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Composite Power System Reliability with Renewables and Customer Flexibility

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***Abstract*—Composite Power System Reliability is defined as the computational procedure that quantifies the probability that the power system will perform the function of delivering electric power to customers adequately, on a continuous basis and with an acceptable quality. This definition leaves many details undefined and exemplifies the ambiguity in reliability analysis. The increasing deployment of wind and PV creates additional uncertainties that make reliability analysis a rather complex issue. Because of increased uncertainty the need for composite reliability analysis and utilization of results in power system planning is critical. New approaches are emerging for dealing with these problems from the operational point of view, including demand response programs, tapping on customer and distributed resource flexibility and new control approaches. The key question to be addressed is: how the new operational paradigms affect composite power system reliability. This paper presents the ongoing work of the IEEE Composite System Reliability Task Force of the IEEE PES Reliability, Risk, Probability Application (RRPA) Subcommittee.**

Keywords— Composite power system, renewables, customer flexibility, uncertainties, reliability methodologies

I. Introduction

Reliability and security calculations have been and remain today of paramount importance to the reliable and economic operation of power systems. Electric utilities maintain sufficient generation, transmission and distribution capacity to ensure continuity of electric service to their customers under normal as well as contingencies and other abnormal conditions compounded with uncertainties associated with load variations, variability of renewable energy sources, etc. Power system reliability and security have received even more attention in the last few decades due to widespread implementation of electricity markets, power industry restructuring, massive integration of renewable energy sources and major blackouts that happened around the globe. Comprehensive probabilistic methods that quantify these effects are very important; they should be capable of taking into account: (a) the uncertainty of variable resources (wind, PV), (b) flexibility enabled with storage and customer-owned resources, (c) uncertainty of primary fuel prices, (d) increased weather uncertainty and environmental constraints, and (e) random forced outages. The desirable outputs of comprehensive probabilistic methods are: (a) expected costs, (b) system reliability quantification (via indices), (c) operational limitations (overloads, undervoltages, ramping violations, etc.), and (d) environmental impacts, and others.

Today, more and more utilities across the globe, in order to stay competitive, operate their systems with heavier flows and with lower security margins. This reality has prompted improvements of existing or development of new methodologies and tools to ensure reliable and secure operation, and prevent widespread disturbances. Bulk power system reliability comprises two basic attributes: adequacy and operating reliability (former security). Adequacy is the ability of the electric system to supply the aggregate electrical demand and energy requirements of the end-use customers at all times, taking into account scheduled and forced outages of system elements. Operating reliability is the ability of the electric system to withstand sudden disturbances such as electric faults and/or random loss of system components [1].

The large size of power systems presents computational challenges for reliability analysis of the entire system that comprises generation, transmission, and distribution, see Figure 1. Instead, the problem is partitioned into subproblems along with the natural splits of the system, i.e. generation, transmission, and distribution, and secondary systems.

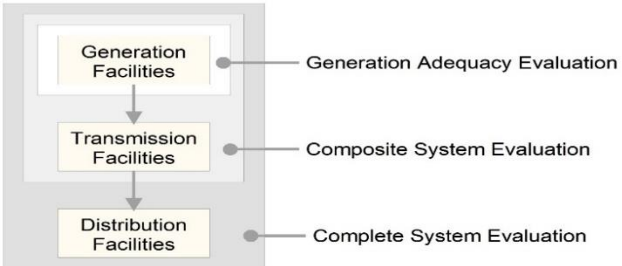

Fig. 1: Definition of Reliability Analysis Problems (Generation Adequacy Evaluation: HL-I, Composite System Evaluation: HL-II and Complete System Evaluation: HL-III)

