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How to Assess Uncertainty-Aware Frameworks for Power System Planning?

Elina Spyrou, *Member, IEEE*, Ben Hobbs, *Life Fellow, IEEE*, Deb Chattopadhyay, Neha Mukhi

***Abstract*—Computational advances along with the profound impact of uncertainty on power system investments have motivated the creation of power system planning frameworks that handle long-run uncertainty, large number of alternative plans, and multiple objectives. Planning agencies seek guidance to assess such frameworks. This article addresses this need in two ways. First, we augment previously proposed criteria for assessing planning frameworks by including new criteria such as stakeholder acceptance to make the assessments more comprehensive, while enhancing the practical applicability of assessment criteria by offering criterion-specific themes and questions. Second, using the proposed criteria, we compare two widely used but fundamentally distinct frameworks: an 'agree-on-plans' framework, Robust Decision Making (RDM), and an 'agree-on-assumptions' framework, centered around Stochastic Programming (SP). By comparing for the first time head-to-head the two distinct frameworks for an electricity supply planning problem under uncertainties in Bangladesh, we conclude that RDM relies on a large number of simulations to provide ample information to decision makers and stakeholders, and to facilitate updating of subjective inputs. In contrast, SP is a highly dimensional optimization problem that identifies plans with relatively good probability-weighted performance in a single step, but even with computational advances remains subject to the curse of dimensionality.**

***Index Terms*—Robust Decision Making, Stochastic Programming, Power System Planning, Deep Uncertainty, Risk Analysis**

I. Introduction

Global investments in generation and transmission assets are expected at unprecedentedly high rates to enable the transition to low CO2-emitting electricity systems [1]. Power system planning procedures facilitate investment decisions by recommending *when* to invest in *which* assets or types of assets and at *what* level. In vertically integrated utilities, planning considers investments in both transmission and generation subject to regulatory approval; meanwhile in unbundled markets, grid owners only plan transmission assets, although they also use supply planning models to project how the market might respond to policy initiatives and grid reinforcements [2].

In both settings, planning processes help agencies to assess and compare investments in terms of 'attributes' that describe the performance on objectives that users care about. These processes usually employ a mathematical model or an ensemble of such models that estimate attributes of investment plans under various possible future states of the system and the world [3], [4]. These attributes can literally number in the dozens, encompassing a diverse set of economic, financial, social, environmental, risk, and other concerns that decision makers, stakeholders, and regulators have. Crucially, in a deeply uncertain planning environment, investors try to avoid near-term commitments that may tie their hands in the future, and instead prioritize plans that can flexibly adjust to different possible future environmental, socio-economic, technical, or policy developments or 'states'. Thus, plans should be regarded as *strategies* that recognize that investments in later years will be contingent on future developments [4], [5].

The combination of multiple states of the world and system, multiple feasible plans at multiple decision stages, and multiple attributes makes planning complex and highly dimensional. To deal with the complexity of multiple states and stages, power system planners *either* ignore long-run uncertainties and focus on near-term decisions without explicitly considering alternative ways in which flexibility might be exercised depending on later developments [6]; *or* they identify a set of possible scenarios that describe future states. In the latter case, they often further simplify the consideration of uncertainty in one of several ways [7]. These include narrowing the problem by either focusing on: one scenario at a time to identify scenario-specific investment plans (this approach is often called scenario planning) [8]; one fixed plan and estimate the sensitivity of the plan's benefits to which scenario is considered [9]; or a small set of plans under a small set of scenarios [10]. Similarly, the dimensionality introduced by the wide range of possible attributes can be reduced by various means, for instance by limiting the number of attributes or plans considered or by weighting and combining attributes into a few aggregate performance indices (e.g., *cost* versus *environment*) or even just one overall utility index [4].

Simplifications such as scenario planning and use of aggregate attribute indices can risk failing to identify investment plans that could be good compromises among attributes [11] while providing robustness and flexibility in the face of uncertain and changing conditions [12], [13]. To address this risk of failure, several frameworks have been devised that indeed consider multiple plans, scenarios, and attributes, and how early decisions constrain later choices or open up possibilities. Most frameworks start by encouraging planners to 'agree' either on a framework's assumptions or on the plans themselves [14]. On one hand, 'agree-on-assumptions' frameworks such as stochastic programming and robust optimization [15] assume that planners can describe (1) uncertainty through scenarios or possible ranges for uncertain parameters; (2) plans by defining a feasible region; (3) preferences for attributes

This work was supported in part by the Leverhulme Foundation, the World Bank, and the NSF EPICS Center. E. Spyrou is with Imperial College London, UK (e-mail: elina.spyrou@ic.ac.uk). B.F. Hobbs is with the Johns Hopkins University, Baltimore, MD 21218 USA. D. Chattopadhyay and N. Mukhi are with the World Bank Group, Washington, DC, USA.

through constraints or by using weighting to combine them into a single decision, or "utility" criterion that is optimized. On the other hand, 'agree-on-plans' frameworks such as Robust Decision Making assume that planners agree on a set of discrete candidate plans to consider, but they want to explore their performance for an assumed scenario space and alternative decision criteria.

As planning frameworks are enhanced to integrate renewable resources and improve resilience, planners, regulators, and their stakeholders seek guidance for tools and methods. For instance, in the USA, "utilities in the Partnership for Energy Sector Climate Resilience note that managers would welcome additional guidance, tools, and methodologies to help them move forward" [16]. Meanwhile, in Great Britain (GB), the Energy System Operator commissioned a study to understand how their network option assessment process compares to processes followed by peers and researchers [10].

While both 'agree-on-assumptions' and 'agree-on-plans' frameworks have significantly advanced in the last decades, the literature lacks comprehensive reviews and comparisons of these two frameworks for combined risk/multi-attribute planning. In particular, literature reviews tend to focus on advancements in solution approaches and techniques for one or the other framework type. For instance, Ref [17] provides an overview of methods and modeling techniques useful for 'agree-on-assumptions' frameworks; and Ref. [14] provides a similar overview of techniques that could be applied within 'agree-on-plans' frameworks. Very few articles have compared different planning frameworks through application on the same case study. Refs. [18], [19], [20] are such articles, but they only compare robust vs. probabilistic criteria within one framework instead of distinct frameworks. The treatment of multiple objectives has also been the subject of many previous reviews [21], [22] and some careful comparative applications [4], but comparisons have not been made of different approaches for integrated consideration of risk and multiple attributes, especially in a multistage long-term planning setting.

To address planners' need for guidance and tools for uncertainty-aware planning, this article makes two contributions. First, we propose a set of readily applied criteria for *holistically* assessing frameworks for power system planning considering multiplicities of uncertainties, attributes, alternatives, and decision stages. For brevity, we term these 'uncertainty-aware frameworks'. Second, this paper contributes the first comparison of two widely-used planning frameworks that are fundamentally distinct, representing either the 'agree-on-assumptions' or 'agree-on-plans' frameworks. Regarding the first contribution, we build upon and extend early work that incorporated uncertainty and risk into power system planning. In a 1989 World Bank report [23], Crousillat compared three power system planning methods using a set of three criteria: (1) modeling capability; (2) practical applicability; (3) transparency and contribution to decision making.

