW)**	**Oil (MW)**	**PV (MW)**
Conflict-Conflict-Conflict	82		196	
Conflict-Conflict-Peace	82		196	
Conflict-Peace-Conflict	82		196	
Conflict-Peace-Peace	82		196	
Peace-Conflict-Conflict	82	239	196	25
Peace-Conflict-Peace	82	239	196	25
Peace-Peace-Conflict	82	239	196	25
Peace-Peace-Peace	82	239	196	25

Table A-51: 2022 Capacity mix recommended by the conflict-aware model with and without financing constraint

	With financing constraint			Without financing constraint		
Scenarios	**Oil (MW)**	**Storage (MW)**	**PV (MW)**	**Oil (MW)**	**Storage (MW)**	**PV (MW)**
Conflict-Conflict-Conflict	71			245		
Conflict-Conflict-Peace	71			245		
Conflict-Peace-Conflict	71		406	245		184
Conflict-Peace-Peace	71		406	245		184
Peace-Conflict-Conflict	227	81	365	232	73	183
Peace-Conflict-Peace	227	81	365	232	73	183
Peace-Peace-Conflict	227	81	506	232	73	494
Peace-Peace-Peace	227	81	506	232	73	494

Table A-52: 2025 Capacity mix recommended by the conflict-aware model with and without financing constraint

	With financing constraint				Without financing constraint			
Scenarios	**Oil (MW)**	**Hydro (MW)**	**Storage (MW)**	**PV (MW)**	**Oil (MW)**	**Hydro (MW)**	**Storage (MW)**	**PV (MW)**
Conflict-Conflict-Conflict	73				332			
Conflict-Conflict-Peace	73			536	332			276
Conflict-Peace-Conflict	316		14	460	326		10	269
Conflict-Peace-Peace	316		14	476	326		10	328
Peace-Conflict-Conflict	286		81	365	280		73	183
Peace-Conflict-Peace	286		81	601	280		73	596
Peace-Peace-Conflict	238		118	601	239		117	596
Peace-Peace-Peace	165	300	118	619	166	300	117	616

APPENDIX B
FURTHER DETAILS ON CHAPTER 4

Appendix B provides detailed information on the quantitative analysis of Chapter 4. Section B.1 explains in detail how flooding projections are integrated into the power system planning model. Section B.2 provides information on the impact of rising temperatures on power system operations included in the analysis of Chapter 4. Section B.3 provides an overview of key inputs and values for uncertain factors. I document the mathematical formulation of the power system planning problem of Chapter 4 in Section B.4 and quantitative information on the SP solution that supports arguments made in the main text in Section B.5. Lastly, Section B.6 employs a set of scenario reduction techniques different from those used in Chapter 4 to select a subset of scenarios for SP and compares the resulting SP solutions.

B.1 INTEGRATION OF FLOOD PROJECTIONS WITHIN POWER SYTSEM PLANNING

B.1.1 Impact of floods on power systems

Floods affect power plants in at least two ways. First, during floods power plants might shut down if their operation is judged as unsafe. The duration of outages, especially after a flood, depends on repairs needed in case of damage. Second, damages and the subsequent repairs lead to additional expenses. Here, I assume that power plants will procure insurance to hedge themselves against damage caused by floods.

As of 2016, there was limited data on outages and damages power plants experience because of floods. In the USA, relevant damage estimates are provided by FEMA [293]. HAZUS 4.2 — the model FEMA employs for multi-hazard loss estimation — estimates damages for power plants up to 10 feet of inundation depth. In Bangladesh though, higher inundation depths have been historically recorded and are currently projected by flooding models. Thus, I interviewed the JHU Power Plant Manager — at the time David Ashwood — and collected data from past floods.

Discussing with Mr. Ashwood, it became clear that the layout of the power plant is important for quantification of the flooding risk. The same inundation depth will cause different levels of damage at a power plant where the turbine and boiler are located at grade level compared to another power plant where the turbine and boiler are located at an operating floor higher than the grade level. Elevation drawings of the power plants would be the ideal source of information to characterize the potential damage due to inundation. However, in the planning stage investments are still conceptual and elevation drawings are only available later when the feasibility of plans is examined. According to Mr. Ashwood, the design and elevation drawing is customized for each power plant based on site specifications and thorough analysis of costs and benefits of different designs. Ideally, elevation drawing for each power plant design along with its associated cost should be available to estimate the depth-damage curves for a power plant. However, to keep the assumptions here simple but at the same time as realistic as possible, I based them on the suggested elevation for equipment found in the feasibility report for Khulna power plant [294] with the operating level relocated from 17m (assumed for Khulna) to 3.5m. Using cost data provided in [294] and assuming that by the time water reaches the equipment replacement is required, I draw the depth-damage curve of Figure B-1.

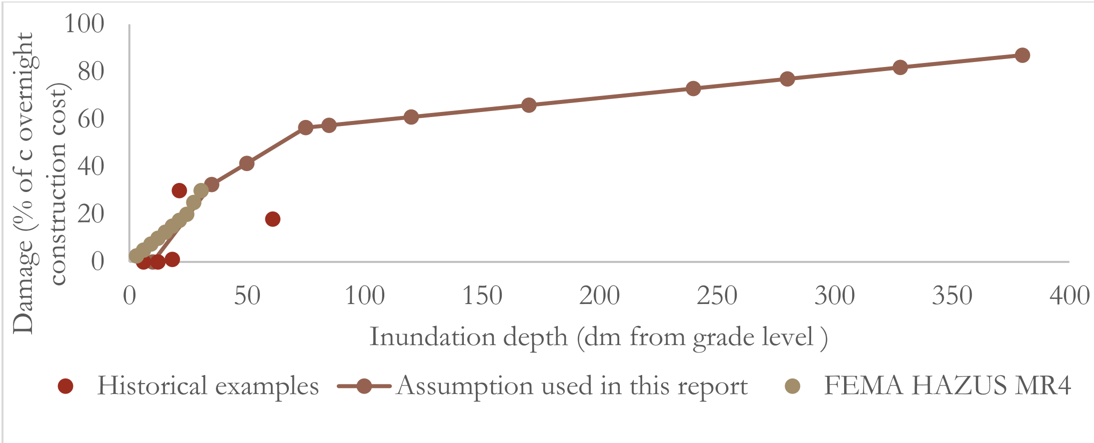

Figure B-1: Flood damage and inundation depth (assumptions and historical datapoints)

Comparing the fragility curve I constructed to data I collected from past floods (see Figure B-1), my assumption seems realistic. However, note that there is one datapoint with inundation depth at ~20 feet and less than 18% damage. That point refers to Watson Power Plant, where the elevation for expensive equipment (see Table B-1) was so high that neither the boilers nor the generator turbines suffered any damage.

Restoration time increases are expected to increase similarly to damages. Similar to depth-damage curve, I constructed a depth-outage curve that provides an estimate for outage days at each inundation depth. The underlying assumption for the depth-outage curve is the following: the duration of the outage is 1 day per dm up to 1.5m, the entire monsoon period for inundation depths between 1.5 and 4.5 m, and the entire year for inundation depths over 4.5m. Note that the observations vary widely. For example, superstorm Sandy caused damages to multiple PSEG assets. In that case, PSEG had to prioritize restoration efforts among different units [295] and repair days ranged from 12 to 63.

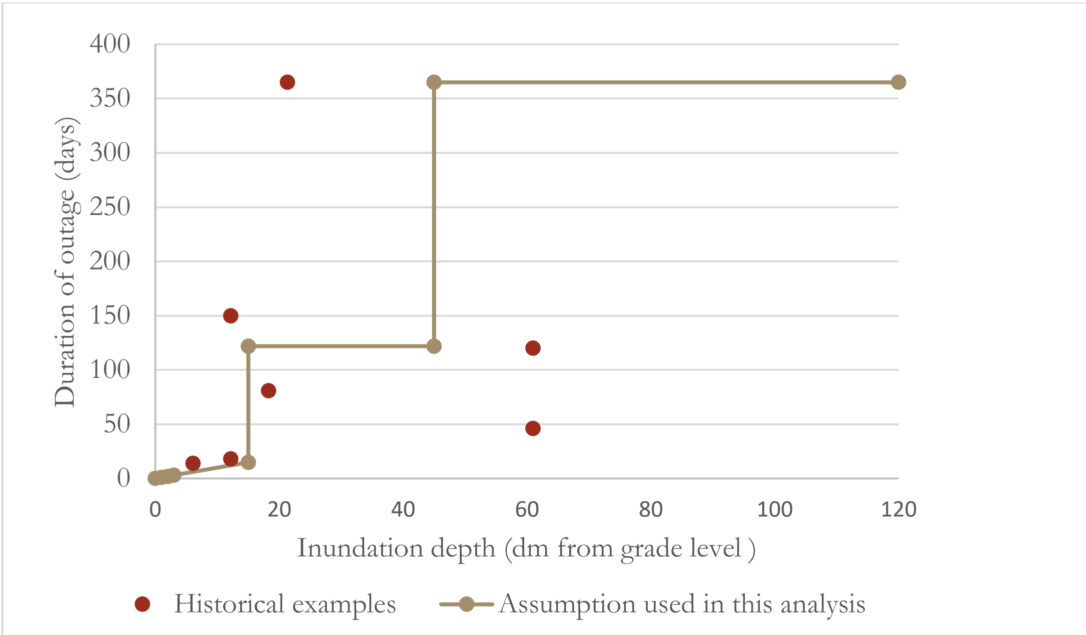

Figure B-2: Outage due to flooding and inundation depth (assumptions and historical datapoints)

Table B-1: Data on flooding damage and outage at a sample of coal power plant facilities

Row	**Power plant**	**Flood event**	**Inundation depth (ft)**	**Repair time (days)**	**Damage (as % of the capex)**
1	Simhapuri, India	11/18/2015	4–5 [296]	18	<0.03% [297]
2	6th street generating station, Iowa (USA)	June 2008	n/a		29% [298]
3	Prairie Creek, Iowa, USA	June 2008	n/a		26% [299]
4	Sutherland [300]	June 2008	2–4	14	0
5	Watson	Hurricane Katrina, 2005	20	46 [301]	<18% [302]
6	Watson	Hurricane Katrina, 2005	20	120 [301]	<18% [302]

Table B-2: Data on flooding damage and outage at a sample of natural gas power plant facilities

Row	Power plant	Flood event	Inundation depth (ft)	Repair time (days)	Damage (as % of the capex)
1	Linden, New Jersey	Hurricane Sandy, 2012		21 [295]	n/a
2	Kearny, New Jersey	Hurricane Sandy, 2012		12 [303]	n/a
3	Sewaren, New Jersey	Hurricane Sandy, 2012		63 [303]	n/a
4 [304]	Michoud, Louisianna	Hurricane Katrina, 2005	<6	<81	1%
5	Sabine, Louisiana	Hurricane Ike 2008	4 [305]	150	
6	Rojana power plant	Thailand, 2011	4–7	~365	29% [306]

Table B-3: Data on flooding damage and outage at a sample of diesel power plant facilities [307]

Row	Power plant	Flood event	Damage (as % of the capex)
1	Hadramount Wadi	Yemen, 2008	4%
2	Hadramount Sahel	Yemen, 2008	29%
3	Mahara	Yemen, 2008	58%

B.1.2 Flood-dependent power system planning parameters

Three power system planning parameters are assumed to be flood-dependent in this thesis: Fixed Operation and Maintenance cost (FOM), Forced Outage Rate (FOR), and capital cost.

Fixed Operation and Maintenance (FOM) cost include expenses that do not vary significantly with generation such as staffing costs, general and administrative expenses [308]. Insurance costs for protection against damage of the property qualify as FOM expenses. The annual cost for insurance in this thesis is assumed to be 2.59 times the expected annual damage cost, in line with premiums recorded during the sale of New York Metropolitan Transportation Authority (MTA) catastrophe bonds. New York MTA catastrophe bonds offered three-year reinsurance protection for storm surge risks. [13]

[13] The probability of the catastrophic event was estimated to be 1 in 60 years and the expected loss was estimated to be 1.71 percent. Investors asked for a 4.5 percent spread [320].

To calculate the expected damage, I adopt a micro-scale approach where the damage potential and the expected damage is evaluated at the object level: power plant [309]. This micro-scale approach uses a depth-damage function that estimates the damage incurred at the power plant at different inundation depths — here the one developed in Section B.1.1. Note that the depth-damage function of equation B-1 assumes that damage depends only on the inundation depth, ignoring any other flood characteristics such as duration of the flood or salinity of the water that might affect the magnitude of the damage.

$$
\begin{aligned}
&Expected\ damage \\
&\quad = \int_{-inf}^{inf} dx * \int_{-inf}^{inf} dy \\
&\quad * \int_{a-x-y}^{b-x-y} dz * D(x+y+z) * f_s(x) * f_s(y) * f_s(z) \quad \text{(Eq. B-1)}
\end{aligned}
$$

I use the integral of equation B-1 to estimate the expected damage under different climate scenarios *s*. In the equation B-1, a is the grade level of the power plant post any protection measure; b is the height of the power plant. The three risks considered here are fluvial (x), pluvial (y) and coastal (z) floods and they are assumed to be independent. For all three risks, I estimate power plant-specific probability distribution functions (pdf) f by fitting a Gumbel pdf to data provided by FATHOM (see Section B.1.3). Function D (see Figure B-1) provides an estimate of the damage at inundation depth $x + y + z$. The expected outage is calculated in the same way as expected damage but using a different damage function.

