A Methodological Framework for Strategic Electricity Generation Planning in India: Assessing Resource Adequacy through Probability Risk Metrics

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Abstract. A country's electricity mix plays a crucial role in shaping its economic and industrial growth. A diversified fuel mix can reduce emissions while ensuring energy supply security, thus enhancing the potential for climate-compatible growth. A decarbonized electricity mix is essential for mitigating the effects of climate change and catering to the core spirit of sustainable development goals (SDGs) as highlighted by the Intergovernmental Panel on Climate Change (IPCC). As of now, the low-carbon electricity mix in India is composed of intermittent energy resources, like Solar, Wind, and Hydropower generation. Although variable renewable energy (VRE) sources lead to a reduction in greenhouse gas emissions, random temporal fluctuations in their availability perturb the stability of the power systems. This necessitates strategic planning, especially on the generation side such that future electricity demand is always met. This study discusses a methodological framework in conjunction with the existing probability-based risk metrics for assessing the resource adequacy of the electricity generation mix considering the generation capacities of different sources, their average availability levels, and the possible outages that these sources may suffer from. The paper illustrates Monte Carlo simulations with an assumed electricity mix in conjunction with relevant parameters to demonstrate the resource adequacy assessment of an electricity generation mix. The simulations show that the available capacity decreases with an increasing number of discrete risk events, which limits the capability of the power system to meet the demand. For a 2-day test simulation (considering a loss of load expectation value of 2 events-days), the loss of load event is found to be 4 events, and expected unreserved energy is estimated as 1400 MWh over the predefined, representative two-day period.

Keywords: Resource adequacy, Electricity generation, Probability risk metrics, Low-carbon electricity mix

1. Introduction

The essential function of a power system is to supply electrical energy at affordable rates with maximum reliability and quality. Power systems are prone to unforeseen mechanical or electrical failures at power plants, substations, or transmission lines. The Institute of Electrical and Electronics Engineers (IEEE) defines System Reliability as the ability of a system to perform its intended functions without failure, within the design parameters, under specific operating conditions, and for a specific period [1]. Over the years, different utilities have defined and developed customized reliability standards to ensure their power systems' robustness, resourcefulness, rapid recovery, and adaptability [2]. The system reliability assessment of a power system can be performed in two ways, a) by focusing on ***system security,*** and b) by ensuring ***system adequacy***. System security refers to the ability of the power system to respond to disturbances (faults in earthing, overload failures) that occur within the system. The disturbances may be local or widespread, resulting in the malfunctioning of major generation facilities and distribution networks. In general, the ability of the utilities is limited regarding the capacity to assess and quantify the system security issues. System adequacy refers to the in-built sufficiency within the system to satisfy the load demands while adhering to the system's operational constraints. The adequacy of a power system can be assessed from the generation capacity as well as the associated transmission and distribution networks [3].

Several techniques, including deterministic and probabilistic methods, are available to analyze the various aspects of system reliability [4]. The power systems behave stochastically since all the input and output state events are random in nature. Consequently, probabilistic methods are used to recognize the sensitivity of the system's behaviour to different variables [4], [5]. Such techniques also provide essential information regarding the likelihood of the occurrence of different abnormal events within the active power system architecture. Central Electricity Authority (CEA) has highlighted the need for integrated resource adequacy planning for strategizing Electricity generation in India [6]. The monitoring and evaluation of generation adequacy are becoming progressively more critical due to the increasing penetration of variable renewable energy (VRE) sources in the country's electricity mix. Moreover, the intermittent and variable nature of VRE necessitates redesigning of measures in the operations as well as in the electricity market to ensure that generation capacity can cater to future demand levels reliably [6]. The recent initiatives adopted towards retiring the subcritical coal-fired thermal power plants with installed capacities of 210 MW or below in a progressive manner to decarbonize the Indian power sector render the generation adequacy even more relevant since coal forms the core of India's energy security [7]. Currently, coal accounts for 47% of the total energy consumption and 72% of the electricity generated in India [8], [9]. As the country is deeply committed to achieving SDG 7, i.e., universal access to affordable, reliable, sustainable, and modern energy, periodical revisits to the resource adequacy aspects are key to ensuring the reliable production, and dispatch of clean energy. This also forms an important part of the country's long-term aspirations to attain 'Net-Zero' carbon emissions by 2070 [10]. Adequacy studies often focus on three functional blocks of the utility-scale power systems, i.e., Generation, Transmission, and Distribution. It is noteworthy that over the past two decades, there has been a rapid evolution in the electric power industry in terms of new technologies, devices, system architecture, control systems, and system security protocols. The progressive use of modern system architecture and phasing out of legacy systems have led to uncertainties in terms of the ability to deliver reliable power. Power system planners have been leaning toward probabilistic reliability assessment tools since such tools have been successfully implemented by various utilities worldwide for adequacy planning studies facing the onslaught of growing complexity [11], [12], [13]. However, it is important to note that appropriate customization of such tools is necessary to ensure their applicability over specific geographical regions (country/ state/ city levels). The applicability of probabilistic tools for the resource adequacy study for the Indian power sector has not been explored in detail. Further, the conceptual abstraction of the probabilistic method for regional resource adequacy planning is not available in the prominent literature. Aiming to bridge this gap, the present study focuses on the adequacy of the total system-level resources at the generation end, considering an illustrative load-side demand. The novelty of the study stems from the fact that it departs from the ***Planning Reserve Margin*** (PRM) approach to adopt the ***Adequacy Reserve Margin*** (ARM) pathway. The ARM approach uses a probabilistic method to identify the instances of shortfall in power generation. This approach enables different utilities to set adequacy threshold limits based on individual financial strength and resource-oriented preparedness. Consideration of frequency, duration, and magnitude of potential curtailment events in the probabilistic risk assessment framework allows for a more pragmatic planning for reserve margin at the national, regional, and state (or local) levels.