The three criteria were proposed as operationally-oriented and the author noted that the choice of criteria was rather subjective. Their description was also brief, making it challenging for potential users to apply them. Moreover, the third criterion in the original report only refers to the decision makers themselves and not all interested parties.

Recent research though has emphasized the importance of stakeholder acceptance of plans and processes. Thus, we propose a significant revision of the criteria extending the scope of the third criterion to include stakeholders in addition to decision makers. Considering that public opposition could be one of four major reasons why a transition to net zero energy systems may fail to occur [24], we anticipate a growing emphasis on planning frameworks that engage with stakeholders to foster acceptance. Hence, the revised third criterion will enable planning agencies to carefully distinguish among various frameworks and assess their suitability for the planning problem at hand.

Moreover, to facilitate the application of the criteria, we here expand them by listing thematic areas and specific questions pertaining to each criterion. By making the criteria less ambiguous and subjective, we hope to help planners to apply the three criteria and choose a framework in a consistent and more easily communicable and defensible manner.

Turning to the second contribution, SP and RDM take very different approaches to modeling and considering uncertainty and engaging stakeholders and decision makers in that process. Both approaches have been widely applied, although to different problem domains. SP has seen frequent use in power system planning research, as well as occasional actual application to planning and operations of the Brazilian hydro-dominated power system [25], as well as in many other capital investment planning problems [26]. Meanwhile, RDM is a framework that recently has seen common use for planning water, transportation, and other non-power infrastructure planning under climate change and other long-run uncertainties [14]. The World Bank recommends RDM as a framework for managing *deep uncertainties*, which describe 'situations in which analysts do not know or cannot agree on (1) models that relate key forces that shape the future, (2) probability distributions of key variables and parameters in these models, and/or (3) the value of alternative outcomes' [27].

Despite the presence of deep uncertainties considering the future of power technologies, demands and policies, RDM has heretofore received limited attention for power system planning. To the best of our knowledge, the only power sector applications have been for hydropower planning in Africa [28] and a World Bank application to power supply in Bangladesh [29], a predecessor to our methodological comparison in Section IV. The present article conducts, for the first time, a careful head-to-head comparison of RDM and SP-centered frameworks in the context of a power planning study; this allows us to offer unique insights on the distinct ways in which RDM and SP can improve power sector decision making. We have used power planning data in the RDM and SP frameworks in as consistent a manner as possible. This consistency results in a fairer 'apples to apples' comparison relative to attempting a comparison based on stand-alone applications of each method to different problems in the literature.

The rest of the paper is structured as follows. In Section II, we present the proposed set of criteria for choosing an uncertainty-aware planning framework. We then briefly describe the RDM and SP frameworks in Section III. We introduce our case study in Section IV, and then devote Section V to discussing the qualitative and quantitative results of the RDM and SP comparison. In Section VI, we summarize major takeaways along with needed future research. Lastly, in Appendices A and B we provide the formulation of our planning model and an overview of data sources, respectively.

II. Criteria for Assessment of Planning Frameworks

An effective and fair assessment of planning frameworks should be holistic and avoid a priori assumptions about users' priorities. Using the three criteria we describe below, planners can identify strengths and weaknesses of any framework and inform the design of their own planning process. Based on recent research findings and experience, those criteria represent elaborations and extensions of three broad criteria that Crousillat first suggested in 1989 [23]. We summarize the criteria in Fig. 1 and refer to parts of Fig. 1 throughout this section using indexes listed in parentheses in Fig. 1.

Criterion 1. Methodological Capability *Modeling capability* is a criterion proposed by Crousillat [23] and it is defined as *"the models' ability to capture the possible consequences of multiple uncertainties inherent to alternative investment plans."* Given that a planning process might include multiple mathematical models, we refer to this criterion as methodological capability. To facilitate the application of this criterion, we suggest four themes: *uncertainty*, *plans*, *consequences: attributes*, *consequences: assessment* (first column of Fig.1).

Uncertainty here refers to "imperfect or incomplete information/knowledge about a hypothesis, a quantity, or the occurrence of an event" [30]. To apply the methodological capability criterion in the context of uncertainty, planners have to identify how imperfect or incomplete information affects the quantity of one or multiple parameters of a planning model [23], and describe which mathematical constructs the framework in question uses to approximate the uncertainty, e.g., scenarios or ranges of possible values for uncertain factor(s) (1.A.1). Planners should also determine how the framework in question handles the absence or availability of probability distributions (1.A.2). Over the course of the planning horizon, new information could resolve some of the uncertainty [31]. Hence, in cases such learning is expected through data collection or other means, planners should consider whether and how the framework in question accounts for chronological evolution of uncertainty (1.A.3). For example, some methodological frameworks use conditional probabilities to represent possible dynamic evolution of states over distinct stages with different uncertainty characteristics [32].

The second theme –*plans* – refers to a set of investment decisions to pursue at specified times [33]. Plans are usually periodically updated [10]. They are also determined in sequential cycles of increasing resolution, starting with an initial plan which is rather abstract (e.g., build a transmission line connecting the electricity grids of Spain and France) and concluding with a final plan that describes details (such as the line's route and equipment) [34]. Therefore, to assess criterion 1 with respect to plans, planners should review: (1.B.1) how the set of feasible plans is described, e.g., enumeration of plans or a set mathematically constructed as a feasible region; (1.B.2) at what temporal-spatial-asset resolution plans are modelled; and (1.B.3) how future plan updates are considered.

The third theme focuses on attributes that quantitatively describe plan consequences/performance. Common attributes include cost, reliability, and environmental metrics [35]. The resolution of attributes, for example defining several attributes to describe impacts on different social groups, matters especially for distributional equity [36]. The precision with which the attributes are estimated is also important and could be affected by modeling uncertainty. Hence, planners should seek evidence here that show how accurately attributes are estimated. Therefore, for the third theme, planners should review (1.C.1) which types of attributes are modeled, (1.C.2) at what resolution and (1.C.3) at what precision.

The last theme reviews how frameworks reflect subjective preferences for different levels of plan consequences. The points of view of different affected parties are often considered by frameworks through utility functions [37]. Utility functions approximate preferences for different levels of attributes, priorities among attributes, and risk attitudes [38] [4]. Utility functions commonly combine different attributes using priority weights, which reflect decisionmaker and stakeholder values. Risk attitudes commonly assumed in planning models are those of risk neutral or risk averse users, who are respectively concerned about probability-weighted (expected) consequences or who weight undesirable outcomes more heavily [39]. For instance, if decisionmakers or stakeholders are interested in a framework's ability to evaluate high-impact/low-probability events, certain criteria such as conditional value at risk might be well suited for assessing extreme outcomes.

Planners are commonly assumed to use utility-maximization as a criterion for plan selection (e.g., least-cost plans [13]) or to be satisfied with performance within certain thresholds (e.g., plans within budget constraints or that satisfy environmental standards [36]). In case a methodology incorporates the optimization of a utility function as a decision criterion, it is critical to ensure that the assumed utility functions actually represent how decisionmakers and stakeholders are willing to trade off attributes against each other [4]. Depending on the framework, decision criteria can be expressed either explicitly in an analytical form or implicitly through a process in which users directly evaluate and compare alternative plans. In summary, to evaluate methodological capabilities with respect to assessment of consequences, planners should review (1.D.1) what decision criteria the methodology can incorporate; (1.D.2) how updates in decision criteria can be handled; and (1.D.3) how the framework elicits weights and other value judgments by stakeholders and users.