The grade level in present calculations is determined by an assumed building standard. Specifically, I assume that there is a building standard that requires power plant developers to protect their facility against the 200-year inundation depth. To the best of my knowledge, as of 2016 such a standard did not exist, but it was common practice by developers as indicated in completed Environmental Impact Assessment and Feasibility studies. The grade level assumption obviously affects the calculation of expected damage, but at the same time it increases the construction cost. Here, I simply assume that the increase of capital cost is equal to the cost of filing material for the area of the power plant. To calculate the volume of filling material needed for each power plant site, land requirements are assumed to be 0.45 acres/MW for coal and 0.1 acres/MW for gas units and the height is equal to the inundation depth at return period of 200 years. Lastly, I multiply the cost of filling material ($39/cubic meter) with the volume and update the capital cost estimate for each power plant site to include this additional cost component.

B.1.3 Probability distribution function for flooding risks

In 2016, WBG purchased flooding data from FATHOM (at that time SSBN) for this project. FATHOM has developed a global flooding model which is documented in [310]. FATHOM provided fluvial and pluvial flooding projections using low, mean, and high projections for 5-day precipitation change from climate scenario RCP 8.5 [249], the scenario with the highest radiative forcing among the scenarios considered in AR5.[14] Coastal flooding risk was provided for various levels of seal level rise from 0 m (historical) to 50 cm.

FATHOM provided flood hazard maps with a ~90 m resolution for three flooding risks at return periods 5, 10, 20, 50, 75, 100, 200, 250, 500 and 1000 years. I use these datapoints to estimate the parameters of a Gumbel distribution. Note that the Bangladesh Power Water Development Board uses Gumbel probability distributions upon recommendation of this type of distribution under the Flood Assistance Program of 1992. For each power plant site (see details later), I calculate the average inundation depth at each return period using ArcGIS. Using the average inundation depth at the return periods, I fit a Gumbel distribution at each site for every climate scenario. In particular, for each site I estimate the location (a) and scale parameter (b) of a Gumbel distribution by performing ordinary least squares for the linear relationship described in (Eq. B-2), which uses as input the mean inundation depth over the power plant area (x) and the respective

[14] RCP 8.5 has also been described as "a high-emission business as usual scenario." [321]

cumulative probability $F(x)$ (see Eq. B-3). For most power plant locations, I was able to fit a distribution with relatively acceptable R-squared.

$$x = a - b * \ln(-\ln(F(x)) \qquad \text{Eq. B-2}$$

$$F(x) = 1 - \frac{1}{return\ period} \qquad \text{Eq. B-3}$$

Upon completing the calculations for each climate scenario, I observe that the difference among the three flooding scenarios provided by FATHOM was negligible in terms of their impact on power system parameters. So, I decided to retain only the high scenario and to create one additional scenario relying on projections published by [250]. According to [250], the return period of a 100-year event under historical climate conditions will be 5–25 years in Bangladesh by the end of the century, as projected by the median model of AR5 in the RCP 8.5 scenario. Using this result, I constructed a new scenario with modified flood profiles in order to project the historical 100-year event as a 20-year event for fluvial/pluvial flooding and as a 25-year event for coastal flooding.

B.2 TEMPERATURE EFFECTS ON POWER SYSTEMS

Here, I consider two effects of temperature on power system: (1) capacity derates and (2) demand increases. Capacity derating of 0.4 percent is assumed for coal, 0.5 percent for combined cycle gas turbine, and 0.7 percent for peaking open cycle gas turbine for every Celcius degree above 27°C.

The impact of cooling degree days on electricity demand is captured through empirical relationships provided in McNeil and Letschert [251]. These relationships rely on GDP and cooling degree days projections to estimate the penetration of air conditioners (AC units) in the residential sector and annual energy consumption per AC unit.

Table B-4: Temperature and CDD projections

	increase in cooling degree days over historical conditions			summation of (max temperature -27) over all 12 months		
	bcc-csm1-1	**cesm1-bgc**	**mri-cgcm3**	**bcc-csm1-1**	**cesm1-bgc**	**mri-cgcm3**
2016	36	451	119	73	77	72
2017	143	351	216	65	81	66
2018	107	513	159	69	85	68
2019	563	564	96	86	84	69
2020	429	332	60	81	73	64
2021	266	363	26	76	85	61
2022	355	520	213	79	84	71
2023	473	603	37	80	85	63
2024	339	447	87	74	81	65
2025	216	292	57	72	75	62
2026	417	348	(21)	80	76	57
2027	476	404	(93)	88	80	51
2028	413	377	97	78	77	63
2029	399	289	209	81	77	69
2030	529	626	(44)	82	90	55
2031	534	554	155	80	82	69
2032	420	365	100	79	76	62
2033	566	680	218	85	93	71
2034	422	813	134	79	93	65
2035	448	721	84	84	89	63
2036	271	628	67	78	87	57
2037	461	495	186	80	88	67
2038	552	415	366	83	79	84
2039	424	345	233	77	82	64
2040	550	434	277	83	80	68
2041	646	530	218	87	88	61

B.3 OTHER INPUTS

The reference year for discounting of the objective function is 2015, and real 2015 U.S. dollars are used. The discount factor is 6 percent and the weighted average cost of capital is 10 percent for new investment projects. The value of lost load is assumed to be 50 U.S. cents/kWh.

With respect to power imports, Bangladesh already has a 500 MW interconnection with India. In addition, new interconnections with Bhutan, Nepal, and India may be possible following the SAARC Regional Trade study. Here, I consider them as possibilities, and use the following assumptions:

- The transmission investment cost is $3,184/MW/km.

- Interconnection capacity is constrained by an annual ceiling that increases from 1,500 MW (2020) to 13,500 MW (2041).
- An upper bound of 8 GW per interconnection option is used.

Price assumptions are as follows:

- For India, for each time block I assume that the price will be set by the most expensive power plant that is online at the moment. I use the energy mix projections provided for the scenario "IEA New Policies"[311] to specify the most expensive type of power plant among the online power plants for each time block. In particular, I assume: high-speed diesel, 2,600 hours; natural gas, 1,828 hours; coal, 2,019 hours; nuclear, 2,313 hours. The price assumptions are: high-speed diesel, $223.4/MWh; LNG, $98–172.32/MWh; coal, $53.6/MWh; and nuclear, $44/MWh. Note that I assume the variable part of the price (assumed to be 67% for HSD, 73% for LNG, 48% for NG, 46% for coal) will increase at the same rate as international prices for fuel.
- For hydropower imported from Nepal, I assume $47/MWh and availability 50 percent of the year.
- For hydropower imported from Bhutan, I assume a price of $37/MWh and $0.5 million/MW based on a review of existing agreements with India [312]; availability 44 percent of the year; and a production profile based on imports from Bhutan to India as reported in executive summaries over the past 10 years [313]

New coal capacity up to a limit of 30 GW is considered, with a capital cost of $2,032/kW for domestic coal (4 sites) and $2,622/kW for foreign coal (13 sites). Given the paucity of land in Bangladesh I do not assume any sites for coal or gas beyond what has been considered in the 2010 PSMP and the Ashugonj Power Station Company's master plan.

Investments in natural gas power plants are considered at a capital cost of $1,342/kW for combined cycle units and $1,012/kW for open cycle units across 95 locations (see Figure B-3).[15] I assume that the new gas power plants can either be developed on land being considered for coal power plant development (that is, competing with foreign coal power plants for the roughly ~13,000 acres of land that in total are available for development) or on land already being used or proposed to be used for gas power plant development (~5,000 acres).

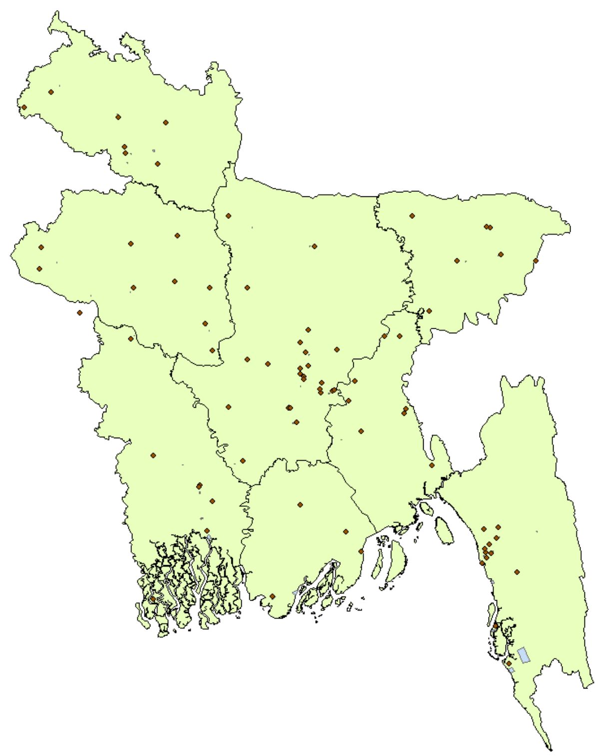

Figure B-3: Map with sites for power plants (existing and candidate)

Regarding investment in renewable sources, biomass is assumed to have a capital cost of $3,000/kW. Its potential is capped at 274 MW in line with the estimate provided in [314]. Photovoltaics' capital cost is set at $2,430/kW; this includes an estimate of $880/kW for land

[15] Some of the 95 locations are quite close to one another. For future runs, I could aggregate them but here I keep as much spatial detail as possible since the flooding risk depends on the elevation of the terrain, which might change abruptly.

acquisition. Investments in wind farms are not considered since the estimated potential is of ~600 MW [314].

B.3.1 Natural gas supply scenarios

Table B-5: Natural gas supply scenarios in mmcfd

	High		Low	
	Domestic gas	**LNG**	**Domestic gas**	**LNG**
2016	2544	0	2544	0
2017	2599	0	2599	0
2018	2562	0	2562	0
2019	2453	500	2453	500
2020	2435	500	2435	500
2021	2108	500	2108	500
2022	2005	500	1835	500
2023	1787	500	1617	500
2024	1690	1000	1490	1000
2025	1681	1000	1381	1000
2026	1708	1000	1308	1000
2027	1754	1500	1254	1000
2028	1700	1500	1200	1000
2029	1645	1500	1145	1000
2030	1627	2000	1127	1000
2031	1609	2000	1109	1000
2032	1590	2000	1090	1000
2033	1590	2500	1090	1000
2034	1590	2500	1090	1000
2035	1554	3000	1054	1000
2036	1463	3000	963	1000
2037	1463	3000	963	1000
2038	1463	3500	963	1000
2039	1463	3500	963	1000
2040	1463	4000	963	1000
2041	1154	4000	654	1000

B.3.2 Coal supply scenarios

Table B-6: Coal supply in thousand tons

	Barapukuria			Phulbari			Kharaspir			Dighipara		
	High_ coal	Base_ coal	Low_ coal	High_c oal	Base_ coal	Low_ coal	High _coal	Base_ coal	Low_ coal	High _coal	Base_ coal	Low_ coal
2016	1000	1000	850									
2017-19	1000	1000	900									
2020-21	1500	1100	1000									
2022	2000	1600	1000									
2023-24	2500	1600	1000									
2025-26	3000	2100	1000									
2027	3000	2100	1000				500	500	500			
2028	3000	2100	1000				1000	1000	1000			
2029	3000	2100	1000				1500	1000	1000	500	500	500
2030	4500	3200	1100	500	500	500	2000	1000	1000	1000	1000	1000
2031	4500	3200	1100	1000	1000	1000	2000	1000	1000	1500	1000	1000
2032	4500	3200	1100	2000	1000	1000	2000	1000	1000	2000	1000	1000
2033	5500	3200	1100	2000	2000	1000	2000	1000	1500	2000	1000	1000
2034	5500	3200	1100	3000	2000	1000	2000	2000	1500	2000	1000	1000
2035	5500	3200	1100	3000	2000	1000	2500	2000	1500	2000	1000	1500
2036	5500	3200	1100	4000	3000	1000	2500	2000	1500	2000	2000	1500
2037	5500	3200	1100	4000	3000	2000	2500	2000	1500	2500	2000	1500
2038	5500	3200	1100	5000	3000	2000	2500	2000	1500	2500	2000	1500
2039	5500	3200	1100	5000	4000	2000	2500	2000	1500	2500	2000	1500
2040-41	5500	3200	1100	6000	4000	2000	2500	2000	1500	2500	2000	1500

B.4 FORMULATION FOR POWER SYSTEM PLANNING IN BANGLADESH

Nomenclature
Sets and Indices

F Fuels indexed by *f*
G Generators indexed by *g*
R Regions indexed by *r*
S Scenarios indexed by *s*

T	Representative hours of the year indexed by t
Y	Years indexed by y

Decision variables

$build\_1st_{g,y,l}$	Generation investment in MW, added at y within 1st stage
$build\_2nd_{s,g,y,l}$	Generation investment in MW, added at y within 2nd stage
$cap_{g,s,l,y}$	Capacity in MW
$gen_{f,g,s,l,t,y}$	Generation in MW at hour t
$ret\_1st_{g,y,l}$	Retirement of generator g in MW at year y within first stage
$ret\_2nd_{s,g,y,l}$	Retirement of generator g in MW at year y within second stage
$use_{s,t,y}$	Unserved energy at node i in MW
$ures_{s,y}$	Deficit in planning reserve margin constraint in MW