Composite system reliability is the reliability analysis of the combined generation and transmission (Fig. 1). It is important that generation and transmission be modeled simultaneously because there is substantial interaction between the generation system reliability and the transmission system reliability. A study of composite system reliability in the 1980's using the program CREAM (a model developed by PSR from Brazil in collaboration with EPRI) quantified this interaction. Results for a specific system indicate that 55% of the unreliability is due to combination of events in the generation and transmission system. Variable energy resources (VERs), with the bulk of it coming from wind and PV, presents a level of uncertainty an order of magnitude above the usual uncertainties of legacy power systems. This uncertainty necessitates probabilistic methods in dealing with reliability analysis, planning and risk mitigation. For proper inclusion of the effects of variable generation, it is necessary to develop reliability models of variable generation. Because of considerable correlation between VER generation models and system demand, it is important to use spatially coupled reliability models of VERs and loads. Since most of the time variable generation (wind, PV) is operating at maximum power tracking, lumping variable generation and demand results in a "net" load model. The net load model must be served by the dispatchable units. This approach provides the basis to include and assess the impact of variable generation on composite system reliability. The process of computing reliability models of the net load is illustrated in Fig. 2.

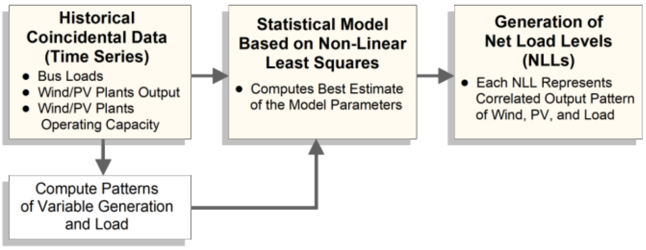

Fig. 2: Construction of Net Load Reliability Model

Reliability assessment of the system requires consideration of the reliability models of all components and the operational practices of the power system. This is illustrated in Fig. 3, which provides the basis to describe reliability analysis needs in the present-day power systems. The paper provides an overview of ongoing work to address the issues presented in Fig. 3.

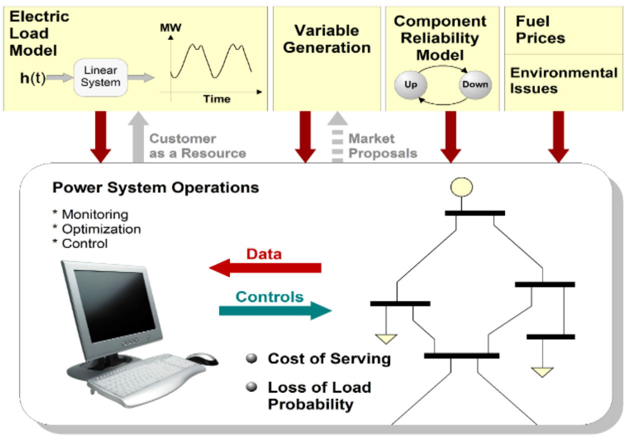

Fig.3: Illustration of Interaction of Renewables, Power System Component Reliability and Operational Practices on Reliability Assessment

II. Analysis of Outage Statistics Collected by NERC TADS

Critical to composite system reliability analysis is the availability of component reliability models. These models are extracted from statistical data of component outages. The North American Electric Reliability Corporation (NERC) uses transmission equipment inventory and outage data to analyze outage trends and assist in identifying significant reliability risks to the bulk power system (BPS). Since 2008, the transmission inventory and automatic outage data from eight NERC regions have been collected in TADS, one of the data systems supported by NERC [3]-[4]. Transmission elements of the BPS reportable in TADS are (1) AC Circuits (Overhead and Underground), (2) Transformers (No generator step-up units), (3) DC Circuits, and (4) AC/DC Back-to-back converters.

TADS data analysis provides the reliability model of individual components. Lack of space prevents detailed description of the methods. We discuss here only component unavailability, as the basic parameter of component reliability models. Unavailability is calculated as the total outage duration of all outage types as a percentage of the time. Unavailability is more informative since it can be tracked by outage type. Fig. 4 provides sample component unavailabilities from the TADS database.