Criterion 2. Practical applicability While time and cost trade-offs are important practical considerations involved in choosing a planning framework [23], experience shows that certain resource needs (digital, intellectual, staff) and regulatory compliance also require particular attention.

Using uncertainty-aware frameworks like RDM and SP to plan power systems can be computationally expensive and, in the case of particularly complex problems, may require high

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	Criterion 1: Methodological capability			***Criterion 3: Contribution to decision making and stakeholder acceptance***	
Theme	How the methodological framework considers:			Engagement goal	Number of views
Uncertainty	Space of possible states (1.A.1)	Probabilities of states (1.A.2)	Chronological evolution (1.A.3)	For each theme in the 1st column, which goal could the framework serve: to inform, to consult, or to collaborate? (3.A)	For each theme in the 1st column, can the framework consider multiple views and how? (3.B)
Plans	Feasible set (1.B.1)	Asset-temporal-spatial resolution (1.B.2)	Future updates to plans (1.B.3)		
Consequences: Attributes	Types (e.g., reliability, cost) (1.C.1)	Resolution (1.C.2)	At what precision (1.C.3)		
Consequences: Assessment	Different types of criteria (e.g., min-max) (1.D.1)	Updates to criteria for assessment of plans (1.D.2)	Process to elicit preferences (1.D.3)		

Criterion 2: Practical applicability
- Computational resources
- Software
- Data requirements
- Human resources
- Regulatory compliance

Fig. 1: Proposed criteria for systematic comparison and assessment of uncertainty-aware power system planning frameworks.

performance computing [17]. Most of the time, specialized software needs to be purchased or developed and maintained. Thus, it is key to assess if software needs will be met with in-house, commercial, or open-source tools. Also, uncertainty characterizations are increasingly data-driven. To feed the data-hungry models of certain frameworks, data acquisition and storage schemes have to be established. The set up of such schemes can be prohibitive for some users [40]. Similarly, specialized workforce skills and knowledge are essential to use new techniques [41]. Finally, where processes are subject to regulatory approval, planners should assess how planning frameworks conform with regulatory guidelines [35].

To fairly compare planning frameworks, it is important to review if the needs for resources and regulatory compliance are one-off or recurring. On one hand, to transition to a new framework, resource needs such as those for regulatory approval are likely to be significant but one-off. On the other hand, application-related needs such as use of computational resources or consultants are likely to be recurring [23].

Criterion 3. Contribution to decision making and acceptance by planners and stakeholders *Transparency and contribution to decision making* represent the third criterion proposed in [23]. The preferred performance for this is described as follows: *"The method should be readily understood by decision makers. The criteria for judging alternatives should be easy to understand and the consequences of differing judgmental inputs should be reviewed without excessive effort."*[23] We extend this criterion in two ways: 1) by expanding its scope to consider stakeholders in addition to planners because their acceptance of plans is essential; and 2) by introducing engagement process goals that planners could consider.

Experience and research since [23] has demonstrated that social acceptance of investment plans is essential for their successful implementation, and can be hard to come by if it is only an afterthought in a planning study [42]. Researchers all over the world have studied social acceptance of power plans and facilities. For instance, in rural Australia, researchers found consultation to be one of the most important factors for acceptance of wind energy development and planning [43]. In Europe, analysis of the consultation process for the construction of a transmission line between Spain and France reveals the importance of dialogue for fostering acceptance of transmission planning [34]. Dialogue establishes two-way communication between decision makers and stakeholders and can be particularly constructive when stakeholders can: (1) choose from multiple plans instead of being forced to accept or reject the plan proffered by the planners; (2) see that divergent points of views are accommodated; and (3) actively contribute to tasks of the planning process [34].

Explicit consideration of tradeoffs among attributes and impacts on different groups has long been recognized as important to engaging power stakeholder interest [12]. As an example, [44] proposes a power system planning framework that combines optimization modeling with multi-criteria decision analysis. To systematically consider stakeholder socio-environmental preferences, [36] and [45] propose the inclusion of an explicit metric (Gini coefficient) for electricity access equality and penalties for the impact of transmission plans on land use, respectively.

To assess a framework's ability to engage with planners and stakeholders, we suggest consideration of the four distinct themes from criterion 1: uncertainty, plans, consequences: attributes, consequences: assessment (first column of Fig.1). The next to last column of Fig.1 shows that, for each theme, criterion 3 'asks' what type of process goal the framework aims to achieve and how multiple perspectives are considered. In line with [46], we distinguish among three process goals: to inform, to consult, and to collaborate. As one example of considering how different engagement processes can support each of those three goals for a theme of Criterion 1, consider the theme of uncertainty. Engagement with respect to uncertainty could support the goal *to inform* if stakeholders/decision makers become familiar with the uncertainties considered by a methodological framework. Engagement could instead support the goal *to consult* if stakeholders can react to uncertainties considered, e.g., by providing feedback as to whether the methodological framework misses some plausible scenarios or includes implausible scenarios. Finally, it could support the goal *to collaborate* if stakeholders can contribute uncertainties, e.g., by contributing scenarios or probability estimates.

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As Fig. 1's last column shows, the integration of multiple perspectives in any of the four themes when engaging with stakeholders can range from considering just a single view, to aggregating multiple views using weighting or other approaches, and finally to explicit description of multiple viewpoints through, e.g., distinct utility functions for assessment of consequences.

Before concluding this section, we summarize some important assumptions. First, we presumed that planning agencies have staff with the time and expertise required to apply the proposed set of criteria. If planning agencies face staffing challenges, then application of the criteria by independent parties or consortia of planning agencies might be more effective. We have also assumed that circumstances are such that planners can reap the benefits of the application of the criteria by choosing to apply alternative planning frameworks or by identifying and addressing limitations of their current processes. However, in practice, tight deadlines, data requirements, and software development needs for application of bespoke methods might pose prohibitive barriers to adopting preferred frameworks. Future work to develop off-the-shelf tools and create open-access databases could address some of these barriers.

III. Multi-Step Uncertainty-Aware Planning Frameworks

This section briefly introduces and summarizes in table I the steps of the two planning frameworks this article studies: Robust Decision Making and Stochastic Programming.

TABLE I: Summary of steps for SP and RDM frameworks

Step	RDM	SP-centered
1	Specify X, R, M	Specify X, l, m
2	Identify strategies to evaluate – specify L	Reduce dimensionality for tractability
3	Evaluate M with models in R for each strategy in L and scenario in X	Solve the (approximate) problem
4	Characterize vulnerabilities	Test solution L for original problem
5	Add strategies to set L and go to Step 3.	Conduct sensitivity and uncertainty analysis

RDM is a multi-step decision analysis framework, that was invented by the RAND Corporation in the 1990s [47]. Since then, it has been used in multiple studies for infrastructure planning [14], but its applications in power system planning are few [28]. The goal of the framework is to identify vulnerabilities and trade-offs of strategies (plans in our case, which the RDM framework designates as set L) [48]. Similar to [48], we describe the framework in five steps. Step 1 specifies (a) a set of exogenous uncertainties, designated as X, that the RDM application will study; (b) a set of metrics (set M) that measure the performance of strategies L; and (c) relationships R that will be applied to estimate M [49]. Step 2 identifies strategies L RDM will study. Step 3 estimates M as a function $R(L, X)$ for each combination of strategy L and instance of X. Step 4 characterizes the vulnerabilities of each plan L. Step 5 adds to set L additional strategies that are anticipated to be less vulnerable than strategies already studied. The vulnerabilities of the new strategies are estimated and characterized by repeating Steps 3 and 4 for the new strategies. The process continues until stakeholders do not have resources to explore additional strategies L or they are comfortable with the vulnerabilities of at least one strategy. RDM is a flexible framework and it does not prescribe specific analytical methods for each step, i.e., different applications of RDM can follow different methods to define strategies L and to characterize and communicate the impact of uncertainties X on performance metrics M [49]. For details on RDM and its variants, the reader is referred to [14].