Parameters

$ANCAP_{g,l,y}$	Annualized capital cost for generator g in $/MW
ACF_g	Maximum annual capacity factor for generator g
$CF_{s,l,g,t,y}$	Capacity factor for generator g at hour t
D_t	Duration of representative hour t in hours
EX_{g,s,y,y_1}	1 for generators within their operational life; 0 otherwise
$FOM_{g,l}$	Fixed Operation and Maintenance costs in US$
HR_g	Heat rate for generator g in MMBTU/MWh
$LAND_l$	Available land at location l in acres
$LANDPERMW_g$	Land requirement in acres per MW for generator g
$LEAD_g$	Lead time (construction time for generator g)
$LOAD_{s,t,y}$	Electricity demand in MW
p_s	Probability of scenario s
$PEAK_{s,y}$	Peak Load in MW
PRM	Planning reserve margin; assumed 15%
PRMP	Penalty for violation of planning reserve margin constraint in $/MW
r	Discount rate; assumed 10%
$VC_{f,g,s,t,y}$	Variable cost in $/MWh
$VOLL$	Value of lost load in $/MWh

$$\text{MINIMIZE (capex + opex + penalty)} \quad \text{Eq. B-4}$$

$$\text{capex} = \sum_{g,l,y} ANCAP_{g,l,y} * build_{1st_{g,l,y}} + \sum_{s,l,g,y} p_s * ANCAP_{g,l,y} * build\_2nd_{s,g,l,y} \quad \text{Eq. B-5}$$

$$opex = \sum_{s,g,ly} p_s * \frac{(FOM_{g,l} * cap_{g,s,l,y} + \sum_{f,t} D_t * VC_{f,g,s,t,y} * gen_{f,g,s,l,t,y})}{(1+r)^{y-2016}} \quad \text{Eq. B-6}$$

$$penalty = \sum_{s,t,y} \frac{p_s * D_t * VOLL * use_{s,t,y}}{(1+r)^{y-2016}} + \sum_{s,y} p_s * \frac{ures_{s,y} * \text{PRMP}}{(1+r)^{y-2016}} \quad \text{Eq. B-7}$$

$cap_{g,s,ly} = cap_{g,s,\mathrm{l},y-1|y>2016} +$ $\forall(g,s,\mathrm{l},y)$ Eq. B-8

$build\_1st_{g,l,y-LEAD(g)} + build\_2nd_{s,g,l,y-LEAD(g)} -$

$ret_{1st_{g,y,l}} - ret_{2nd_{s,g,y,l}}$

$cap_{g,s,\mathrm{l},y} \leq \sum_{y_1} EX_{g,s,y,y_1} * (build\_1st_{g,l,y_1} +$ $\forall(g,s,\mathrm{l},y)$ Eq. B-9

$build\_2nd_{s,g,l,y_1})$

$gen_{f,g,s,l,t,y} \leq CF_{s,l,g,t,y} * cap_{g,s,\mathrm{l},y}$ $\forall(f,g,s,l,t,y)$ Eq. B-10

$\sum_{f,t} D_t * gen_{f,g,s,l,t,y} \leq ACF_g * cap_{g,s,\mathrm{l},y} * 8760$ $\forall(g,s,l,y)$ Eq. B-11

$\sum_{g,\mathrm{l},t} D_t * gen_{f,g,s,l,t,y} * HR_g \leq FUEL_{s,f,y}$ $\forall(s,f,y)$ Eq. B-12

$\sum_{f,g,l} gen_{f,g,s,\mathrm{l},t,y} + use_{s,t,y} = LOAD_{s,t,y}$ $\forall(s,t,y)$ Eq. B-13

$\sum_g cap_{g,s,l,y} * LANDPERMW_g \leq LAND_l$ $\forall(s,l,y)$ Eq. B-14

$\sum_{g,l} cap_{g,s,l,y} \geq (1 + PRM) * PEAK_{s,y}$ $\forall(s,y)$ Eq. B-15

B.5 ANALYSIS OF SP SOLUTION

In Section 4.6.1, I briefly describe system operations when the solution of the SP with the seven scenarios of Table 4-7 is followed. There, I mention that the investment in power plants using imported coal is relatively low. For instance, in 159 out of 162 scenarios with high demand the perfect foresight plans recommend higher investment in imported coal. In this subsection, I aim to identify which resources generate electricity to compensate for the lower generation from power plants using imported coal. This analysis supports arguments in Section 4.6.1 such as *"Meanwhile, planners resort to imports of electricity or natural gas to meet varying levels of demand in the first stage and the early years of the second stage."* In particular, I analyze the generation mix in two cases (a) the highest regret solution obtained under the vulnerability assessment of the SP (b) the solution provided for the subset of 7 scenarios by the SP.

B.5.1 Highest regret scenario in the vulnerability assessment of SP

The scenario with the highest regret has high demand, IEA 450 fuel prices, high supply of domestic coal and low natural gas supply. Under the SP solution, less electricity is generated by imported and/or domestic coal in years 2025, 2030, and 2035 compared to the perfect-foresight solution. Instead, imports from India and LNG increase under the SP solution to meet the demand. Finally, at the end of the horizon both solutions (SP and perfect foresight) are identical.

Table B-7: Generation mix for years 2020, 2025, 2030, 2035 and 2040 when the SP strategy is followed under the scenario with high demand, IEA 450 fuel prices, high supply of domestic coal and low natural gas supply. The mix under the SP solution and the perfect-foresight solution are provided left and right of the "/", respectively.

Fuel	2020	2025	2030	2035	2040
Domestic Coal	1.5/1.5	3/9	10/23	37/37	44/44
Domestic Gas	47/47	27/27	22/22	21/21	20/20
Imports	11/11	15/15	28/14	13/11	49/49
Imported coal	0/0	64/63	102/113	176/180	227/227
LNG	9/9	4/0	9/0	0/0	10/10
Oil	11/11	<1/<1	1,<1	<1/0	0/0

B.5.2 Generation mix under the subset of 7 SP scenarios

Figures in this subsection provide the generation mix for years 2020, 2025, 2030, 2035 and 2040 recorded by the SP of Figure 4-2. Note that I refer to scenarios by numbers 1 to 7 following the same order as Table 4-7. My observations are similar to Section B.5.1, i.e., LNG and electricity imports generate more electricity in case domestic gas supply is low in 2025, while in 2030 LNG and electricity imports constitute flexible resources, with varying levels of production across scenarios.