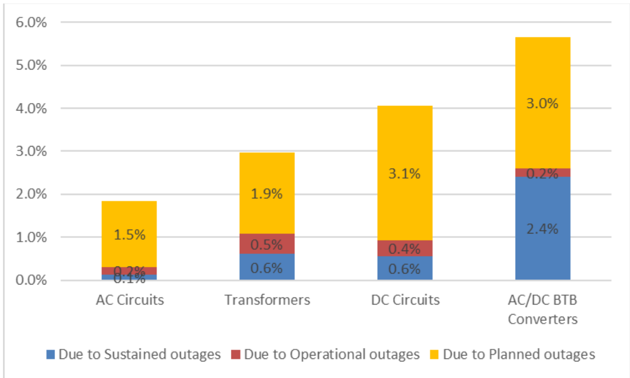

Fig. 4: Component Unavailability by Outage Type (2010-2014)

Historical outage data are the basis to estimate model parameters of component outages, e.g., outage frequencies and durations. It is a common practice to calculate these parameters via a maximum likelihood estimation (MLE) assuming the same frequency and duration for the same type of components across different data sources and a Poisson process to describe outage occurrences. This practice, however, neglects the variability among utilities/transmission owners/regions. The factors that may have significant impacts on the outage frequency or the duration may include environmental conditions and maintenance schedules that differ across utilities. To capture this variability, a formal statistical testing was introduced in [5] to determine the "poolability" of outage data of different types of grid components from various NERC regions. For non-poolable outage data of different sources, lognormal distributions were developed for the frequencies and durations of various component outages (see [6] for the detailed documentation of the distributions).

III. Deterministic vs. Probabilistic Criteria

Deterministic criteria and techniques have been developed and employed by utility industry in power system planning and operation for many years and will continue to be a benchmark criterion. Planning and operation has been traditionally driven by reliability standards and criteria (e.g., NERC standards, WECC reliability criteria). NERC has developed mandatory and enforceable reliability standards for planning (TPL-001-4) and operation (TOP-002-4, IRO-017-1) to ensure reliable operation of the power grid [1]. Critical infrastructure protection (CIP) standards (CIP-002-5) deal with cyber-security of power systems and they are also mandatory and enforceable [1].

Considerable published work over the last several decades has been devoted to the various aspects of reliability, security and risk calculations for planning and operation. Generally, the research in these areas moves along three different directions: (a) evaluation of planning projects and calculation of security margins based on deterministic criteria [7]-[9]; (b) reliability and security assessment based on hybrid deterministic-probabilistic approaches often called risk-based approaches [10]-[12]; and (c) reliability and security assessment based on probabilistic approaches [13]-[20]. Deterministic approaches analyze, on a case-by-case basis, a certain number of reference scenarios by simulating them and evaluating reliability and security margins. The traditional way to operate a power system involves the deterministic N-1 criterion. Operating criteria are designed in a such way that the power system shall be operated at all times so that instability, uncontrolled separation, cascading outages, or voltage collapse, will not occur as a result of any single contingency or credible multiple contingencies [1]. The fundamental objective of transmission planning is to develop the system as economically as possible and maintain an acceptable reliability level.

Deterministic approaches have been successfully used over many years, they conceptually require simple implementation, they are easy to understand, and enable straightforward assessment and judgment by planners and operators. However, the deterministic methodologies have several shortcomings, which are discussed in references [10]-[12]. Deterministic planning and operational criteria consider the consequence of outages, but the probabilities of outages are overlooked. System planning alternatives based only on deterministic analysis may not be the best selected reinforcement option. Multiple component failures are often excluded from consideration. Another weakness of deterministic assessment is that they cannot account for the stochastic nature of system behavior including random behavior of components and system operating states. Many major outage events across the world have indicated that the N-1 criterion established by the deterministic approach may be insufficient for a reasonable level of system reliability. Systems typically shift into multiple outages during major disturbances, making the N-1 approach irrelevant. However, because of many years of successful use and the relative simplicity of deterministic approaches, planners are not eager to apply other approaches. The expectation is to develop hybrid approaches that may resolve the deficiencies of deterministic criteria and add the values of risk-based approaches [10], [12].