SP is an optimization problem (mathematical program) with constraint and objective function parameters that can be scenario-dependent [50], [51]. Similar to any constrained optimization problem, stochastic programming has three sets of components: decision variables l, an objective function $m(l)$, and a set of constraints $h(l)$. SP suffers from the 'curse of dimensionality' in that the optimization must simultaneously choose the optimal values for all decision variables under each and every scenario, so the problem to be solved can be very large. (In contrast, RDM can be executed using a smaller model for one combination of strategy and scenario at a time, which also facilitates parallel computation.) Given the computational challenge SP poses, applications usually resort to approximations that limit the problem size by shrinking the problem horizon, omitting some variables, aggregating decision stages, sampling scenarios and/or discretizing time, states, decisions [52]. Among all approximations, scenario reduction methods [53] and decomposition strategies [17] have been widely applied, and ex-post and ex-ante out-of-sample simulations are a common way to assess the quality of approximations [17]. In summary, for the application of SP, we specify five steps: Step 1 structures the problem, Step 2 yields an approximate problem; Step 3 prescribes an investment plan solving the approximate problem of Step 2; Step 4 does a full sample analysis (to yield information that RDM uses to show vulnerabilities); and Step 5 performs uncertainty/sensitivity analysis that could motivate the tuning of plans.

IV. Case Study

We apply the two uncertainty-aware frameworks to a case study based on a 2015 power sector planning exercise for Bangladesh [54]. At that time, the country was assessing investments in power plants under significant uncertainty with respect to the growth of electricity demand, the evolution of fuel prices, the supply of natural gas, its national policy on fossil fuel mining and imports, and climate change [55]. According to projections perceived as plausible by the local planners [54] and state-of-the-art models at the time [56], [57], [58], [59], a few discrete scenarios were laid out based upon two to three possibilities for each uncertain factor. Due to deep uncertainty, the joint probability of scenarios for different factors was unknown and not agreed upon by planners and stakeholders. For that reason, we define X as including 486 scenarios covering all possible combinations of factor-specific scenarios. We provide detailed information on all factor-specific scenarios along with the respective data sources in Appendix B.

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Solving the planning problem with a 25-year horizon (2016-2041), we obtain perfect-foresight plans, one for each of the 486 scenarios. The 486 plans are considerably different in terms of the amount of power plant development at each of six sites within the first 10 years of the planning horizon. For instance, the 486 plans include interconnection with India at levels that vary between 1 and 4 GW (see Fig. 2). Figures 2, 3, 5, and 6 are boxplots created with the default options of matplotlib.pyplot in Python. Each box covers the area between the first (Q^1) and third (Q^3) quartiles of the underlying series of values. Any values that are lower than $Q^1 - 1.5 \cdot (Q^3 - Q^1)$ or higher than $Q^3 + 1.5 \cdot (Q^3 - Q^1)$ are identified as outliers and depicted with circles. The whiskers note the minimum and maximum value of the underlying series, excluding outliers.

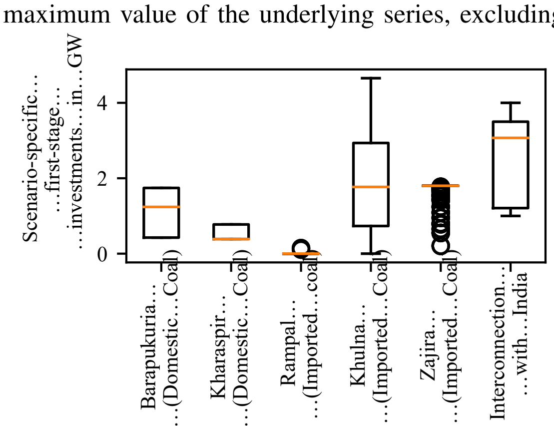

Fig. 2: Boxplots of 486 perfect foresight investments that started between 2016 and 2025. Sites shown have more than 20 MW difference in investment among all 486 scenarios.

The perfect foresight plans vary a great deal due to differences among scenarios. For instance, uncertainty about future fuel prices significantly affects the capacity of interconnections with India (see Fig. 3 (left)). Uncertainty about future demand growth affects the levels of investment in power plants that use imported coal (see Fig. 3 (center)); and uncertainty about domestic coal mining policy affects the construction of power plants that use that fuel (see Fig. 3 (right)).

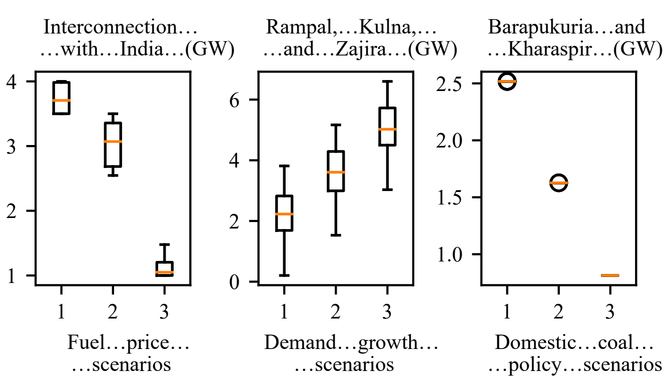

Fig. 3: Boxplots of scenario-specific investments started between 2016 and 2025 (left) in interconnection with India for different fuel price scenarios; (center) in three sites using imported coal for different electricity demand growth scenarios; (right) in two sites using domestic coal for different domestic coal availability scenarios. Each box includes 162 scenarios.

Recognizing that planners must commit to some investments before the planning process repeats in 5-10 years, when some of the uncertainty might have resolved, we apply the two uncertainty-aware frameworks. We do not apply the fifth step as it relies on interactions with planners and stakeholders.

To structure the problems (Step 1 of both RDM and SP), we assume that the planning agency's preferred decision criterion is the minimization of an aggregate social cost attribute (M, m) that combines investment and operational costs with penalties for unmet electricity demand. We also assume that the agency uses a capacity expansion model to reflect relationships $(R, h(l))$ between investments and attributes such as import share, costs, and unmet demand (see Appendix A for the detailed model formulation, which parallels classic generation expansion problems [2]).

Given that the planning exercise is repeated every 5-10 years [54], we consider two investment stages. The first and second stages span from 2016 to 2025 and from 2026 to 2041, respectively. Investments in the first stage are identical among all scenarios ('here-and now' variables), while investments pursued during the second stage are scenario-dependent ('wait-and-see' or 'recourse' variables). Second-stage scenario-dependent plans optimistically assume that uncertainty will have cleared to a large extent by the time of any subsequent planning cycle.