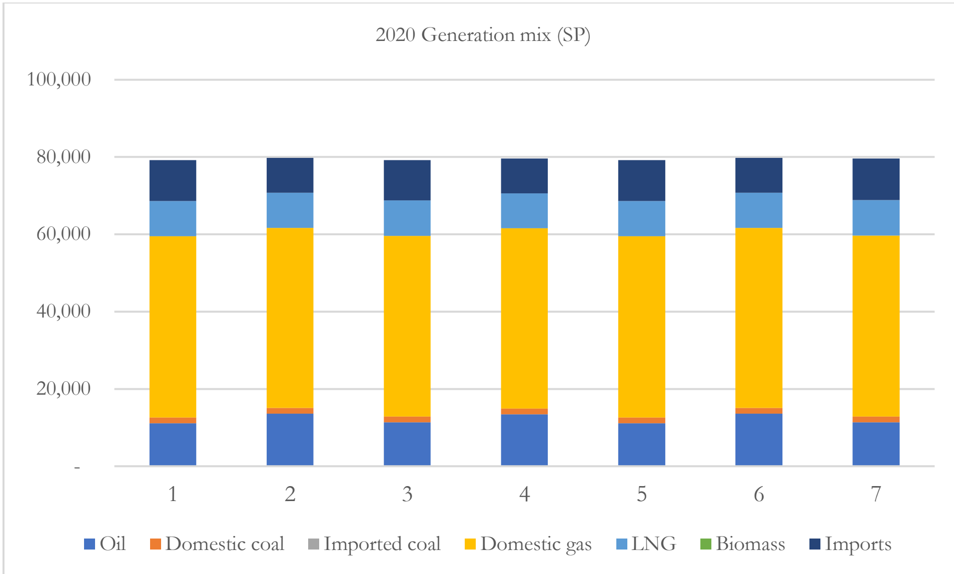

Figure B-4: 2020 generation mix recorded by the SP

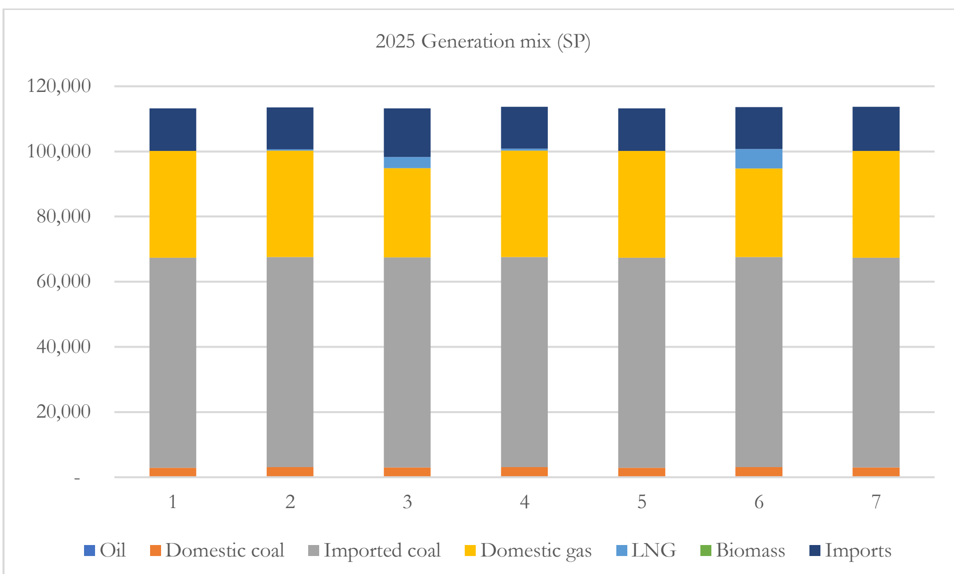

Figure B-5: 2025 generation mix recorded by the SP

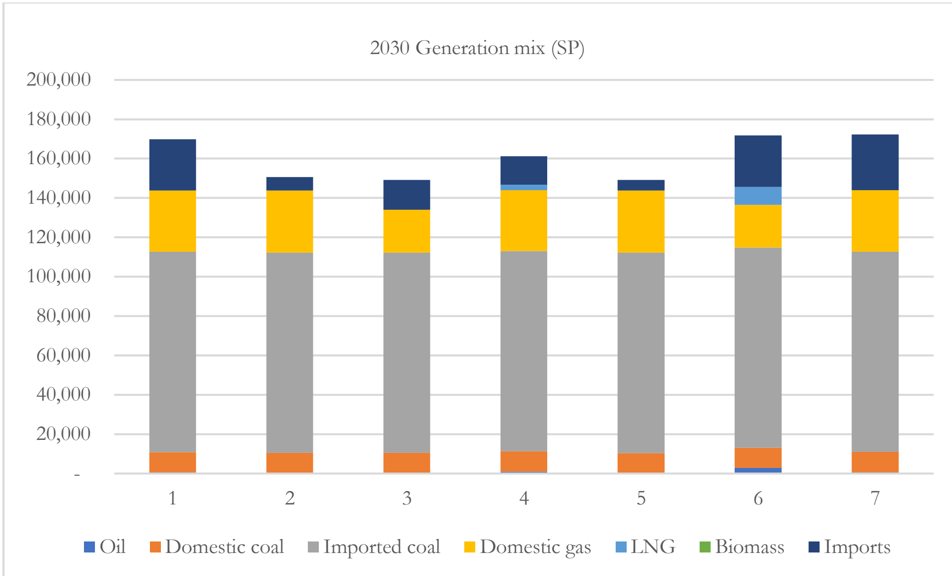

Figure B-6: 2030 generation mix recorded by the SP

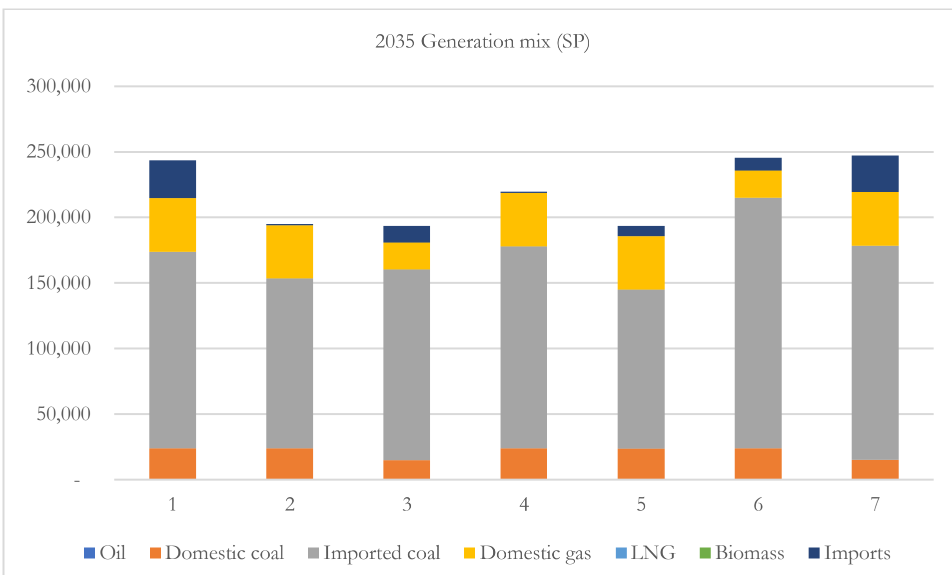

Figure B-7: 2035 generation mix recorded by the SP

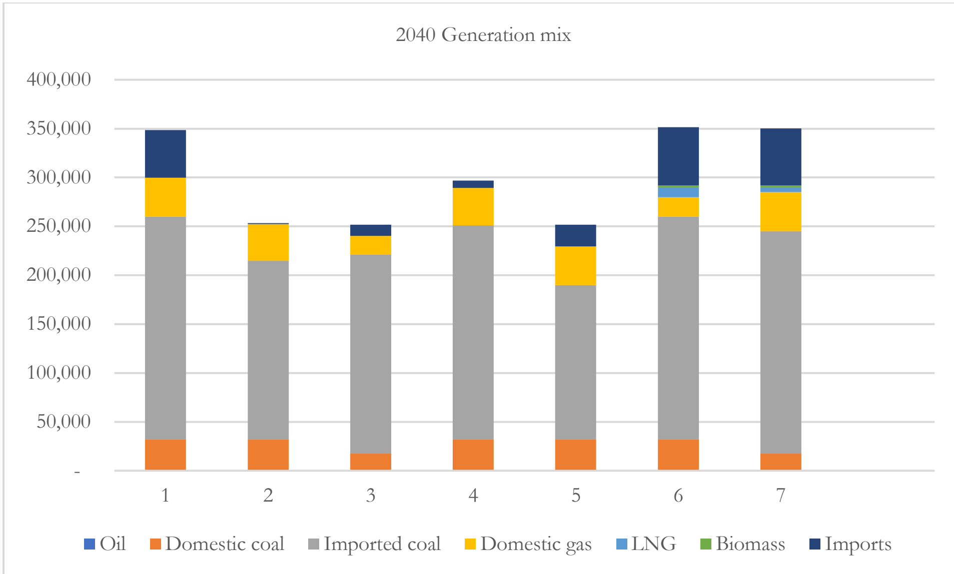

Figure B-8: 2040 generation mix recorded by the SP

B.6 ALTERNATIVE SCENARIO REDUCTION SCHEMES

In Section 4.5.2, I selected a subset of 7 scenarios for the SP using a heuristic similar to the one described in [252]. There are many heuristic methods for scenario reduction. Here, I apply three additional heuristics to select three alternative subsets of seven scenarios and I record the strategy they recommend and their expected performance across the entire set of 486 scenarios. The first heuristic is proposed by [214] and clusters the scenarios based on the cost of perfect-foresight solutions. The second heuristic is similar to the one I implemented in Section 4.5.2 but instead of selecting a representative scenario based on the min-max Chebychev distance, it selects a representative scenario using the fast-forward-selection algorithm and it more closely approximates [252]. Lastly, the third heuristic is identical to the second heuristic but instead of using k-means, it uses hierarchical clustering to decide on seven clusters. According to Table B-8, one heuristic led to lower expected regret than the one in the main text by ~4 million and the other two to worse by 4–6 million US$. The fact that heuristic 1 identified a solution with lower expected regret than the SP solution in the main body of the text supports the statement made in Section 4.6.1 that the SP might not have found the least-expected-regret solution overall.

Table B-8: Performance of alternative heuristics

	Expected regret (in million 2015 US$)
Alternative heuristic 1	551
Alternative heuristic 2	559
Alternative heuristic 3	601

In Table B-9, I provide the first-stage investment levels for the six candidate power plants of Section 4.4.3 recommended by each heuristic. Alternative heuristic 2 recommends a strategy similar to the one in Section 4.6.1 with the exception of higher investment in power plants using imported coal. Whereas, heuristic 3 recommends higher level of investment in all options compared to the heuristic in Section 4.6.1. Both heuristics 2 and 3 lead to worse expected regret than the heuristic of Section 4.6.1. However, alternative heuristic 1 identifies a better performing strategy by slightly reducing the investment in interconnection, while at the same time increasing the investment in coal power plants (using imported and domestic fuel).

Table B-9: First-stage investment levels under SP with different subsets of 7 scenarios

		Heuristic in Section 4.6.1	Alternative heuristic 1	Alternative heuristic 2	Alternative heuristic 3
Domestic coal	Barapukuria	426	739	426	520
	Kharaspir	387	387	387	387
Imported coal	Khulna	1,380	2,286	1,741	2,596
	Zajira	1,800	1,800	1,800	1,800
	Interconnection	2,968	2,595	3,050	3,050

Finally, I compare how well the four heuristics (the one in Section 4.6.1 and the three applied here) approximate the probabilistic distribution of each uncertain factor. According to the distances between the original probabilistic distribution and the approximate by each heuristic, alternative heuristic 1 has the lowest sum of distances among the four heuristics. In particular, it has the lowest distance for fuel supply and the second lowest distance for the other four uncertain factors. Note that this low distance does not guarantee that the subset of scenarios is representative of the full set of 486 scenarios since the metric examines the probabilistic description of one uncertain factor each time. However, this calculation is helpful to demonstrate if any of the heuristics is biased towards a particular scenario.

Table B-10: Comparison of probabilistic description of uncertain factors by alternative heuristics

Uncertainty	Scenarios	Full set of 486 scenarios	Heuristic in Section 4.6.1	Alternative heuristic 1	Alternative heuristic 2	Alternative heuristic 3
Temperature/ CDD	bcc-csm1-1	0.3	0.2	0.6	1.0	1.0
	cesm1-bgc	0.3	0.3	0.3	-	-
	mri-cgcm3	0.3	0.5	0.1	-	-
	Norm 2 from original		0.055175	0.133118	0.666667	0.666667
Demand growth	Low	0.3	0.5	0.3	0.5	0.3
	Base	0.3	0.1	0.4	0.5	0.4
	High	0.3	0.4	0.3	-	0.3
	Norm 2 from original		0.059747	0.017206	0.170401	0.014403
Fuel prices	IEA New Policies	0.3	0.5	0.4	0.7	0.2
	IEA 450	0.3	0.2	0.2	-	0.5
	WB17	0.3	0.3	0.4	0.3	0.3
	Norm 2 from original		0.064091	0.039857	0.222222	0.033608
Coal supply	High	0.3	-	0.3	0.5	0.0
	Base	0.3	0.7	0.4	0.1	0.6
	Low	0.3	0.3	0.3	0.4	0.3
	Norm 2 from original		0.244704	0.017206	0.062262	0.198217
Gas supply	Low	0.5	0.2	0.4	1.0	0.7
	High	0.5	0.8	0.6	-	0.3
	Norm 2 from original		0.134431	0.007621	0.5	0.115912
Flooding scenarios	Historical	0.3	0.4	0.3	0.6	0.3
	High by FATHOM	0.3	0.3	-	0.2	0.4
	High based on [239]	0.3	0.3	0.7	0.2	0.2
	Norm 2 from original		0.011203	0.26727	0.137403	0.024691

REFERENCES

[1] World Bank, "State of electricity access report 2017 (Vol. 2): Full report (English)," World Bank Group, Washington DC, 2017.

[2] United Nations, "Goal 7: Ensure access to affordable, reliable, sustainable and modern energy for all," *Sustainable Development Goals*. [Online]. Available: http://www.un.org/sustainabledevelopment/energy/.

[3] F. Kahrl, A. Mills, L. Lavin, N. Ryan, and A. Olsen, "The future of electricity resource planning," Lawrence Berkeley National Laboratory, LBNL-1006269, 2016.

[4] E. Kahn, "Crossroads in electric utility planning and regulation," Lawrence Berkeley National Laboratory, LBL-18091, 1984.

[5] P. Massê and R. Gibrat, "Application of linear programming to investments in the electric power industry," *Manage. Sci.*, vol. 3, no. 2, pp. 149–166, 1957.

[6] A. J. Covarrubias, "Expansion planning for electric power systems," *IAEA Bull.*, vol. 21, no. 2/3, pp. 55–64, 1979.

[7] R. T. Jenkins and D. S. Joy, "Wien Automatic System Planning Package (WASP) — An electric utility optimal generation expansion planning computer code," Oak Ridge National Laboratory ORNL-4945, 1974.

[8] B. F. Hobbs, "Optimization methods for electric utility resource planning," *Eur. J. Oper. Res.*, vol. 83, no. 1, pp. 1–20, 1995.

[9] R. P. O' Neill, "Computational challenges in electric power markets," in *Workshop on Optimization and Equilibrium in Energy Economics, IPAM, UCLA*, 2016.

[10] J. L. Ho *et al.*, "Planning transmission for uncertainty: Applications and lessons for the Western Interconnection," The Western Electricity Coordinating Council, 2016.

[11] I. Herrero, P. Rodilla, and C. Batlle, "Electricity market-clearing prices and investment

incentives: The role of pricing rules," *Energy Econ.*, vol. 47, pp. 42–51, 2015.

[12] E. E. Sauma and S. S. Oren, "Proactive planning and valuation of transmission investments in restructured electricity markets," *J. Regul. Econ.*, vol. 30, pp. 358–387, 2006.

[13] B. Ki-Moon, "Powering sustainable energy for all," *The New York Times*, pp. 1–2, 11-Jan-2012.

[14] L. Cozzi, O. Chen, H. Daly, and A. Koh, "Population without access to electricity falls below 1 billion," *International Energy Agency Newsroom*, 2018. [Online]. Available: https://www.iea.org/newsroom/news/2018/october/population-without-access-to-electricity-falls-below-1-billion.html.

[15] IEA, *World Energy Outlook 2018*. Paris: IEA, 2018.

[16] S. Szabó, M. Moner-Girona, I. Kougias, R. Bailis, and K. Bódis, "Identification of advantageous electricity generation options in sub-Saharan Africa integrating existing resources," *Nat. Energy*, vol. 1, no. 10, 16140, pp. 1–8, 2016.

[17] K. B. Debnath and M. Mourshed, "Challenges and gaps for energy planning models in the developing-world context," *Nat. Energy*, vol. 3, pp. 172–184, 2018.

[18] R. Pachauri and L. A. Meyer, "Climate Change 2014 Synthesis Report Contribution of Working Groups I,II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change," IPCC, Geneva, Switzerland, 2014.

[19] "Climate change and the U.S. energy sector: Regional vulnerabilities and resilience solutions," U.S. Department of Energy Office of Energy Policy and Systems Analysis, 2015.

[20] G. Barbose, "U.S. Renewables Portfolio Standards 2017 Annual Status Report," Lawrence Berkeley National Laboratory Energy Technologies Area, 2017.

[21] R. Chen, "Natural gas and renewables make up most of 2018 electric capacity additions," *US EIA Today in Energy*, 07-May-2018.

[22] J. O. Ebinger and W. Vergara, *Climate Impacts on Energy Systems: Key Issues for Energy Sector*

Adaptation. Washington, D.C: World Bank, 2011.

[23] D. T. Ton and W.-T. P. Wang, "A more resilient grid: The U.S. Department of Energy joins with stakeholders in an R&D plan," *IEEE Power Energy Mag.*, vol. 13, no. 3, pp. 26–34, 2015.

[24] ""FERC Order 890—Preventing undue discrimination and preference in transmission service"," 2007. [Online]. Available: https://www.ferc.gov/whats-new/comm-meet/2007/021507/e-1.pdf.

[25] B. M. Nickell, "Regional transmission planning in the West," in *FERC Technical Conference on Planning Models and Software*, 2010.

[26] E. Kahn, "Wind integration studies: Optimization vs. simulation," *Electr. J.*, vol. 23, no. 9, pp. 51–64, 2010.

[27] MISO, "Regional Generation Outlet Study." [Online]. Available: https://www.misoenergy.org/Planning/Pages/RegionalGenerationOutletStudy.aspx.

[28] ERCOT System Planning, "Competitive Renewable Energy Zones (CREZ): Transmission Optimization Study," 2008.

[29] M. Madrigal and S. Stoft, *Transmission Expansion for Renewable Energy Scale-Up: Emerging Lessons and Recommendations. A World Bank Study*. Washington, DC: World Bank, 2012.

[30] EnerNex Corporation, "Eastern wind intergration and transmission study," National Renewable Energy Laboratory, Golden, CO, NREL/SR-5500-47078, 2011.

[31] IEA, "Energy Access Outlook 2017: From poverty to prosperity," IEA, Paris, 2017.

[32] IEA, "Africa Energy Outlook: A focus on energy prospects in Sub-Saharan Africa," IEA, Paris, 2014.

[33] J. J. Messner *et al.*, "Fragile States Index 2017," The Fund for Peace, Washington DC, 2017.

[34] P. Collier, "Fragile states and international support," Foundation pour les etudes et recherches sur le developpement international, Development policies Working paper 175, 2016.

[35] L. Christiansen, C. Schaer, C. Larsen, and P. Naswa, "Monitoring & Evaluation for climate change adaptation: A summary of key challenges and emerging practice. Understanding, discussing and exemplifying the key challenges of M&E for adaptation," UNEP DTU Partnership Working Paper Series; Climate Resilient Development Programme, 2016.

[36] "Global Warming of 1.5 °C: An IPCC special report on the impacts of global warming of 1.5 °C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate chang," IPCC, Switzerland, 2018.

[37] OECD, "Tools to mainstream adaptation into decision-making processes," in *Climate Change Risks and Adaptation: Linking Policy and Economics*, Paris, 2015, pp. 117–141.

[38] F. D. Munoz, B. F. Hobbs, J. L. Ho, and S. Kasina, "An engineering-economic approach to transmission planning under market and regulatory uncertainties: WECC case study," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 307–317, 2014.

[39] R. J. Lempert, D. G. Groves, S. W. Popper, and S. C. Bankes, "A general, analytic method for generating robust strategies and narrative scenarios," *Manage. Sci.*, vol. 52, no. 4, pp. 514–528, 2006.

[40] R. Dittrich, A. Wreford, and D. Moran, "A survey of decision-making approaches for climate change adaptation: Are robust methods the way forward?," *Ecol. Econ.*, vol. 122, pp. 79–89, 2016.

[41] P. Watkiss, A. Hunt, W. Blyth, and J. Dyszynski, "The use of new economic decision support tools for adaptation assessment: A review of methods and applications, towards guidance on applicability," *Clim. Change*, vol. 132, no. 3, pp. 401–416, 2015.

[42] E. O. Crousillat, "Incorporating risk and uncertainty in power system planning," The World Bank, Washington D.C., Industry and Energy Department Working Paper Energy Series Paper No. 17, 1989.

[43] S. Hallegatte, A. Shah, R. Lempert, C. Brown, and S. Gill, "Investment decision making

under deep uncertainty–Application to climate change," The World Bank, WPS 6193, 2012.

[44] S. C. Parkinson and N. Djilali, "Robust response to hydro-climatic change in electricity generation planning," *Clim. Change*, vol. 130, no. 4, pp. 475–489, 2015.