Probabilistic criteria and methods are classified into two main techniques: (a) selective contingency enumeration and (b) Monte Carlo simulations. Both methods are discussed in section V and they have their advantages and drawbacks. It is important to know how and when to use either technique so they can complement each other. Both methods can use a certain depth of contingencies (multiple independent and/or common mode outages) depending on the objectives of the study. As the depth level increases the computational requirements increase exponentially. Monte Carlo simulation is easy to implement; however, for statistically meaningful results the number of contingency simulations must be huge leading to computational challenges [18]-[20].

The deterministic criteria served the electric utility industry well over many years but in order to be able to provide customers with the optimum service reliability at the right cost, the movement towards reliability-based planning and operational criteria and models is inevitable. The risk-based method is not intended to replace the deterministic criterion but adds one more dimension to enhance the transmission planning and operation processes. It considers both the impact and the likelihood of occurrences of outage events and hence, can identify and rank contingencies that may be problematic for the system operation. When combined with the severity or consequence of a specific event, risk can be quantified. The advantages of probabilistic approaches are substantial but not well developed. Currently, only adequacy performance is addressed in commercial probabilistic reliability programs.

IV. VER Modeling for Reliability Analysis

VER generation and system loads exhibit a degree of correlation. Their deciles (intervals of range divided into 10 equal-probability segments) and vigiciles (20 equal-probability segments) may be strongly correlated [21]. This means for this data the lowest 5% of wind speeds may tend to occur in the same hours as the upper 5% of hourly loads. The importance of this correlation increases as the penetration of VERs in the generation mix increases.

The most common approach uses synchronously observed hourly time series for wind speed or solar insolation [22]. Synchronous historical hourly weather data, including wind speed, insolation, and temperature data, from which electricity demand may be calculated, provide a way to capture the correlation between different VER facilities and between VER generation and loads. For reasonable accuracy, a sufficient amount of historical data is needed. Bothwell and Hobbs address this question for resource adequacy analysis at HL-I [23]. Starting with 10 years of data, they show the impacts of using different subsets of years, finding that five years of data are about as good as 10, but less than five years risks distorting the results significantly. They strongly advise against using mean observed wind speeds, as they understate variability [24]. Decades of historical meteorological data are available at a medium level of geographical resolution and may be combined with site-specific data for a shorter period using "reanalysis" to obtain longer site-specific series [25]. Use of any historical meteorological data should consider adjustments for climate change [26].

An alternative approach is to use synthetic time series generated by sampling from a time series model estimated from historical data, as described in [27]. Methods to link the synthetic time series to load models and other VER facilities include a multivariate normal model (also used in analyzing the effects of correlation of bus loads) [28]; copulas [29]- [30]; inverse transformation [31], Nataf transformation with Latin hypercube sampling [32], dimension reduction [33], and multi-dimensional clustering [34]-[36]. Chen et al. created models of wind speed for two sites in the Netherlands using: inverse transformation, Nataf transformation, and Copula method, with Weibull distributions for the marginal distributions of the wind speeds at the two locations. For these two sites, the Gumbel copula is found to provide the best fit to the means, variances, Weibull distribution parameters, and Kendall correlation coefficient [37].

Presently, outages/intermittency of renewable generators are modeled without considering their effect on generation ramping. Ramping can cause significant impacts to the power grid, similar to a generator outage [39]. The concept of **I**ntermittency **I**nduced **O**utages (IIOs) has been proposed to capture the impact of intermittency. Probabilistic outage models for IIOs with loss of generation, under- and over-generation modes due to wind ramping-down and -up events are presented in [39]. The IIO concept was further extended to the modeling of common mode outages (CMOs) for multiple correlated renewable plants [6].