To yield problem approximations (Step 2 of both methods), we must specify a limited set of scenarios and strategies for SP and RDM, respectively. To specify the two sets in a consistent manner, we consider the perfect-foresight scenario-specific investments. We focus on six *key* potential investments because the rest of the sites have less than 20 MW difference across any two scenarios (see Fig. 2).

Applying k-means clustering to the 486 sets of perfect-foresight first-stage *key* investments, we obtain seven clusters of similar investments. For each cluster, we choose a representative plan and scenario as input for RDM and SP, respectively [60]. For each representative scenario, we use a probability equal to the cluster size divided by the total number of scenarios (486). Thus, RDM will compare just seven combinations of first-stage investments, while SP will consider in Step 3 an infinite number of possible combination of investments implicitly defined by its constraint set. Fig. 4 illustrates this difference: SP can choose any feasible point in the cube as first-stage investments, while RDM is restricted to analyzing only 7 points in that space, represented by the tips of the 7 colorful/numbered bars. However, RDM will still consider all 486 scenarios, while the second stage variables and constraints of SP only considers 7 representative scenarios.

For the second-stage investments, SP yields an approximate solution in Step 3. However, for both RDM and SP, we finalize second-stage investments in Steps 3 and 4, respectively. That way, we tailor the second-stage investments to each of the 486 scenarios by solving a capacity expansion problem for each of combination of the 486 scenarios and each plan of first-stage investments. The problem treats first-stage investments as pre-determined parameter values, and second-stage investments as decision variables. Ref. [61] had followed the same approach for yielding second-stage investments within the RDM framework. In detail, for the RDM case, there are 7 plans, as described above, yielding 486*7 models to be solved; averaging over the 486 scenarios yields the average

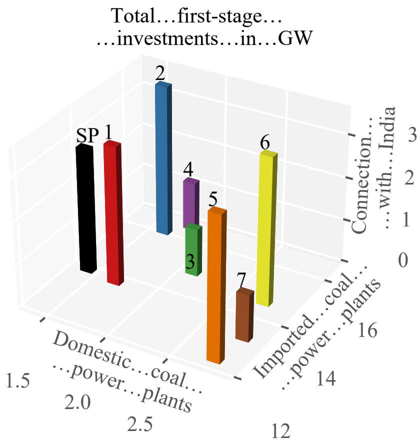

Fig. 4: The decision space SP and RDM consider corresponds to any feasible point in the cube and the tips of the numbered bars, respectively. The bars show first-stage investments under 7 considered RDM plans and 1 optimum SP plan.

performance of each of the 7 predefined plans. Meanwhile for the SP model, only the optimal first stage investments are treated as a plan in this step, so only 486 models are solved; the average over their values is the estimated expected performance of the SP model's solution for the full set of scenarios, which is likely a more realistic characterization of its expected performance than the Step 2 SP model solution based on 7 representative scenarios.

V. Results of the RDM vs. SP comparison

In this section, we apply the criteria of section II to identify the pros and cons of the two frameworks in a qualitative way and discuss relevant quantitative results. We do not apply those criteria to the planning framework Bangladesh followed in practice to yield their power system plan [62] because it was not an uncertainty-aware multi-stage engineering-economic framework. In other words, the framework does not consider the interplay of operations and investment costs across multiple scenarios and later opportunities to modify plans.

Criterion 1: Methodological Capability We first discuss quantitative results from the case study and then move on to a qualitative application of this criterion. In terms of plans, the two frameworks differ in the way they: (a) represent feasible plans; and (b) consider inter-dependencies within a plan between first- and second-stage investments.

As discussed in Section IV, SP considers an infinity of possible plans and chooses one that yields the minimum value of the objective function (probability-weighted social cost, across the limited set of seven representative scenarios). This SP plan (see black bar in Fig. 4), which is similar to one of the seven candidate RDM plans (RDM1), prioritizes interconnection with India in the first stage and makes moderate and small investments, respectively, in power plants that use imported and domestic coal.

SP chooses this plan because it recognizes that plans can be adjusted once uncertainty is resolved. Hence, instead of trying to find a plan that will be best for a subset of scenarios, it finds a first-stage plan that meets the first-stage electricity demand without investing too much in technologies that might lock the system into a path with stranded or costly to operate assets. In this particular case, SP defers a decision on building capital-intensive coal power plants near domestic coal mines that could provide cheap fuel but they might never operate due to environmental concerns, as in 2026 (first year of the second stage) half of the scenarios build less than 1 GW of such plans (see Fig. 5). On the other hand, building a low capital cost interconnector with India seems to be a prudent first-stage decision to SP as it could provide electricity in any scenario and the uncertainty only affects how competitively imported electricity is priced.

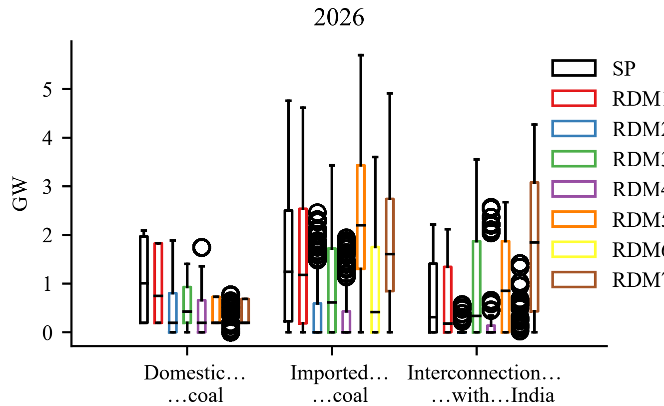

Fig. 5: Investments in 2026 (first year of second stage) for all plans.

In terms of uncertainty, the two frameworks use the same set of scenarios, but they need probabilities at different steps. On one hand, SP needs them as input in the very first step, while on the other hand, RDM explicitly or implicitly relies on them to aggregate metrics across scenarios in Step 4.

Finally, in terms of attributes, Step 3 of SP only optimizes the probability-weighted cost. Hence, at first glance SP appears to provide information on performance on fewer attributes. However, under a full sample analysis like the one we perform in Step 4, it is straightforward to use the same set of attributes for SP as for RDM. For instance, Fig. 6 shows the regret, which here is defined as the difference in terms of aggregate social cost attribute between the strategy in question (averaging over all 486 scenarios, considering the best second-stage decisions given the first-stage investments) and the perfect foresight strategy, averaged across all 486 scenarios for every plan. The perfect foresight strategy is sometimes called the perfect information case, where both first and second stage decisions are made with full knowledge of which scenario will occur. Comparing expected regret for that SP solution with RDM's solutions (see Fig. 6), we see that SP yields a 10% lower regret than plan RDM1, which is the RDM plan closest to the SP first stage solution. The regret of SP's solution and RDM1 is much smaller compared to the regret of other RDM plans and the expected social costs of plans (see Fig. 6).