[45] R. Cervigni, R. Liden, J. E. Neumann, and K. M. Strzepek., *Enhancing the Climate Resilience of Africa's Infrastructure: Th e Power and Water Sectors*. Washington, DC: The World Bank, 2015.

[46] E. Spyrou, J. Ho, B. Hobbs, R. Johnson, and J. McCalley, "What are the benefits of co-optimizing transmission and generation investment? Eastern Interconnection case study," *IEEE Trans. Power Syst.*, vol. 32, no. 6, 2017.

[47] N. Mukhi, D. Chattopadhyay, B. Hobbs, and E. Spyrou, "Building climate resilience into power system planning : the case of Bangladesh," Washington D.C., ACS23320, 2017.

[48] L. Aniti, "Investment in electricity transmission infrastructure shows steady increase," *US EIA Today in Energy*, 26-Aug-2014.

[49] IEA, "World Energy Investment Outlook," IEA, Paris, 2014.

[50] Edison Electric Institute, "Transmission Projects : At A Glance," 2015.

[51] J. Pfeifenberger, J. Chang, and J. Tsoukalis, "Investment trends and fundamentals in US transmission and electricity infrastructure," 2015. [Online]. Available: http://www.brattle.com/system/publications/pdfs/000/005/190/original/Investment_Trends_and_Fundamentals_in_US_Transmission_and_Electricity_Infrastructure.pdf?1437147799.

[52] J. Pfeifenberger, J. Chang, and A. Sheilendrananth, "Towards more effective transmission planning: Addressing the costs and risks of an insufficiently flexible electricity grid," WIRES and The Brattle Group, 2015.

[53] J. W. Chang, J. P. Pfeifenberger, and J. M. Hagerty, "The benefits of electric transmission: Identifying and analyzing the value of investments," WIRES report by The Brattle Group, Cambridge,MA, 2013.

[54] P. L. Joskow, "Electricity Sectors in Transition," *Energy J.*, vol. 19, no. 2, pp. 25–52, 1998.

[55] J. Pfeifenberger, J. Chang, M. Davis, and M. Geronimo, "Contrasting competitively-bid transmission investments in the U.S. and abroad." The Brattle Group, presented at UBS Conference Call, 2014.

[56] J. H. Eto, "Planning electric transmission lines: A review of recent regional transmission plans," Lawrence Berkeley National Laboratory, LBNL-10063, 2016.

[57] "FERC Order 1000—Transmission planning and cost allocation," 2011. [Online]. Available: https://www.ferc.gov/industries/electric/indus-act/trans-plan.asp.

[58] Califronia ISO, "Storage as a transmission asset: Enabling storage assets providng regulated cost-of-service-based transmission service to access market revenues," 2018.

[59] Planning Division Transmission Planning Department, "PJM Region Transmission Planning Process," 2016. [Online]. Available: http://www.pjm.com/~/media/documents/manuals/m14b.ashx.

[60] R. Piwko, D. Osborn, R. Gramlich, G. Jordan, D. Hawkins, and K. Porter, "Wind energy delivery issues [transmission planning and competitive electricity market operation]," *IEEE Power Energy Mag.*, vol. 3, no. 6, pp. 47–56, 2005.

[61] Public Utility Commission of Texas, "Texas Public Utility Commission approves wind transmission plan," *News Release*, 2008. [Online]. Available: http://www.puc.texas.gov/agency/resources/pubs/news/2008/071708.pdf.

[62] WECC Staff, "2013 Interconnection-wide plan tools and models," WECC, Salt Lake City, UT, 2013.

[63] A. Liu *et al.*, "Co-optimization of transmission and other supply resources," prepared for EISPC & NARUC, 2013.

[64] D. Pozo, E. Sauma, and J. Contreras, "A three-level static MILP model for generation and transmission expansion planning," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 202–210, 2013.

[65] S. Jin and S. M. Ryan, "A tri-level model of centralized transmission and decentralized generation expansion planning for an electricity market — Part I," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 132–141, 2014.

[66] A. Motamedi, H. Zareipour, M. O. Buygi, and W. D. Rosehart, "A transmission planning framework considering future generation expansions in electricity markets," *IEEE Trans. Power Syst.*, vol. 25, no. 4, pp. 1987–1995, 2010.

[67] J. Aghaei, N. Amjady, A. Baharvandi, and M.-A. Akbari, "Generation and transmission expansion planning: MILP–based probabilistic model," *IEEE Trans. Power Syst.*, vol. 29, no. 4, pp. 1592–1601, 2014.

[68] Eastern Interconnection Planning Collaborative, "Phase 1 report: formation of stakeholder process, regional plan integration and macroeconomic analysis," 2011.

[69] "Eastern Interconnection Planning Collaborative (EIPC)." [Online]. Available: http://www.eipconline.com/.

[70] R. M. Sawey and C. D. Zinn, "A mathematical model for long range expansion planning of generation and transmission in electric utility systems," *IEEE Trans. Power Appar. Syst.*, vol. 96, no. 2, pp. 657–666, 1977.

[71] E. E. Sauma and S. S. Oren, "Economic criteria for planning transmission investment in restructured electricity markets," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1394–1405, 2007.

[72] Y. Gu, J. D. McCalley, and M. Ni, "Coordinating large-scale wind integration and transmission planning," *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 652–659, 2012.

[73] J. H. Roh, M. Shahidehpour, and Y. Fu, "Market-based coordination of transmission and generation capacity planning," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 1406–1419, 2007.

[74] PJM, "PJM Manual 14B: PJM Regional Transmission Planning Process Revision 41," 2018.

[75] SPP, "2017 Integrated Transmission Plan 10-Year Assessment Report," 2017.

[76] W. W. Hogan, "Multiple market-clearing prices, electricity market design and price

manipulation," *Electr. J.*, vol. 25, no. 4, pp. 18–32, 2012.

[77] MISO, "Multi Value Project Portfolio Analysis." [Online]. Available: https://www.wecc.biz/Administrative/2016 TEPPC Study Program - 2016 May.pdf.

[78] Eastern Interconnection Planning Collaborative, "State of the Eastern Interconnection 'A description of Eastern Interconnection Planning Collaborative activities and summary of results from studies and analyses on the collective transmission plans in the Eastern Interconnection,'" 2018.

[79] Monitoring Analytics, "2017 State of the Market Report for PJM," 2018.

[80] S. Mufson, "JPMorgan Chase to pay $410 million penalty in electricity pricing scheme," *The Washington Post*, 30-Jul-2013.

[81] O. Ozdemir, F. D. Munoz, J. L. Ho, and B. F. Hobbs, "Economic analysis of transmission expansion planning with price-responsive demand and quadratic losses by successive LP," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1096–1107, 2016.

[82] R. Wasserstein, "George Box: A model statistician," *Significance*, vol. 7, pp. 134–135, 2010.

[83] D. A. Tejada-Arango, M. Domeshek, S. Wogrin, and E. Centeno, "Enhanced representative days and system states modeling for energy storage investment analysis," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 6534–6544, 2018.

[84] Y. Liu, R. Sioshansi, and A. J. Conejo, "Hierarchical clustering to find representative operating periods for capacity-expansion modeling," *IEEE Trans. Power Syst.*, vol. 33, no. 3, pp. 3029–3039, 2018.

[85] K. Poncelet, H. Hanspeter, E. Delarue, A. Virag, and W. D'haeseleer, "Selecting representative days for capturing the implications of integrating intermittent renewables in generation expansion planning problems," vol. 32, no. 3, pp. 1936–1948, 2017.

[86] Charles River Associates (CRA International), "Working draft of MRN-NEEM modeling assumptions and data sources for EIPC capacity expansion modeling," prepared for Eastern Interconnection Planning Collaborative, 2010.

[87] Open Access Technology International Inc, “Assessment of historical transmission schedules and flows in the Eastern Interconnection,” prepared for Lawrence Berkeley National Laboratory, 2014.

[88] A. Bloom, A. Townsend, and D. Palchak, “The Eastern Renewable Generation Integration Study: Flexibility and high penetrations of wind and solar,” in *IEEE PES General Meeting*, 2015.

[89] S. W. Hadley, D. J. Gotham, and R. L. Luciani, “Additional EIPC study analysis: Final report,” Oak Ridge National Laboratory, Oak Ridge, TN, ORNL/TM-2014/480, 2014.

[90] California ISO, “ISO 2013-2014 transmission planning process supplemental sssessment: Harry Allen-Eldorado 500 kV transmission project economic need,” 2014.

[91] V. Krishnan and J. D. McCalley, “Building foresight in long-term infrastructure planning using end-effect mitigation models,” *IEEE Syst. J.*, vol. 11, no. 4, pp. 2040–2051, 2017.

[92] Electric Power Research Institute, “EGEAS Capabilities Manual, v11,” 2015.

[93] L. P. Garcés, A. J. J. Conejo, R. García-Bertrand, and R. Romero, “A bilevel approach to transmission expansion planning within a market environment,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1513–1522, 2009.

[94] A. P. Perez, E. E. Sauma, F. D. Munoz, and B. F. Hobbs, “The economic effects of interregional trading of Renewable Energy Certificates in the U.S. WECC,” *Energy J.*, vol. 37, no. 4, pp. 267–296, 2016.

[95] R. Bo, L. Hecker, Y. Gu, J. Okullo, J. Bakke, and M. Ni, “A new congested flowgate ranking strategy in MISO Market Efficiency Planning Study,” *IEEE Power Energy Soc. Gen. Meet.*, pp. 1–5, 2013.

[96] R. Bo *et al.*, “Novel cngested flowgate grouping methods in economic transmission planning,” in *2014 IEEE PES General Meeting | Conference & Exposition*, 2014, pp. 1–5.

[97] The World Bank IRENA IEA UNSD WHO, “Tracking SDG7: The Energy Progress Report 2018,” Washington D.C., 2018.

[98] P. A. Trotter, M. C. McManus, and R. Maconachie, "Electricity planning and implementation in sub-Saharan Africa: A systematic review," *Renew. Sustain. Energy Rev.*, vol. 74, no. March, pp. 1189–1209, 2017.

[99] M. Labordena, A. Patt, M. Bazilian, M. Howells, and J. Lilliestam, "Impact of political and economical barriers for concentrating solar power in Sub-Saharan Africa," *Energy Policy*, vol. 102, no. March 2017, pp. 52–72, 2017.

[100] H. Zerriffi, H. Dowlatabadi, and N. Strachan, "Electricity and conflict: Advantages of a distributed system," *Electr. J.*, vol. 15, no. 1, January–February, pp. 55–65, 2002.

[101] M. Bazilian and D. Chattopadhyay, "Considering power system planning in fragile and conflict states," *Energy Sustain. Dev.*, vol. 32, pp. 110–120, 2016.

[102] United Nations; World Bank, *Pathways for Peace: Inclusive Approaches to Preventing Violent Conflict*. Washington DC: World Bank, 2018.

[103] OECD, *States of Fragility 2016: Understanding Violence*, no. 43. Paris: OECD Publishing, 2016.

[104] The World Bank Group, "Fragility, Conflict and Violence." [Online]. Available: http://www.worldbank.org/en/topic/fragilityconflictviolence/overview#1.

[105] H. Hegre, N. W. Metternich, H. M. Nygård, and J. Wucherpfennig, "Introduction: Forecasting in peace research," *J. Peace Res.*, vol. 54, no. 2, pp. 113–124, 2017.

[106] M. K. Chiovenda, "The illumination of marginality: How ethnic Hazaras in Bamyan, Afghanistan, perceive the lack of electricity as discrimination," *Centr. Asian Surv.*, vol. 33, no. 4, pp. 449–462, 2014.

[107] H. Zerriffi, H. Dowlatabadi, and N. D. Strachan, "Electricity and conflict: An evaluation of distributed cogeneration as an economic and reliable solution," Carnegie Mellon Electricity Industry Center, Pittsburgh, PA, CEIC Working Paper 01-04, 2001.

[108] L.-E. Cederman and N. B. Weidmann, "Predicting armed conflict: Time to adjust our expectations?," *Science (80-.).*, vol. 355, no. 6324, pp. 474–476, 2017.

[109] T. Chadefaux, "Conflict forecasting and its limits," *Data Sci.*, vol. 7, no. 17, pp. 7–17, 2017.

[110] J. F. Mata and S. Ziaja, *Users' Guide on Mesasuring Fragility*. Bonn: German Development Institute and the United Nations Development Programme, 2009.

[111] B. Celiku and A. Kraay, "Predicting conflict," World Bank Group, Washington D.C., WPS8075, 2017.

[112] Carleton University, "Country Indicators for Foreign Policy: Conflict Risk Assessment: Indicator Descriptions." [Online]. Available: https://carleton.ca/cifp/conflict-risk-assessment/indicator-descriptions/. [Accessed: 06-Dec-2018].

[113] J. Goldstone, "Using quantitative and qualitative models to forecast instability," United States Institute of Peace, Washington D.C., Special Report 204, 2008.

[114] J. E. Margolis, "Estimating state instability," *Stud. Intell.*, vol. 56, no. 1, pp. 13–24, 2012.

[115] J. van der Lijn, "Scenarios for South Sudan in 2020," Stockholm International Peace Research Institute (SIPRI) SIPRIPAX Netherlands Peace Foundation (PAX) PAX, 2016.

[116] P. Young-Ho and K. Hyeong Ki, *2010 Unification Clock. When Will We See a Unified Korea?*, no. December. Korean Institure for National Unification, 2010.

[117] H. Hegre, J. Karlsen, H. M. Nygard, H. Urdal, and H. Strand, "Predicting armed conflict, 2011 – 2050," *Int. Stud. Q.*, vol. 57, no. 2, pp. 250–270, 2013.

[118] J. J. Messner *et al.*, "Fragile States Index 2015," The Fund for Peace, Washington D.C., 2015.