A. *Wind Speed Stochastic Model*

A time series model has a stochastic element. Various stochastic elements have been used in wind speed models. These include the autoregressive (AR) process (perhaps the most common) [27]; birth-and-death Markov train [38]; hybrid of Markov and AR processes [39]; and estimating the stochastic model after applying a Logit transform [41].

B. *Wind Turbine Availability Model*

Ref [42] states that equipment outages in WFs "can be neglected in many practical situations without creating unreasonable errors in the calculated reliability indices". This may be true with low penetration levels of VERs but at higher penetration levels, the effect can be significant. Approaches for incorporating WT equipment outages have been developed; failure rates may be dependent on wind speed as it has been observed that WT outage rates tend to increase with wind speed [38]. These include: individual WT availability; grouped availability; derated availability; state probability table; capacity outage probability and frequency table (COPAFT); and copula for relationship between wind speed and failure rate [38]-[39], [43]-[45].

C. *Solar PV*

We note two approaches to modeling solar PV: (a) Bottom-up model of plant availability [46], and (b) Chronological probability model [47]. These are combined with solar equipment availabilities in similar ways as discussed for wind systems to provide the reliability models of solar farms.

D. *General Approaches*

When the correlation among VERs and between VERs and loads is neglected, one may use a synthetic multi-state generator – deriving a multi-state generator model from synthetic hourly wind speed time series data [48]-[49]. A five-state model provides a reasonable WF model for CSR analysis [42]. Otherwise more sophisticated approaches must be used [70].

E. *Applications and Results*

A synthetic time series to develop models for two locations in Saskatchewan is presented in [27]. The approach is used to estimate a model from three years of actual wind speed data for a particular location, and calculates synthetic wind speed and the total output for a wind farm with 100 turbines for a large number of years [48]. Then the simulated output series are input to a generation reliability analysis (HL-I) for a test system with the wind farm added to a fleet of conventional generation. They find that about 6000 years of synthetic wind speed data are needed for convergence of calculated LOLE for this case.

Reference [50] applies ARMA models, one of which was presented in [27], to represent two WFs. The models are used in a composite system reliability analysis that considers 11 alternatives for interconnecting the wind farms to a modified IEEE reliability test system using a sequential Monte Carlo approach.

Several wind speed models are reviewed in [24]. The analysis includes calculating various reliability indices for a test system using both the original data and the wind speed models. They are compared on the basis of the following criteria: (a) differences between resulting wind speed distributions from the models and the original data, (b) differences between the calculated reliability indices using the models and reliability indices using the original data, and (c) correlation between wind power output and hourly loads.

The findings include: (a) The ARMA model provides a more comprehensive representation of wind speeds. It does a good job at matching the observed correlation for all loads and for loads above 80% of peak demand, and (b) The Markov chain model does poorly on the wind-load correlations.

Reference [51] also compares wind speed models and the values of system reliability indices they yield. It finds (a) an ARMA model is better than other approaches in that it yields reliability indices closest to those obtained from observed wind speeds; (b) simple sampling from a wind speed probability distribution yields higher frequencies of transitions between healthy, marginal, and at-risk system states and shorter state durations; therefore, this method is not recommended if frequency and duration indices are desired; and (c) using mean wind speeds results in relatively optimistic indices.

HL-I and HL-II results using various wind speed models are compared against the results from the original data for various test systems [52]. A key finding is that an ARMA model based on only a few years of data produces reliability indices closer to what would be obtained from using observed hourly wind speeds for a larger number of years.

V. Methodologies and Framework for CSR Analysis

The objectives of reliability calculations are to determine for a given design whether continuity of electric service to their customers is ensured under normal and certain abnormal conditions, including uncertainties associated with load variations, variable renewable energy sources, etc.