Although Fig. 6 indicates that SP and RDM1 as the best solutions from a social cost point of view, consideration of other attributes could result in other solutions being preferred. In particular, from the qualitative application in Table II, it

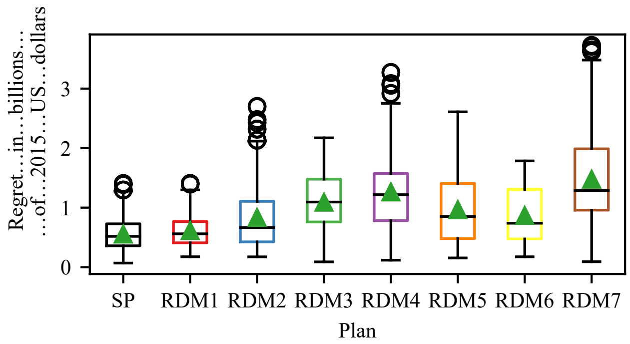

Fig. 6: Regret of plans across all 486 scenarios (in billions of 2015 U.S. dollars, present worth). Triangles show average values. For comparison, the expected social cost of the perfect foresight and the SP plans are 100.91 and 101.47 (in billions of 2015 U.S. dollars, present worth), respectively.

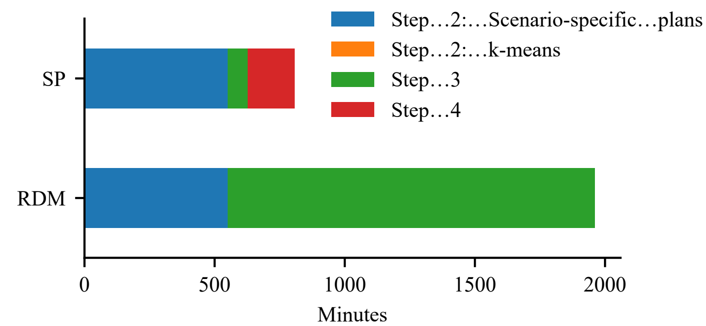

Fig. 7: Computational time (clock-time) for RDM and SP-centered frameworks. Simulations were performed on a desktop with an Intel core processor i7-5930K at 3.50GHz and 32 GB RAM. For Step 3 (RDM) and Step 4 (SP), runs were performed in parallel for ∼4 scenarios at a time.

is worth emphasizing that contrary to the present case study which uses one decision criterion, in a practical application, decisionmakers and stakeholders could estimate performance for additional criteria using reported attribute values; and even decide to pursue a plan different than RDM1. Whereas assessment of criterion (1.D.3) is not possible in this case, future applications of both frameworks could incorporate methods for engaging with decisionmakers and stakeholders and eliciting their preferences. For instance, the objective function and constraints could be informed by multi-criteria decision-making processes [4] and iterative interactions between decisionmakers and analysts under RDM could guide the development of plans, scenarios, criteria, and models [63].

Overall, in our application, both frameworks model uncertainty, plans, and consequences in a similar manner. SP is distinct in its ability to model the inter-dependency of decisions at different stages. In other words, SP can decide to adjust the levels of first-stage investments, considering the opportunity for recourse decisions in the second stage. In our case study, SP prioritizes in the first stage relatively low-capital-cost investments with relatively flexible operation levels (interconnection with India) and defers to the second stage relatively capital intensive investments with scenario-dependent operational performance (plants using domestic coal). RDM's strengths arise from the thorough simulations and accompanying results, which help stakeholders and planners better understand each plan. Its performance depends to a great extent on the set of plans L considered.

Criterion 2: Practical applicability Over all five dimensions of practical applicability, we observe a key difference in computational resources and a few similarities. RDM requires more than twice the execution time of the SP-centered framework. According to Fig 7, Step 3 is the most computationally expensive step of RDM, taking 70% of the total RDM time. While this step is computationally intensive, it can be largely parallelized to leverage available computational resources. Hence, the clock time to completion for the RDM framework is not necessarily prohibitive, but nevertheless more computations and output-related data need to be accommodated compared to the SP-centered approach.

In terms of similarities, the needs for data inputs, software, and staff resources are almost identical for this case study. Both frameworks use optimization problems as their quantitative basis, requiring similar qualifications from staff. In terms of input data, the same set of scenarios describes uncertain factors and the same parameters are used by those optimization problems to estimate the costs and benefits of different plans.

Criterion 3: Contribution to decision making and acceptance by planners and stakeholders Although this work was done with staff from the World Bank [60], it was undertaken without the participation of planners and stakeholders from Bangladesh. Thus, this criterion is challenging to apply. Nevertheless, we can reach some conclusions for each of the four themes (uncertainty, plans, consequences: attributes, consequences: assessment) considering the nature of each framework's inputs and outputs and drawing upon our planning experiences in other contexts.

With respect to uncertainties, both frameworks could serve a process goal of *collaboration* as both decisionmakers and stakeholders could contribute scenarios and probabilities. In the case of RDM, updated probabilities could be considered without a need to re-run the simulations (as long as the set L has not changed), while addition of scenarios would create a need for simulations only for the new scenarios. Instead, for SP the computational effort would be higher since either updated probabilities or new scenarios would create a need for re-application of the framework.

With respect to plans, RDM could serve a process goal of full *collaboration* as stakeholders could contribute plans for assessment, but SP could at best serve a process goal of more limited *consultation* where stakeholders could specify constraints for the feasible region of plans.

With respect to attributes, both frameworks appear equally limited by the simulation models. Hence, the process goal that both frameworks could serve is *information*. In case of engagement with stakeholders, the process goal could be updated to *consultation* if stakeholders could propose attributes that are important to them and, in response, analysts reconfigure simulations to generate additional outputs.

Finally, with respect to assessment of consequences, SP only considers one decision criterion to yield an optimal plan. SP could consider in additional Step 3 simulations other

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TABLE II: Assessment of methodological capability (criterion 1)

Subcriterion	RDM	SP-centered
Uncertainty		
State space (1.A.1)	486 scenarios with multiple values for 6 uncertain factors	
Probabilities (1.A.2)	Used to aggregate scenario-specific attributes	Used to yield plan L and aggregate scenario-specific attributes
Chronological evolution (1.A.3)	Uncertainty resolution in 2025: scenario-specific parameters after 2025	
Plans		
Feasible set (1.B.1)	Set of discrete plans	Feasible region defined by constraints
Resolution (1.B.2)	Plan of MW investments per type of generation, at candidate locations, in different years	
Decision cycles (1.B.3)	Second-stage plans adjust to the realized scenario, **but** first-stage plans derived without considering the possibility of adjustment in second stage	Second-stage plans adjust to scenario realized, **and** first-stage plans derived recognizing the possibility of adjustment in second stage
Consequences		
Attribute types (1.C.1)	(1) Investment/Operational cost (2) unserved load (3) imports as share of electricity generation	
Attribute resolution (1.C.2)	**Temporal**: Hourly resolution for representative hours for each year in the model horizon; **Spatial**: Plant-level investment/operational cost; system-wide unserved load; import share per interconnector	
Attribute precision (1.C.3)	Precision in both frameworks is unknown. If data were available, precision could be estimated by running follow-on production cost simulations with higher spatial and temporal resolution or through back-casting. Similar approaches could be followed for other modeling approximations.	
Assessment		
Criteria (1.D.1)	Probability-weighted regret criterion considered	Probability-weighted regret criterion optimized for approximate SP
Updates to criteria (1.D.2)	Possible if new criteria rely on reported attributes; require reapplication of method if the perfect foresight objective function not relevant anymore	Require reapplication of SP to find optimal plan for new criterion
Eliciting preferences (1.D.3)	No process to elicit preferences in this case study due to limited interactions with stakeholders	

decision criteria through constraints or additional weighted objective function terms. RDM can easily incorporate updated decision criteria that rely on available attribute values. For example, if stakeholders were interested in attributes that reflect energy independence, reliability, and costs, analysts could report results on the share of electricity imports, penalties for unserved energy, and investment and operating cost, respectively. Drawing the performance in a 3D space as in Fig. 8, we observe that RDM makes trade-offs between energy independence and cost and reliability obvious. Hence, both frameworks could serve a process goal of *consultation* and RDM could offer insights on trade-offs and alternative plans with no additional computational effort.