[119] H. Hegre, H. Buhaug, K. V Calvin, J. Nordkvelle, S. T. Waldhoff, and E. Gilmore, "Forecasting civil conflict along the shared socioeconomic pathways," *Environ. Res. Lett.*, vol. 11, no. 5, 54002, pp. 1–8, 2016.

[120] M. Aristizabal and S. Cortez, "Transmission line restoration techniques in Colombia, South America," *Proc. ESMO '93. IEEE 6th Int. Conf. Transm. Distrib. Constr. Live-Line Maint.*, 1993.

[121] R. R. Arshad and J.-F. Aoun, "Syria damage assessment of selected cities Aleppo, Hama, Idlib (English)," World Bank Group, Washington D.C., 2017.

[122] World Bank, United Nations, European Union, Islamic Development Bank, and

Cooperation, "Republic of Yemen - Joint social and economic assessment (English)," World Bank, Washington, DC, 2012.

[123] J. Lemoyne, "War in El Salvador is brought close to the capital," *The New York Times*, 21-Jan-1986.

[124] J. Giroux, P. Burgherr, and L. Melkunaite, "Research note on the Energy Infrastructure Attack Database (EIAD)," *Perspect. Terror.*, vol. 7, no. 6, p. 13, 2013.

[125] T. Ford, "Liberia's battle to put the lights back on," *The Guardian*, 06-Feb-2012.

[126] C. Pfaff, "Safeguarding Hoover Dam during World War II," *Prologue Mag.*, vol. 35, no. 2, 2003.

[127] E. Bala-Gbogbo, "Nigeria power plants must overcome gas-pipeline sabotage," *Bloomberg Business*, 10-Jun-2015.

[128] National Research Council of the National Academies, *Terrorism and the Electric Power Delivery System*. Washington, DC: The National Academies Press, 2012.

[129] R. M. Lee, M. J. Assante, and T. Conway, "Analysis of the cyber attack on the Ukrainian power grid," Electricity Information Sharing and Analysis Center, Washington, DC, 2016.

[130] World Bank, "Iraq - Dokan and Derbandikhan Emergency Hydro Power Project (English)," World Bank, Washington, DC, 2006.

[131] Swiss Federal Institute of Technology (ETH) and Paul Scherrer Institute, "Energy Infrastructure Attack Database (EIAD)." [Online]. Available: http://trackingenergyattacks.com/EIAD. [Accessed: 03-Oct-2017].

[132] N. J. H. Mai, A. T. Mayai, and N. Tiitmamer, "Sporadic fuel crisis in South Sudan: Causes, impacts, and solutions," The Sudd Institute, Juba, 2016.

[133] "Israel-Palestinian conflict: Life in the Gaza Strip," *BBC News*, 15-May-2018.

[134] B. Hubbard, C. Krauss, and E. Schmitt, "Rebels in Syria claim control of resources," *The New York Times*, 28-Jan-2014.

[135] M. Humphreys, "Economics and violent conflict," Harvard University, 2003.

[136] P. Collier, "On the economic consequences of civil war," *Oxford Econ. Pap. Symp. Trade, Technol. Growth*, vol. 51, no. 1, pp. 168–183, 1999.

[137] United Nations Economic Commission for Africa, *Conflicts in the Democratic Republic of Congo: Causes, impacts and implications for the Great Lakes region*. Addis Ababa: United Nations, 2015.

[138] R. Sab, "Economic impact of selected conflicts in the Middle East: What can we learn from the past?," International Monetary Fund, WP/14/100, 2014.

[139] M. P. Peschka, J. J. Emery, and K. Martin, "The role of the private sector in fragile and conflict-affected states," World Bank, Washington, DC, World Development Report 2011 Background Paper, 2010.

[140] P. Collier, A. Hoeffler, and C. Pattillo, "Africa's exodus: Capital flight and the brain drain as portfolio decisions," *J. Afr. Econ.*, vol. 13, no. 2, pp. ii15-ii54, 2004.

[141] J. Lelyveld, "Bombs damage atom plant site in South Africa," *The New York Times*, 20-Dec-1982.

[142] O. S. Ohunakin, M. S. Adaramola, O. M. Oyewola, and R. O. Fagbenle, "Solar energy applications and development in Nigeria: Drivers and barriers," *Renew. Sustain. Energy Rev.*, vol. 32, pp. 294–301, 2014.

[143] D. Butler and N. Adomaitis, "Conflict-hit southeast Turkey dealt fresh blow as power project shelved," *Reuters*, 04-Feb-2016.

[144] Energy and Extractives Global Practice Country Department, "Implementation Completion and Results Report (IDA-H1700 IDA-H6250) on a grant in the amount of SDR 14.6 million to the Republic of Sierra Leone for the Bumbuna Hydroelectric Environmental and Social Management Project," The World Bank International Development Association, ICR2972, 2014.

[145] African Development Bank (AfDB) Group, "Summary of the Environmental and Social Management Plan (Expansion of the Azito thermal plant (Phase 3))." [Online]. Available: https://www.afdb.org/fileadmin/uploads/afdb/Documents/Environmental-and-Social-

Assessments/cote d%27ivoire - Expansion of the Azito thermal plant %28Phase 3%29 - Summary PGES.pdf. [Accessed: 10-May-2018].

[146] S. Jones and S. Howarth, "Supporting infrastructure development in fragile and conflict-affected states : Learning from experience," Oxford Policy Management, Oxford, 2012.

[147] AEMS, "The impact of the Syrian crisis on the Lebanese power sector and priority recommendations," Ministry of Energy and Water and the UNDP, 2017.

[148] I. N. Kessides, "Powering Africa's sustainable development: The potential role of nuclear energy," *Energy Policy*, vol. 74, pp. S57–S70, 2014.

[149] I. Onyeji, M. Bazilian, and P. Nussbaumer, "Contextualizing electricity access in sub-Saharan Africa," *Energy Sustain. Dev.*, vol. 16, no. 4, pp. 520–527, 2012.

[150] P. Soderholm, "The political economy of power generation in Zimbabwe since 1980," *Nat. Resour. Forum*, vol. 23, pp. 335–346, 1999.

[151] S. Bawakyillenuo, "Deconstructing the dichotomies of solar photovoltaic (PV) dissemination trajectories in Ghana, Kenya and Zimbabwe from the 1960s to 2007," *Energy Policy*, vol. 49, pp. 410–421, 2012.

[152] P. A. Trotter, R. Maconachie, and M. C. McManus, "Solar energy's potential to mitigate political risks: The case of an optimised Africa-wide network," *Energy Policy*, vol. 117, no. March, pp. 108–126, 2018.

[153] T. Levin and V. M. Thomas, "Modeling the impact of stochastic outages for electricity infrastructure development," *Energy Syst.*, vol. 5, no. 3, pp. 519–550, 2014.

[154] J. R. Birge and F. Louveaux, *Introduction to Stochastic Programming*, Second. Springer Series in Operations Research and Financial Engineering, 2011.

[155] D. Bertsimas, D. B. Brown, and C. Caramanis, "Robust Optimization," *SIAM Rev.*, vol. 53, no. 3, pp. 464–501, 2011.

[156] U.S. Energy Information Administration, "Country analysis brief: Sudan and South Sudan," pp. 1–15, 05-Mar-2018.

[157] "South Sudanese celebrate peace deal signed by Kiir and Machar," *BBC News*, 06-Aug-2018.

[158] M. K. Dessu and S. Tadesse, "Sanctions prove key to ending South Sudan's civil war," *Institute for Security Studies- ISS Today*, 14-Aug-2018.

[159] World Bank, "Access to electricity (% of population)," *Sustainable Energy for All (SE4ALL) database from the SE4ALL Global Tracking Framework led jointly by the World Bank, International Energy Agency, and the Energy Sector Management Assistance Program.* .

[160] International Energy Agency, "Electricity generation by fuel," *Statistics*, 2017. .

[161] "The Republic of South Sudan Sustainable Energy for All Rapid Situation Assessment and Gap Analysis Report," Ministry of Electricity and Dams, Republic of South Sudan and The United Nations Development Programme, 2013.

[162] U.S. Energy Information Administration, "Country analysis brief: Sudan and South Sudan," pp. 1–16, 03-Sep-2014.

[163] The Republic of South Sudan Ministry of Electricity Dams Irrigation and Water Resources, "Clean Power East Africa," *East African Power Industry Convention*. presented by Minister Hon Jema Nuna Kumba, Nairobi, 2015.

[164] UN Office on Drugs and Crime's International Homicide Statistics database., "Intentional homicides (per 100,000 people)," *The World Bank*. [Online]. Available: https://data.worldbank.org/indicator/VC.IHR.PSRC.P5?locations=CO. [Accessed: 02-Dec-2018].

[165] M. Nduru, "South Sudan president directs oil minister to speed up work on oil refineries," *S&P Global, Platts*. [Online]. Available: http://www.platts.com/latest-news/oil/juba/south-sudan-president-directs-oil-minister-to-26483162. [Accessed: 04-May-2017].

[166] World Bank, "HFS Market Surveys in South Sudan (2012 to 2016)," 2016. [Online]. Available:

http://dataviz.worldbank.org/views/MarketSurveys/ProductPrices?%3AisGuestRedirectFromVizportal=y&%3Aembed=y. [Accessed: 03-Aug-2018].

[167] Bloomberg Business, "South Sudan devalues currency by 84% as dollar peg abandoned," *Bloomberg Business*, 2015.

[168] International Monetary Fund, "World Economic Outlook Database," *October*, 2016. [Online]. Available: https://www.imf.org/external/pubs/ft/weo/2016/02/weodata/index.aspx. [Accessed: 04-May-2017].

[169] Hatch, "Hydropower expansion plan and regional integration plan of South Sudan into regional electricity grid - Draft report," Nile Basin Initiative Nile Equatorial Lakes Subsidiary Action Plan Program, H346953-0000-10-124-003, 2014.

[170] U.S. Energy Information Administration, "Cost and Performance Characteristics of New Generating Technologies," *Cost and Performance Characteristics of New Generation Technologies, Annual Energy Outlook 2018*, 2018. [Online]. Available: https://www.eia.gov/outlooks/aeo/assumptions/pdf/table_8.2.pdf.

[171] A. Ansar, B. Flyvbjerg, A. Budzier, and D. Lunn, "Should we build more large dams? The actual costs of hydropower megaproject development," *Energy Policy*, vol. 69, pp. 43–56, 2014.

[172] S. Gbedemah, "Delayed projects in Sub Saharan Africa: The usual suspects," Navigant Consulting Inc., 2015.

[173] United Nations High Commissioners for Refugees (UNHCR), "Global trends: Forced displacment in 2016," 2016.

[174] "SPLA confirms 200 people died fleeing Malakal," 2014. [Online]. Available: https://reliefweb.int/report/south-sudan-republic/spla-confirms-200-people-died-fleeing-malakal.

[175] The UN Refugee Agency, "Fresh fighting in South Sudan displaces up to 26,000 in Malakal

area," 2016. [Online]. Available: http://www.unhcr.org/news/briefing/2016/2/56c6e9ef6/fresh-fighting-south-sudan-displaces-26000-malakal-area.html. [Accessed: 03-Aug-2018].

[176] M. A. Arias, A. M. Ibáñez, and P. Querubin, "The desire to return during civil war: Evidence for internally displaced populations in Colombia," *Peace Econ. Peace Sci. Public Policy*, vol. 20, no. 1, pp. 209–233, 2014.

[177] "Juba power distribution system rehabilitation and expansion project," African Development Fund, South Sudan, Energy, Environment and Climate Change Department (ONEC), 2013.

[178] S. Collins *et al.*, "Integrating short term variations of the power system into integrated energy system models: A methodological review," *Renew. Sustain. Energy Rev.*, vol. 76, no. September 2017, pp. 839–856, 2017.

[179] R. Kyte, "Keynote talk." Duke, Accelerating Global Energy Access Launch of the Energy Access Project at Duke University, Washington D.C., 2018.

[180] B. B. Crost, J. Felter, and P. Johnston, "Aid under fire: Development projects and civil conflict," vol. 104, no. 6, pp. 1833–1856, 2014.

[181] P. Collier and A. Hoeffler, "Aid, policy and peace: Reducing the risks of civil conflict," *Def. Peace Econ.*, vol. 13, no. 6, pp. 435–450, 2002.

[182] S. Meakin, "The Rio Earth Summit: Summary of the United Nations Conference on Environment and Development," *United Nations Science and Technology Division*, 1992. [Online]. Available: http://publications.gc.ca/Collection-R/LoPBdP/BP/bp317-e.htm. [Accessed: 12-Jun-2018].

[183] W. D. Nordhaus, *A question of balance: Weighting the options on global warming policies*. Yale University Press, 2008.

[184] "EU Emisssions Trading System (EU ETS)." [Online]. Available: https://ec.europa.eu/clima/policies/ets_en. [Accessed: 02-Dec-2018].

[185] "Program overview and design: Elements of RGGI," *RGGI, Inc.*, 2018. [Online]. Available: https://www.rggi.org/program-overview-and-design/elements. [Accessed: 28-Nov-2018].

[186] "Cap-and-trade program." [Online]. Available: https://www.arb.ca.gov/cc/capandtrade/capandtrade.htm.

[187] K. Mogelgaard and H. McGray, "With new climate plans, adaptation is no Longer an overlooked issue," *World Resources Institute*, 2015. .

[188] "COP22- Focus on National Adaptation Plans (NAPs)," *United Nations Development Programme*, 2018. .

[189] Climate Investment Funds, "Climate Resilience." [Online]. Available: https://www.climateinvestmentfunds.org/topics/climate-resilience. [Accessed: 02-Dec-2018].