Increased interest in probabilistic methods prompted surveys to identify organizations that use probabilistic methods and tools for solving practical problems in planning or operations [53]-[55]. A recent survey [56] was conducted by the IEEE Composite System Reliability Task Force to assess the industry practice in probabilistic assessment in general, and composite system reliability (CSR) analysis in particular. Increased interest has been seen in evaluating the reliability impact of high penetration of renewables such as photovoltaics and wind, retirement of coal plants, regulatory requirements and other policies.

An effort to develop methods and tools that take into account impact of common-mode and dependent outage events has been initiated and continues [57]. Multiple common-mode and dependent outages are the results of physical proximity; relaying misoperations, breaker failures, weather conditions (e.g., hurricanes); cyber-attacks; etc. and they are much more likely to threaten grid reliability. Results of outage data analysis in [57] show that common and dependent mode (CDM) outage events may also have a significant impact on the resilience of the power grid.

A. Monte Carlo Methods

Probabilistic models for individual power system components collectively define a probabilistic model for the composite system. To estimate reliability metrics for this system, one must analyze the possible states of this system and assess the effects on the power supply to end users and associate with these effects their probability of occurrence. As the complexity of a system model increases, enumerating all relevant states becomes cumbersome and error-prone at first, and eventually impossible due to the explosion of possibilities.

A reliability assessment method for large systems relies on Monte Carlo (MC) methods to evaluate probabilistic model outputs. Power system states are sampled at random according to the probabilistic system model and analyzed according to the requested reliability metrics. Almost without exception, metrics of interest are expectation values of random variables $H(X)$ that represent the 'impact' associated with random (outage) states X of the system (e.g. the EENS is the expectation of the energy not supplied across states). Using MC integration, the value of this reliability metric is approximated by the sample average approximation:

$$\hat{r} = \frac{1}{n}\sum_{i=1}^{n} H\left(x^i\right) \tag{1}$$

Here, state samples x^i are drawn from the system's state distribution $f(x)$ and their impact is calculated by the function $H(x)$. We can distinguish *state sampling MC*, where states are snapshots of the system at a particular point in time, and *time-sequential MC,* where a single sampled 'state' represents a time trace of the system. The latter type of analysis is clearly more computationally demanding, but is in general necessary when the system has significant temporal dependencies in its internal state (e.g. due to the dispatch of storage, or modelling of startup/ramp constraints) or when reliability metrics explicitly depend on time.

Another output of interest is the probability distribution of the outcome $H(X)$ [58]. Those can also be expressed in terms of expectations of (cumulative) distributions [59], so that the same general approach can be used. Risk-averse CVaR constraints in system planning can similarly be expressed in the form of expectations [60].

Although MC methods are easily adapted to complex system models and provably generate unbiased results, the random selection of states introduces a sampling error in the estimate $\hat{r}$ of the reliability metric. For large numbers of samples n, the error is approximately normally distributed with standard deviation:

$$\hat{s}\left(\hat{r}\right) = \sqrt{\mathrm{var}\left(H\left(\hat{X}\right)\right)/n} \tag{2}$$

This expression both quantifies the sampling error and illustrates the two essential methods to reduce the error incurred: by *increasing* the sample count n, or by *reducing* the sample variance $var(H(\hat{X}))$. Increasing the sample count can be done by running the program for longer, coding it efficiently, or using advanced computational resources such as GPUs [61] or parallel computing [62]. *Variance reduction* methods are effective in reducing computational burden, examples are: (a) **Low variance sampling.** Choosing x^i to reduce fluctuations in sample placement. This broad category includes stratified sampling, dagger sampling, Latin hypercube sampling, antithetic variates, and quasi-MC methods. (b) **Targeted sampling.** Choosing x^i in accordance with $H(x^i)$ to increase the contribution from each sample. This category includes importance sampling methods, often in combination with the cross-entropy method to optimize importance sampling parameters [63]. In addition, as there are many states for which $H(x^i) = 0$, various authors have pursued methods to avoid sampling these states and replacing their contribution to $\hat{r}$ with the value 0. Examples of this approach include state space pruning [64], machine-learning of non-contributing states [65]-[66] and the subset simulation method [67]. And (c) **Output interpolation.** Leveraging approximations of $H(x)$ (surrogate models) to better estimate $\hat{r}$. Control variates $V(x)$ that closely resemble $H(x)$ are used in [68] (by another name) and [69] to reduce the variance of the differences $H(x) - V(x)$. This approach has been generalized using the multilevel MC framework in [59].