We note, however, that RDM's solutions (definition of 7 first stage plans in Step 1, and definition of the optimal second stage decisions in Step 2 for each of 486 scenarios) relied on just the social cost objective. A more complete accounting of other attributes by RDM would necessitate formulation of model objectives based on those attributes and their inclusion in Steps 1 and 2 of RDM, which would require appreciably more work, just as SP would.

With respect to consideration of viewpoints for each theme, multiple perspectives can be included and considered to create a suite of alternative plans, uncertainties, or attributes. The sensitivity of plans to alternative decision criteria can also be tested in both frameworks. However, for both frameworks, public participation processes would need to occur to identify a plan that is accepted by stakeholders and decision makers.

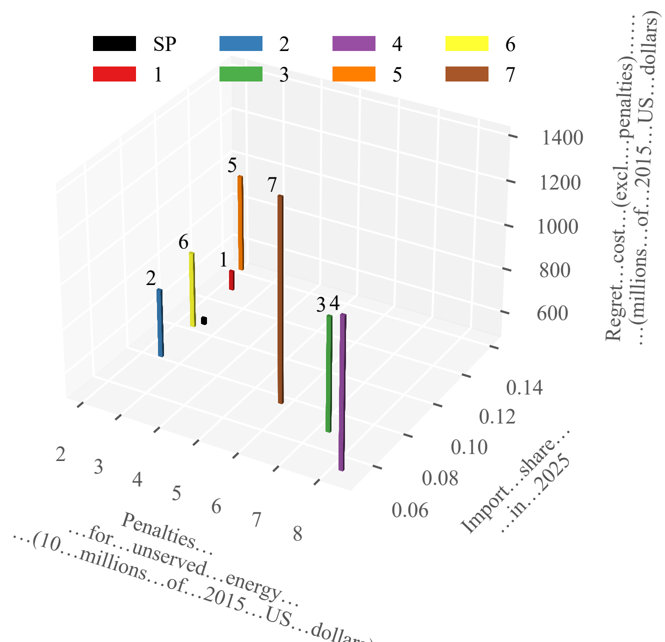

Fig. 8: Values of three attributes for SP and 7 RDM plans

VI. Conclusions

As researchers and consultants continue to develop frameworks that plan investments in power systems under uncertainty, planning agencies seek guidance and insights as to which existing or new frameworks would be most helpful in practice. The most authoritative guidance comes from systematic assessments and cross-comparisons of available frameworks as applied to realistic problems. Unfortunately, the existing literature has few careful reviews and especially realistic comparisons, and most of them narrowly focus on effects of alternative attribute sets or utility functions.

To help planners to assess frameworks for themselves, and to facilitate systematic cross-comparisons, this article significantly revises a set of three criteria, originally proposed in

[23]. These revisions include adding new criteria and criterion-specific themes to make the set more comprehensive and readily applied. The three revised criteria are: methodological capability, practical applicability, and contribution to decision making and acceptance by stakeholders and planners. This article also compares for the first time two widely used but fundamentally distinct frameworks for a power system planning problem: an 'agree-on-plans' framework, Robust Decision Making (RDM); and an 'agree-on-assumptions' framework, Stochastic Programming (SP). The comparison is conducted for a realistically detailed but hypothetical case of resource planning in Bangladesh.In doing so, we show how those criteria can be operationalized to provide useful advice.

We find that both methods can yield adaptive plans when uncertainty is described through scenarios. SP can proactively identify flexible investment plans by recognizing the ability to adjust plans when uncertainty has cleared; while RDM recognizes flexibility in relative terms by comparing regrets of predetermined plans across different scenarios. Our analysis does not find that one framework clearly dominates the other. On one hand, the Stochastic Programming centered framework quickly identifies a single plan with better performance than any of the plans yielded by RDM, especially in terms of expected cost (as measured by probability-weighted regret). On the other hand, although RDM takes more time to study more plans, there are benefits from the extra effort in that planners and stakeholders gain insights as to the trade-offs and advantages of different plans in terms of their performance under a wide range of scenarios and in terms of multiple attributes. If those attributes address the diverse concerns of stakeholders, this information can facilitate dialogue between decision makers and the public as their views would be sought on multiple plans instead of a single plan that they called to accept, reject, or challenge with limited information.

As discussed in Section V , RDM's performance greatly depends on the quality of the set of plans L, while its computational time linearly increases with the size of L. Hence, for planning problems in which there is a potentially large set L with many dimensions (i.e., alternative decisions), there is an increased likelihood that the user might fail to identify and include potentially superior plans in L. SP would automatically consider all feasible solutions, and so SP might emerge as a more promising framework in that situation. However, for problems where the set L is necessarily relatively small and has few dimensions, e.g., because there are just a few mutually exclusive feasible configurations, RDM might be preferred as a transparent method that clearly shows trade-offs among a few plans.

Future research could cross-compare planning frameworks for a planning study that involves actual stakeholders and decision makers and could include in the comparisons planning frameworks that are currently being developed to model competing objectives, sources of risk, and risk appetites of different stakeholders in power system planning [64]. Follow-on work could also aim to draw mathematical generalizations with respect to structure of problems that could favor one framework over another. It would also be interesting to explore how frameworks could be combined to exploit the strengths of each approach, resulting in improved modeling capabilities and applicability, and more insights that help build planner and stakeholder understanding and confidence in planning outcomes. Last but not least, it is worth noting that future research might result in proposals for new/modified criteria or sub-criteria that assess factors found to be important for yielding effective power system plans.

Appendix A: Planning Problem Formulation

Nomenclature

Decision variables

$b^1_{g,y}$ First-stage generation investment in MW, added at year y belonging to 1st stage

$b^2_{g,s,y}$ Second-stage generation investment in MW, added at year y belonging to 2nd stage

$e_{s,t,y}$ Unserved energy in MW

$o_{g,s,y,t}$ Electricity output in MW

$p_{g,s,y}$ Power capacity in MW

$ret^1_{g,y}$ Generator retirement in MW at year y of 1st stage

$ret^2_{g,s,y}$ Generator retirement in MW at year y of 2nd stage

$r_{s,y}$ Deficit in planning reserve margin constraint

Sets and Indices

F Fuels, indexed by f

G Generators, indexed by g

L Locations, indexed by l

S Scenarios, indexed by s

T Representative hours of the year, indexed by t.