[190] M. Mendiluce, "Risky business: Building a resilient power sector," *IEEE Power Energy Mag.*, vol. 12, no. 5, pp. 34–41, 2014.

[191] P. Audinet, J.-C. Amado, and B. Rabb, "Climate Risk Management Approaches in the Electricity Sector: Lessons from Early Adapters," in *Weather Matters for Energy*, Springer, 2014, pp. 335–349.

[192] The Guardian, "Heatwave hits French power production," 12-Aug-2003.

[193] F. Bate, "France's EDF cuts output at two nuclear reactors due to heatwave," *Reuters*, Paris, 18-Jul-2017.

[194] E. Shugerman, "Heatwave forces France to shut down four nuclear reactors," *Independent*, 04-Aug-2018.

[195] B. Lehner, G. Czisch, and S. Vassolo, "The impact of global change on the hydropower potential of Europe: A model-based analysis," *Energy Policy*, vol. 33, no. 7, pp. 839–855, 2005.

[196] Public Utilities Commission California, "Order instituting rulemaking to consider strategies

and guidance for climate change adaptation," San Francisco, California, R. 18-04-019, 2018.

[197] M. Wei, "Building a healthier and more robust future: 2050 low carbon energy scenarios for California. Modeling climate change for the 2050 grid and supporting high renewables in 2030." Davis Policy Forum, 2018.

[198] K. Raff-Douglas, "Climate adaptation in the electric Sector: Vulnerability assessments and resiliency plans," California Public Utilities Commission, 2016.

[199] R. J. Lempert, S. . Popper, and S. C. Bankes, "Robust Decision Making: Coping with uncertainty," *Futurist*, vol. 44, no. 1, 2010.

[200] R. J. Lempert, S. W. Popper, and S. C. Bankes, "Shaping the Next One Hundred Years: New Methods for Quantitative, Long-Term Policy Analysis," prepared for The Rand Pardee Center, Santa Monica, CA, RAND Corporation, MR-1626, 2003.

[201] R. Lempert and N. Kalra, "Managing climate risks in developing countries with Robust Decision Making," World Resources Report,World Resources Institute, Washington, DC, 2011.

[202] R. J. Lempert and D. G. Groves, "Identifying and evaluating robust adaptive policy responses to climate change for water management agencies in the American west," *Technol. Forecast. Soc. Change*, vol. 77, no. 6, pp. 960–974, 2010.

[203] N. Kalra *et al.*, "Robust Decision Making in the water sector: A Strategy for implementing Lima's long-term water resources master plan," World Bank Group, Policy Research Working Paper 7439, 2015.

[204] B. F. Hobbs and P. Meier, *Energy Decisions & The Environment: A Guide to the Use of Multicriteria Methods*. Boston/ Dordrecht/London: Kluwer Academic Publishers, 2000.

[205] R. J. Lempert and M. T. Collins, "Managing the risk of uncertain threshold responses: Comparison of robust, optimum, and precautionary approaches," *Risk Anal.*, vol. 27, no. 4, pp. 1009–1026, 2007.

[206] J. E. Shortridge and S. D. Guikema, "Scenario discovery with multiple criteria: An

evaluation of the Robust Decision-Making framework for climate change adaptation," *Risk Anal.*, vol. 36, pp. 2298–2312, 2016.

[207] S. W. Popper, C. Berrebi, J. Griffin, T. Light, E. M. Daehner, and K. Crane, *Natural Gas and Israel's Energy Future: Near-Term Decisions from a Strategic Perspective*. Santa Monica, CA: RAND Corporation, 2009.

[208] R. J. Lempert *et al.*, "Ensuring robust flood risk management in Ho Chi Minh City," The World Bank, WPS6465, 2013.

[209] G. B. Dantzig, "Linear programming under uncertainty," *Manage. Sci.*, vol. 1, no. 3/4, pp. 197–206, 1955.

[210] E. M. L. Beale, "On minizing a convex function subject to linear inequalities," *J. R. Stat. Soc. Ser. B*, vol. 17, no. 2, pp. 173–184, 1955.

[211] S. M. Ryan, R. J. B. Wets, D. L. Woodruff, C. Silva-Monroy, and J. P. Watson, "Toward scalable, parallel progressive hedging for stochastic unit commitment," in *IEEE Power and Energy Society General Meeting*, 2013.

[212] W. B. Powell and S. Meisel, "Tutorial on stochastic optimization in energy- Part II : An energy storage illustration," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1468–1475, 2016.

[213] M. Sun, F. Teng, I. Konstantelos, and G. Strbac, "An objective-based scenario selection method for transmission network expansion planning with multivariate stochasticity in load and renewable energy sources," *Energy*, vol. 145, pp. 871–885, 2018.

[214] K. Bruninx and E. Delarue, "Scenario reduction techniques and solution stability for stochastic unit commitment problems," in *2016 IEEE International Energy Conference, ENERGYCON 2016*, 2016.

[215] J. A. Bloom, "Solving an electricity generating capacity expansion planning problem by generalized Benders' decomposition," *Oper. Res.*, vol. 31, no. 1, pp. 84–100, 1983.

[216] R. T. Rockafellar and R. J.-B. Wets, "Scenarios and policy aggregation in optimization under uncertainty," *Math. Oper. Res.*, vol. 16, no. 1, pp. 119–147, 1991.

[217] B. C. Flach, L. A. Barroso, and M. V. F. Pereira, "Long-term optimal allocation of hydro generation for a price-maker company in a competitive market: latest developments and a stochastic dual dynamic programming approach," *IET Gener. Transm. Distrib.*, vol. 4, no. 2, pp. 299–314, 2010.

[218] J. Dupacova, "Stability and sensitivity analysis for stochastic programming," *Ann. Oper. Res.*, vol. 27, pp. 115–142, 1990.

[219] F. D. Munoz, B. F. Hobbs, and J. P. Watson, "New bounding and decomposition approaches for MILP investment problems: Multi-area transmission and generation planning under policy constraints," *Eur. J. Oper. Res.*, vol. 248, no. 3, pp. 888–898, 2016.

[220] I. Tobin *et al.*, "Assessing climate change impacts on European wind energy from ENSEMBLES high-resolution climate projections," *Clim. Change*, vol. 128, no. 1–2, pp. 99–112, 2015.

[221] D. J. Sailor, M. Smith, and M. Hart, "Climate change implications for wind power resources in the Northwest United States," *Renew. Energy*, vol. 33, no. 11, pp. 2393–2406, 2008.

[222] L. C. Cradden, G. P. Harrison, and J. P. Chick, "Will climate change impact on wind power development in the UK?," *Clim. Change*, vol. 115, no. 3–4, pp. 837–852, 2012.

[223] M. T. H. van Vliet, J. R. Yearsley, F. Ludwig, S. Vögele, D. P. Lettenmaier, and P. Kabat, "Vulnerability of US and European electricity supply to climate change," *Nat. Clim. Chang.*, vol. 2, no. 9, pp. 676–681, 2012.

[224] W. S. Jaglom *et al.*, "Assessment of projected temperature impacts from climate change on the U.S. electric power sector using the Integrated Planning Model®," *Energy Policy*, vol. 73, pp. 524–539, 2014.

[225] S. N. Chandramowli, "Impact of climate change on electricity systems and markets," Ph.D. dissertation, Graduate School-New Brunswick Rutgers,The State University of New Jersey, New Brunswick, NJ, 2015.

[226] S. Li, D. W. Coit, and F. Felder, "Stochastic optimization for electric power generation

expansion planning with discrete climate change scenarios," *Electr. Power Syst. Res.*, vol. 140, pp. 401–412, 2016.

[227] S. Jerez *et al.*, "The impact of climate change on photovoltaic power generation in Europe," *Nat. Commun.*, vol. 6, no. 10014, 2015.

[228] J. A. Crook, L. A. Jones, P. M. Forster, and R. Crook, "Climate change impacts on future photovoltaic and concentrated solar power energy output," *Energy Environ. Sci.*, vol. 4, no. 9, pp. 3101–3109, 2011.

[229] M. T. H. van Vliet, D. Wiberg, S. Leduc, and K. Riahi, "Power-generation system vulnerability and adaptation to changes in climate and water resources," *Nat. Clim. Chang.*, vol. 6, no. 4, pp. 375–380, 2016.

[230] M. D. Bartos and M. V. Chester, "Impacts of climate change on electric power supply in the Western United States," *Nat. Clim. Chang.*, vol. 5, no. 8, pp. 748–752, 2015.

[231] S. M. Cohen, J. Macknick, K. Averyt, and J. Meldrum, "Modeling climate-water impacts on electricity sector capacity expansion preprint." NREL, To be presented at the ASME 2014 Power Conference Baltimore, Maryland, 2014.

[232] A. F. P. de Lucena, R. Schaeffer, and A. S. Szklo, "Least-cost adaptation options for global climate change impacts on the Brazilian electric power system," *Glob. Environ. Chang.*, vol. 20, no. 2, pp. 342–350, 2010.

[233] Y. Chen, B. F. Hobbs, J. Hugh Ellis, C. Crowley, and F. Joutz, "Impacts of climate change on power sector NOx emissions: A long-run analysis of the US mid-atlantic region," *Energy Policy*, vol. 84, pp. 11–21, 2015.

[234] B. F. Hobbs, "Choosing how to choose: Comparing amalgamation methods for environmental impact assessment," *Environ. Impact Assess. Rev.*, vol. 5, pp. 301–319, 1985.

[235] M. V. F. Pereira and L. M. V. G. Pinto, "Multi-stage stochastic optimization applied to energy planning," *Math. Program.*, vol. 52, pp. 359–375, 1991.

[236] M. C. Hu and B. F. Hobbs, "Analysis of multi-pollutant policies for the U.S. power sector

under technology and policy uncertainty using MARKAL," *Energy*, vol. 35, no. 12, pp. 5430–5442, 2010.

[237] S. W. Wallace and S.-E. Fleten, "Stochastic Programming Models in Energy," in *Handbooks in Operations Research and Management Science*, vol. 10, Elsevier Science B.V., 2003, pp. 637–677.

[238] I. Khan, F. Alam, and Q. Alam, "The global climate change and its effect on power generation in Bangladesh," *Energy Policy*, vol. 61, pp. 1460–1470, 2013.

[239] Japan International Cooperation Agency The Tokyo Electric Power Company, "Power System Master Plan 2010," People's Republic of Bangladesh Ministry of Power Energy and Mineral Resources Power Division, 2011.

[240] C. Harvey, "A new power plant could devastate the world's largest mangrove forest," *The Washington Post*, 18-Jul-2016.

[241] "Open-pit coal mine project in Bangladesh threatens human rights – UN experts," *UN News Centre*, 2012. [Online]. Available: https://news.un.org/en/story/2012/02/404922-open-pit-coal-mine-project-bangladesh-threatens-human-rights-un-experts. [Accessed: 23-Nov-2018].

[242] (TEPSCO) Tokyo electric Power Services Co. and (Japan International Cooperation Agency Study Team), "Report on Environmental Impact Assessment of Construction of Matarbari 600X2 MW Coal Fired Power Plant and Associated Facilities," Coal Power Generation Company of Bangladesh Limited, 2013.

[243] "Power System Master Plan 2016," Power Division Ministry of Power Energy and Mineral Resources Government of the People's Republic of Bangladesh, supported by Japan International Cooperation Agency (JICA) Tokyo Electric Power Services Co., Ltd. Tokyo Electric Power Company Holdings, Inc., 2016.

[244] S. K. Rose, D. B. Diaz, and G. J. Blanford, "Understanding the Social Cost of Carbon: a Model Diagnostic and Inter-Comparison Study," *Clim. Chang. Econ.*, vol. 08, no.

02,1750009, pp. 1–28, 2017.

[245] The Bangladesh Power Development Board, "Annual Report 2015-2016." 2017.

[246] A. Abreu, "Bangladesh's Petrobangla to start regular LNG imports from Sep 9," *S&P Global, Platts*, Dhaka, 05-Sep-2018.

[247] Japan International Cooperation Agency (JICA) Tokyo Electric Power Services Co. Ltd. Tokyo Electric Power Company., "Survey on Power System Master Plan 2015 Draft Final Report April 2016," People's Republic of Bangladesh Ministry of Power, Energy and Mineral Resources Bangladesh Power Development Board, 2016.

[248] The World Bank Group, "World Bank commodities price forecast," 2017. [Online]. Available: pubdocs.worldbank.org/en/926111485188873241/CMO-Januart-2017-Forecasts.pdf. [Accessed: 01-Jan-2017].

[249] Bangladesh Climate Change Resilience Fund The World Bank Group International Center for Tropical Agriculture, "Climate Change Knowledge Portal Climate Analysis Tool-Powered by Climate Wizard." [Online]. Available: http://climatewizard.ciat.cgiar.org/wbclimateanalysistool/. [Accessed: 01-Jan-2016].

[250] Y. Hirabayashi *et al.*, "Global flood risk under climate change," *Nat. Clim. Chang.*, vol. 3, no. 9, pp. 816–821, 2013.

[251] M. A. McNeil and V. E. Letschert, "Future air conditioning energy consumption in developing countries and what can be done about it: the potential of efficiency in the residential sector," Lawrence Berkeley National Laboratory, 2008.

[252] Y. Feng and S. M. Ryan, "Scenario construction and reduction applied to stochastic power generation expansion planning," *Comput. Oper. Res.*, vol. 40, no. 1, pp. 9–23, 2013.

[253] B. D. Leibowicz, "The cost of policy uncertainty in electric sector capacity planning: Implications for instrument choice," *Electr. J.*, vol. 31, pp. 33–41, 2018.

[254] J. E. Bistline and J. P. Weyant, "Electric sector investments under technological and policy-related uncertainties: A stochastic programming approach," *Clim. Change*, vol. 121, no. 2,

pp. 143–160, 2013.