B. Selective Enumeration Methods

The perennial problem of planning for a reliable power supply system at acceptable, optimized cost is becoming increasingly challenging with the clear need to quantify risks. The process should account for increased variability in generation resources (wind, PV), increased flexibility on the customer side as well as additional fast responding storage such as pumped hydro, BESS, customer storage (electric vehicles, thermally controlled loads and other), and demand response programs, increased concerns of more frequent bad weather, and increased volatility in prices and environmental concerns.

A framework for a fully probabilistic methodology to power system reliability analysis and planning is shown in Fig. 5. The framework is based on a stochastic dynamic programming approach that will integrate computational reliability analysis procedures over a long period of time into a systematic probabilistic planning tool. Each node in the figure represents a system "state" at a specific time interval ("stage"). The system state represents specific planning decisions. There is a transition from each state to any other state on the next time interval (stage). The number of stages define the planning horizon, for example twenty stages, one year each, will make a 20 year planning problem. Transitions can be feasible or unfeasible (if a transition requires the dismantling of a healthy facility, it is infeasible, if a transition requires the addition of a facility that cannot be constructed/completed by this time interval, it is infeasible, etc.).

The computational complexity resides in the probabilistic evaluation of each state at a stage. This evaluation uses a selective enumeration of contingencies algorithm [71-72] as shown in the upper right corner of the figure and probabilistic computational algorithms [73-76], which are integrated to provide a number of probabilistic performance measures (metrics) for the state at that stage. The metrics are numerous. An incomplete list of metrics is: (a) actual costs (i.e. investment cost, operational cost), (b) cycling of thermal units and level of ramp rate violations, (c) reliability indices categorized into four classes: (1) probability indices (i.e. LOLP), (2) frequency indices, (3) duration and (4) expectation indices, i.e. EUE (expected unserved energy), expected overloads, expected undervoltages, expected ramping