Y Years, indexed by y and y'

Parameters

$\overline{LOAD}_{s,y}$ Annual peak electricity demand in MW

Π_s Probability of scenario s

ρ Discount rate; assumed 10%

ACF_g Maximum annual capacity factor

$CAP_{g,y}$ Annualized capital cost in \$/MW

$CF_{g,s,t,y}$ Maximum hourly capacity factor

D_t Weight of representation hour t in hours

FC_g Fixed operation and maintenance costs in US\$ per MW of installed capacity

HR_g Heat rate in MMBTU/MWh

$I^B_{g,y,y'}$ 1 for generators g that were added by the planning model in year y' and were ready to generate electricity any year before year y

$I^F_{f,g}$ 1 for generators g that use fuel f

$I^L_{l,g}$ 1 for generators g that are located at l

$I^{EX}_{g,s,y,y'}$ 1 for generators within their operational life; 0 otherwise

L_g Land requirement in acres/MW

$LOAD_{s,t,y}$ Electricity demand in MW

PRM Planning reserve margin; assumed 15%

$VC_{g,s,t,y}$ Variable cost in \$/MWh

$VOLL$ Value of lost load in \$/MWh

VOR Penalty for violation of planning reserve margin

$LAND_l$ Available land in acres

The $Objective$ is defined as follows:

$$\sum_{g,y} CAP_{g,y} \cdot (b^1_{g,y} + \sum_s \Pi_s \cdot b^2_{g,s,y}) \tag{1a}$$

$$+\sum_{g,s,y}\Pi_s \cdot \frac{FC_g \cdot p_{g,s,y} + \sum_t D_t \cdot VC_{g,s,t,y} \cdot o_{g,s,t,y}}{(1+\rho)^{y-2016}} \quad (1b)$$

$$+\sum_{s,y}\Pi_s \cdot \frac{VOR \cdot r_{s,y} + \sum_t D_t \cdot VOLL \cdot e_{s,t,y}}{(1+\rho)^{y-2016}} \quad (1c)$$

Constraints for capacity expansion:

$$p_{g,s,y} = p_{g,s,y-1} + \sum_{y'} I^B_{g,y,y'} \cdot (b^1_{g,y'} + b^2_{g,s,y'}) - ret^1_{g,y} - ret^2_{g,s,y} \quad \forall g,s,y \quad (2)$$

$$\sum_g p_{g,s,y} + r_{s,y} = (1+PRM) \cdot \overline{LOAD_{s,y}} \quad \forall s,y \quad (3)$$

$$p_{g,s,y} \leq \sum_{y'} I^{EX}_{g,s,y,y'} \cdot (b^1_{g,y'} + b^2_{g,s,y'}) \quad \forall g,s,y \quad (4)$$

$$\sum_g I^L_{l,g} \cdot L_g \cdot p_{g,s,y} \leq LAND_l \quad \forall l,s,y \quad (5)$$

Constraints for operations of installed capacity:

$$\sum_g o_{g,s,t,y} + e_{s,t,y} = LOAD_{s,t,y} \quad \forall s,t,y \quad (6)$$

$$o_{g,s,t,y} \leq CF_{g,s,t,y} \cdot p_{g,s,y} \quad \forall g,s,t,y \quad (7)$$

$$\sum_t D_t \cdot o_{g,s,t,y} \leq ACF_g \cdot p_{g,s,y} \cdot 8760 \quad \forall g,s,y \quad (8)$$

$$\sum_{g,t} I^F_{f,g} \cdot D_t \cdot HR_g \cdot o_{g,s,t,y} \leq FUEL_{f,s,y} \quad \forall f,s,y \quad (9)$$

In brief, our planning problem minimizes an objective function that consists of capital costs (eq. 1a), approximate operational costs (eq. 1b), and penalties for unserved load or unmet capacity reserves (eq. 1c).

The model includes constraints for capacity expansion and operation of installed capacity. In detail, the constraints for capacity expansion keep track of the installed capacity in the system over time (eq. 2), ensure that there is enough installed capacity in the system in each year (eq. 3), consider the lead time it takes to build a power plant (eq. 4), and account for land usage and site limitations (eq. 5). The operational constraints ensure that enough electricity is generated any time (eq. 6) considering availability of each generating resource at specific times (eq. 7), and throughout the year (eq. 8) along with any fuel usage constraints (eq. 9).

Appendix B: Data Sources

The values for multiple parameters of the power system planning model are not known with certainty. Hence, when we compiled the input databases for the planning model, we relied on multiple sources that provided the best available information at the time. In Table III, we provide an overview of assumed scenarios and sources for the six uncertain factors: demand growth, fuel prices, coal and natural gas availability, temperature and flooding. In the rest of the Appendix, we discuss how we constructed the scenarios based on our sources.

TABLE III: Uncertain factors considered

Uncertain factor	**Number of scenarios (values)**	**Data source**
Demand growth	3 (pg. 17 in [55])	Japan International Cooperation Agency (JICA) [54]
Fuel prices	3	JICA [54] and The World Bank Group [57]
Domestic coal availability	3 (pg. 209 in [60])	JICA [54]
Natural gas availability	2 (pg. 208 in [60])	JICA [54]
Temperature	3 (pg. 204 in [60])	[58]
Flooding	3 (Section B.1 in [60])	FATHOM and [59]

We relied on [54] for scenarios on socio-economic uncertainties. For demand, three scenarios are modeled. Annual peak demand grows from the 2015 level of 9 GW to 40–60 GW in 2041. For natural gas supply, we drafted two scenarios: 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 natural gas supplies of [54] are available. For domestic coal availability, we used the same scenarios as in [54]. For fuel prices, we consider two scenarios from [54]: the central scenario ("IEA New Policies") and "IEA 450" (plausible if the global average temperature does not increase more than 2ºC compared to pre-industrial averages by the end of this century). We modified the "low oil price scenario" to reflect the latest fuel price projections by the World Bank. Lastly, we omitted the "IEA current policies" scenario from [54] as it did not seem plausible.

Projections for two climate variables (and associated power-sector climate indicators) are used in this analysis: temperature (and cooling degree days) and flood depths (derived from precipitation projections). For temperature and cooling degree days projections, we consider three scenarios based on clustering of the 17 scenarios available at [58] (resource with the only climate data downscaled for Bangladesh in 2017). For flooding, we considered three scenarios: (a) a business as usual case; (b) a high flooding scenario based on projections for precipitation change purchased in 2016 from FATHOM[1] [56], a global leader in flood risk modeling; (c) an additional scenario based on [59]. Ref. [59] projected that 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. In scenario (c), flood profiles project the historical 100-year event as a 20-year event for fluvial/pluvial flooding and as a 25-year event for coastal flooding.

We consider all possible combinations of the single-factor scenarios, described in Table III, to create multi-factor scenarios for the power-system-planning model (486 scenarios, where $486 = 2 \cdot 3^5$). In other words, we adopt the perspective of a "naïve" planner who does not consider interdependencies among individual uncertain factors, e.g., by disregarding certain combinations as implausible (e.g., high fuel prices and high fuel availability). Thereby, the "naïve" planner considers

[1] FATHOM's projections were based on climate scenario RCP 8.5, the scenario with the highest radiative forcing among the scenarios considered in AR5 (IPCC 5th Assessment Report).

the 486 scenarios as equi-probable.

Last but not least, in addition to the system planning data, operational data around existing plant parameters were collected from the National Load Dispatch Center as part of an accompanying work that the World Bank team had been carrying out concurrently [65].

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