[255] H. Raiffa, *Applied statistical decision theory*. Harvard University Press, 1961.

[256] P. J. Ward *et al.*, "Usefulness and limitations of global flood risk models," *Nat. Clim. Chang.*, vol. 5, no. 8, pp. 712–715, 2015.

[257] W. J. Cole *et al.*, "Variable Renewable Energy in Long-Term Planning Models : A Multi-Model Perspective," National Renewable Energy Laboratory, Golden, CO, NREL/TP-6A20-70528, 2017.

[258] C. Bothwell and B. F. Hobbs, "Crediting wind and solar renewables in electricity capacity markets: The effects of alternative definitions upon market efficiency," *Energy J.*, vol. 38, no. Special Issue 1, pp. 173–188, 2017.

[259] S. Wogrin, P. Duenas, A. Delgadillo, and J. Reneses, "A new approach to model load levels in electric power systems with high renewable penetration," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2210–2218, 2014.

[260] S. Pineda and J. M. Morales, "Chronological time-period clustering for optimal capacity expansion planning with storage," *IEEE Trans. Power Syst.*, vol. 33, no. 6, pp. 7162–7170, 2018.

[261] International Energy Agency, "Electric vehicles: Tracking clean energy progress," 2018. [Online]. Available: https://www.iea.org/tcep/transport/evs/. [Accessed: 25-Nov-2018].

[262] IEA, *World Energy Outlook 2017*. Paris: IEA, 2017.

[263] B. Mow, "Community Choice Aggregation (CCA) Helping Communities Reach Renewable Energy Goals," *NREL Blog*, 2017. [Online]. Available: https://www.nrel.gov/state-local-tribal/blog/posts/community-choice-aggregation-cca-helping-communities-reach-renewable-energy-goals.html. [Accessed: 25-Nov-2018].

[264] J. Fordney, "California utilities propose new CCA rules," *RTO Insider*, 08-Apr-2018.

[265] "High Penetration of Energy Storage Resources on the Electricity System," TO: Honorable Patricia Hoffman, Acting Assistant Secretary for Electricity Delivery and

Energy Reliability, U.S. Department of Energy, from Electricity Advisory Committee Susan Tierney, Chair, 2017.

[266] W. Pizer, D. Burtraw, W. Harrington, R. Newell, J. Sanchirico, and M. Toman, "General and partial equilibrium modeling of sectoral policies to address climate change in the United States," Resources for the Future, Washington, D.C., 2003.

[267] D. D. Dudenhoeffer, M. R. Permann, and M. Manic, "CIMS: A framework for infrastructure interdependency modeling and analysis," in *Proceedings of the 2006 Winter Simulation Conference*, 2006.

[268] J. Caron, S. M. Cohen, M. Brown, and J. M. Reilly, "Exploring the impacts of a national US CO2 tax and revenue recycling options with a coupled electricity-economic model," *Clim. Chang. Econ.*, vol. 09, no. 01, 1840015, pp. 1–40, 2018.

[269] J. H. Eto and G. Gallo, "Regional transmission planning: A review of practices following FERC Order Nos. 890 and 1000," Lawrence Berkeley National Laboratory, LBNL-2001079, 2017.

[270] B. Kroposki *et al.*, "Achieving a 100% renewable grid," *IEEE Power Energy Mag.*, no. March/April, pp. 61–73, 2017.

[271] S. Kasina, "Essays on unit commitment and interregional cooperation in transmission planning," Ph.D. dissertation, Department of Environmental Health and Engineering,The Johns Hopkins University, Baltimore, MD, 2017.

[272] J. Choi, T. D. Mount, and R. J. Thomas, "Transmission expansion planning using contingency criteria," *IEEE Trans. Power Syst.*, vol. 22, no. 4, pp. 2249–2261, 2007.

[273] F. P. Sioshansi, *Evolution of Global Electricity Markets: New paradigms, new challenges, new approaches.* Academic Press, 2013.

[274] W. Hogan, J. Rosellón, and I. Vogelsang, "Toward a combined merchant-regulatory mechanism for electricity transmission expansion," *J. Regul. Econ.*, vol. 38, pp. 113–143, 2010.

[275] E. B. Fisher, R. P. O' Neill, and M. C. Ferris, "Optimal transmission switching," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1346–1355, 2008.

[276] J. Salmeron, K. Wood, and R. Baldick, "Analysis of electric grid security under terrorist threat," *IEEE Trans. Power Syst.*, vol. 19, no. 2, pp. 905–912, 2004.

[277] M. A. Trigg *et al.*, "The credibility challenge for global fluvial flood risk analysis," *Environ. Res. Lett.*, vol. 11, no. 9, 094014, pp. 1–10, 2016.

[278] S. Steinschneider, R. McCrary, L. O. Mearns, and C. Brown, "The effects of climate model similarity on probabilistic climate projections and the implications for local, risk-based adaptation planning," *Geophys. Res. Lett.*, vol. 42, no. 12, pp. 5014–5022, 2015.

[279] R. Olson, Y. Fan, and J. P. Evans, "A simple method for Bayesian model averaging of regional climate model projections: Application to southeast Australian temperatures," *Geophys. Res. Lett.*, vol. 43, no. 14, pp. 7661–7669, 2016.

[280] "COP23 Presidency Event Towards a resilient future : Frontiers of risk sharing," 2017. [Online]. Available: https://unfccc.int/sites/default/files/resource/CNPresidencyEventResilience.pdf. [Accessed: 26-Nov-2018].

[281] United Nations Framework Convention on Climate Change, "The Fiji Clearing House for Risk Transfer." [Online]. Available: http://unfccc-clearinghouse.org/. [Accessed: 26-Nov-2018].

[282] World Bank Group, "Sovereign Climate and Disaster Risk Pooling World Bank Technical Contribution to the G20," International Bank for Reconstruction and Development, Washington DC, 2017.

[283] "Climate-resilient infrastructure," UNFCCC Standing Committee on Finance Forum, Rabat, Morocco, presented by Michael Mullan, Team Leader-Climate Change Adaptation and Development Environment Directorate OECD, 2017.

[284] United Nations Department of Economic and Social Affairs Population Division, "World

Population Prospects: The 2017 Revision," 2017. .

[285] International Monetary Fund, "World Economic Outlook Database." [Online]. Available: https://www.imf.org/external/pubs/ft/weo/2018/02/weodata/index.aspx.

[286] International Monetary Fund, "2016 Article IV Consultation—Press release; Staff report; and statement by the executive director for South Sudan," International Monetary Fund, Washington, D.C., IMF Country Report No.17/73, 2017.

[287] Wittgenstein Centre for Demography and Global Human Capital, "Wittgenstein Centre Data Explorer." [Online]. Available: http://www.oeaw.ac.at/fileadmin/subsites/Institute/VID/dataexplorer/index.html.

[288] UNICEF, "Statistics by topic/education/ secondary education." [Online]. Available: https://data.unicef.org/topic/education/secondary-education/. [Accessed: 31-Oct-2017].

[289] Republic of Kenya- Ministry of Energy and Petroleum, "Development of a power generation and transmission master plan Kenya long term plan," 2016.

[290] D. Mozersky and D. M. Kammen, "South Sudan's renewable energy potential: A building block for peace," United States Institute of Peace, Washington, DC, Special Report 418, 2018.

[291] The World Bank Group, "Global Solar Atlas." [Online]. Available: https://globalsolaratlas.info/.

[292] Nattional Renewable Energy Laboratory, "PVWatts Calculator," 2017. [Online]. Available: https://pvwatts.nrel.gov/. [Accessed: 28-Nov-2018].

[293] M. D. C. Department of Homeland Security, Federal Emergency Management Agency, "Multi-hazard Loss Estimation Methodology Flood Model Hazus MR4 Technical Manual." [Online]. Available: http://www.fema.gov/media-library-data/20130726-1715-25045-8157/hazus_mr4_flood_tech_manual.txt.

[294] NTPC Limited, "Final Feasibility Report: Khulna Thermal Power Project (2X660 MW) Bangladesh," Bangladesh Power Development Board, Dhaka, DOC.NO.-9635-999-NOG

J-001-REV-'C,' 2012.

[295] S. Disavino, "Power company restarts a quarter of NJ plants hit by Sandy," *Reuters*, 19-Nov-2012.

[296] The Hindu Staff Reporter, "Simhapuri power plant partly submerged," *The Hindu*, 21-Nov-2015.

[297] D. Bosco, "Puducherry seeks Rs 182.45 crore immediate flood relief assistance," *The Times of India*, 26-Nov-2015.

[298] D. Dewitte, "Steam customers say Alliant offer not viable: Customers would have to bear the cost," *The Gazette*, 2009. [Online]. Available: http://callcenterinfo.tmcnet.com/news/2009/01/07/3895228.htm. [Accessed: 01-Jan-2016].

[299] "Prairie Creek Generating Station restarts after flood," *Power Engineering*, 2009. [Online]. Available: http://www.power-eng.com/articles/2009/01/prairie-creek-generating-station-restarts-after-flood.html. [Accessed: 01-Jan-2016].

[300] Alliant Energy Corporation, "Sutherland generating station back to powering Iowa homes and businesses after historic floods," *PRNewswire*, 2008. [Online]. Available: http://www.prnewswire.com/news-releases/sutherland-generating-station-back-to-powering-iowa-homes-and-businesses-after-historic-floods-57549947.html. [Accessed: 01-Jan-2016].

[301] Mississippi Power, "Mississippi power's plant Watson fully restored, ready for summer peaking season," *PRNewswire*, 2006. [Online]. Available: http://www.prnewswire.com/news-releases/mississippi-powers-plant-watson-fully-restored-ready-for-summer-peaking-season-56140092.html. [Accessed: 01-Jan-2016].

[302] Missisippi Power Company, "2005 Annual Report," 2005.

[303] United States Environmental Protection Agency, "Air Markets Program Data." [Online]. Available: https://ampd.epa.gov/ampd/. [Accessed: 01-Jan-2016].

[304] J. Smith, "Entergy New Orleans' Michoud power plant returns to service," *Entergy*, 2006. [Online]. Available: http://www-temp.entergy.com/News_Room/newsrelease.aspx?NR_ID=824.

[305] "Hurricane Ike made landfall at Galveston," *OASIS OATI*, 2008. [Online]. Available: http://www.oasis.oati.com/EES/EESDocs/sept. 14 2008 -- hurricane gustavike restoration -- 1130 a.m. cdt.txt. [Accessed: 01-Jan-2016].

[306] TrisRating, "Rojana Industrial Park," *Credit News*, 2012. [Online]. Available: http://www.trisrating.com/en/pdf/announcement/ROJANA870-e-Sfas98z.pdf. [Accessed: 01-Jan-2016].

[307] Global Facility for Disaster Risk Reduction, "Damage, losses and needs assessment October 2008. Tropical storm and floods, Hadramout and Al-Mahara, Republic of Yemen," 2009.

[308] U.S. Energy Information Administration, "Updated capital cost estimates for utility scale electricity generating plants," Washington, DC, 2013.

[309] F. Messner and V. Meyer, "Flood Damage, vulnerability and risk perception – Challenges for flood damage," in *Flood Risk Management: Hazards, Vulnerability and Mitigation Measures*, NATO Scien., vol. 67, J. Schanze, E. Zeman, and J. Marsalek, Eds. Springer, Dordrecht, 2006.

[310] C. C. Sampson, A. M. Smith, P. D. Bates, J. C. Neal, L. Alfieri, and F. J. E., "A high-resolution global flood hazard model," *Water Resour. Res.*, vol. 51, pp. 7358–7381, 2015.

[311] IEA, "WEO-2015 Special Report: India Energy Outlook," IEA, Paris, 2015.

[312] L. Premkumar, "A study of the India-Bhutan energy cooperation agreements and the implementation of hydropower projects in Bhutan," Vasudha Foundation, New Delhi, India, 2016.

[313] Government of India Ministry of Power Central Electricity Authority New Delhi, "Monthly Executive Summary on Power Sector." [Online]. Available:

http://www.cea.nic.in/reports/monthly/executivesummary/2016/exe_summary-10.pdf. [Accessed: 04-Dec-2017].

[314] "Scaling up Renewable Energy in low income countries (SREP): Investment plan for Bangladesh," Sustainable & Renewable Energy Development Authority Power Division Ministry of Power Energy & Mineral Resources Government of the Peoples Repulblic of Bangladesh, Ref No: 27.02.0000.000.24.002.14-501, 2015.

[315] H. R. Varian, *Intermediate Microeconomics A modern approach*, 8th ed. New York: W. W. Norton & Company, 2010.

[316] O. Ben-Ayed and C. E. Blair, "Computational difficulties of bilevel linear programming," *Oper. Res.*, vol. 38, no. 3, pp. 556–560, 1990.

[317] Y. Ermoliev and L. Hordijk, "Facets of robust decisions," in *Coping with Uncertainty Modeling and Policy Issues*, Lecture no., K. Marti, Y. Ermoliev, M. Makowski, and G. Pflug, Eds. Springer, 2006, pp. 3–28.

[318] M. Rahman, D. Bhattacharya, K. G. Moazzem, and T. I. Khan, "State of the Bangladesh economy in FY2015 and the closure of sixth five year plan," Centre for Policy Dialogue, DRAFT, 2015.

[319] V. Kumar, J. K. Chhabra, and D. Kumar, "Performance Evaluation of Distance Metrics in the Clustering Algorithms," in *Infocomp*, 2014, vol. 13, no. 1, pp. 38–52.

[320] P. Kusche and L. Coyne, "How to utilize the influx of capital markets capacity, including CAT bonds," in *The Risk Management Society Annual Conference*, 2015.

[321] K. Riahi *et al.*, "RCP 8.5-A scenario of comparatively high greenhouse gas emissions," *Clim. Change*, vol. 109, pp. 33–57, 2011.

VITA

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