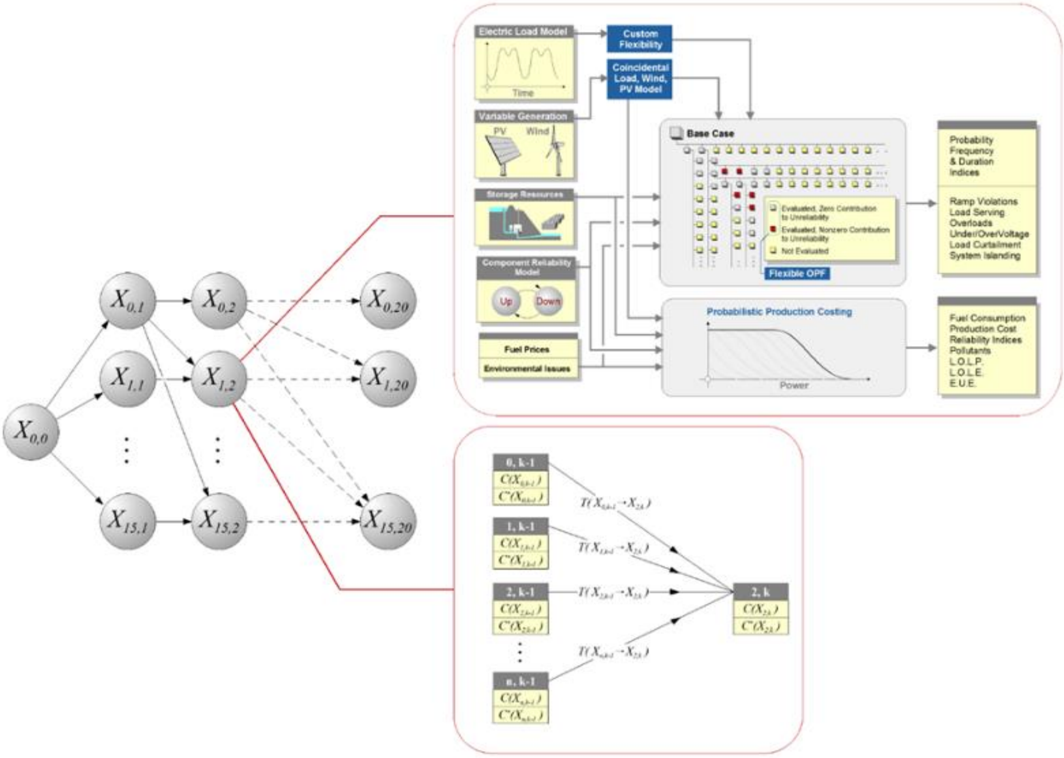

Fig. 5 Framework for composite reliability analysis and planning

violations, etc., (d) production metrics, i.e., consumption by fuel, etc., and (e) environmental metrics, i.e., expected pollutants, NO_x, CO_2, etc.

The results of above analysis are used in the stochastic dynamic programming to define the optimal expansion plan, optimal is defined in the sense of a linear combination of metrics and parametrically in terms of existing flexibility in the system. Obviously, changing the coefficients of the linear combination of the metrics (relative importance) the optimal expansion plan may change. The stochastic dynamic programming enables the evaluation of the expansion plans with different combination of metrics and it results in a number of "best" expansion plans. The dynamic programming optimization is symbolically illustrated in the figure. The subscripts *i,k* of state *X* (highlighted in Fig. 5) represent the state *i* of the bulk transmission system at stage *k* (time interval *k*). Note that at each stage a number of candidate bulk power system states are generated in terms of possible expansion decisions. The generation of the states uses a combination of sensitivity methods, identification of congested paths and available transmission paths.

The computational problem can be defined as determining the optimal sequence of decisions as the plan moves from stage 0 (present time) to the final stage of the horizon period. The optimization algorithm computes the optimal cost of reaching a designation state in a stage by computing the minimum cost transition from any state in stage *k–1* to a state *i* in stage *k*, $X_{i,k}$, symbolically shown in Fig. 5. The proper formulation of the dynamic programming algorithm guarantees that the optimal trajectory computations are limited to transitions between two successive stages, resulting in an efficient algorithm. On the other hand, the number of states (decisions) in a stage may be very large resulting in a very large decision space (curse of dimensionality). This issue is addressed by using a successive dynamic programming algorithm that limits the number of states (decisions) to only a small number around the current optimal trajectory. The end result is an efficient method to a challenging computational problem. An important feature of the method is the identification of the first n best expansion plans, best defined in terms of the selected linear combination of a number of metrics, allowing planners to perform trade-off analysis. This feature is very important for planners as it is important to have several options for the expansion of the system and to know the cost and reliability implications of each one of these plans.

VI. Conclusions

The power industry currently relies on planning methods that systematically understate the probability and depth of high impact events that can simultaneously impact multiple generating units. Power supplies are vulnerable to the increasing frequency of severe weather events such as recent freezing temperatures, constraints on natural gas supplies, cyber-attacks, variability in the output of wind and solar resources, and various multi-factor events. Current resource adequacy metrics such as Effective Load Carrying Capability (ELCC), Loss of Load Expectation (LOLE) and reserve margin do not adequately recognize the probability of correlated impacts on the output of multiple resources; measure the depth, breadth, or duration of outages; or account for their economic, public health and safety impacts. The methodologies used to calculate resource adequacy typically assume that outages and reductions in generator output are independent and uncorrelated. This assumption of independence, as our report points out, is no longer valid.

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