The organization of the rest of this paper is as follows: **Section 2** of this paper delves into exploring relevant literature to set the background regarding the need for resource adequacy planning in India. This section also discusses the low-carbon firm power options for decarbonizing the baseload generation in India by taking into account the futuristic energy generation technologies. **Section 3** explains the resource adequacy fundamentals, and also delineates the probabilistic risk metric-based approach used in this study for projecting the likelihood and extent of shortfall in generation based on a particular resource portfolio. **Section 4** presents the results of the Monte Carlo simulations demonstrating the capacity availability for varying numbers of discrete risk events. **Section 5** highlights the key components of a consolidated conceptual framework associated with strategic resource adequacy planning for reliable electricity generation. The section also provides possible directions for resource adequacy planning specific to the context of the Indian power sector. **Section 6** concludes the paper by summarizing the overarching significance of this study.

2. Literature Review and Background

2.1 Need for Resource Adequacy Planning in India

Over the last decade, India's economy and electricity demand grew at an annual average rate of 7%. The power demand is expected to continue to increase to support India's growing manufacturing sector and meet the rising aspirations of its people [14], [15]. Managing a continuously growing electricity demand reliably would require a robust and resilient power system, accompanied by efficient integration among the different functional blocks. *The key issues that require attention in the context of resource adequacy planning for the Indian Power Sector are highlighted below*:

- **Higher RE Integration:** At higher projected RE penetration, the power system is bound to face additional challenges as RE generation is highly dependent on the varying weather events. Literature suggests that several countries have achieved effective integration with lower levels of RE curtailment by diversifying the locations of RE generation, devising innovative models to accommodate varying weather events, or changing the market designs [16], [17], [18]. The government of India had declared an aspirational target of achieving an installed RE generation capacity of 175 GW by 2022, including 60 GW of wind and 100 GW of solar [19]. Despite being able to realize only 66 percent (116 GW) of the 2022 target (this includes 57.5 GW of Solar and 41.2 GW of Wind), the country's green energy aspirations have grown further looking at the 2030 timeline. The country aims to achieve 450 GW of renewables and 500 GW of non-fossil capacity by 2030. Although global experiences demonstrate that power systems can integrate wind and solar at scale, evidence-based planning in the local context would help India in facilitating this integration at the least cost [20].
- **Retirement of coal power plants:** With the expected progressive retirement of coal-based thermal power plant (TPP) units equipped with old, inefficient, and obsolete subcritical technology in the future, the firm energy generation capacity is expected to get depleted in India until new baseload generation capacities are augmented [7]. Thus, a proper stocktaking of available resources that can substitute conventional firm energy sources is essential to prevent the unlikely occurrence of load outages. Experiences from the utilities indicate that the probabilistic risk metrics tend to exhibit higher scores with the progressive retirement of the old and

obsolete incumbent generation units, highlighting the need for new (or alternative) firm energy resources to stabilize the load [21], [22].

- **Shifting of risk events (shortfall) from the peak-load duration to off-peak hours/ seasons:** Most of the classical adequacy models are based on allocating a specific percentage of the peak load as the '*planning reserve margin*' to cope with the higher levels of demand during the peak hours/ seasons. However, the Northwest Power Plan (2021) highlights that there could be a shift in the risk events (shortfalls) among different quarters of the same year. Hence, it is important to assess this shift in shortfall among different months/ quarters of the year owing to the changes in meteorological conditions and other uncertainties.
- **Lead time required for planning new generation sources:** The state distribution/ procuring utilities have ceased holding competitive bidding processes owing to expected lower demand levels and untied installed capacities. Through methodical adequacy planning, the expected electricity demand for a particular time horizon can be forecasted, ensuring a transparent and competitive bidding process while procuring a quintessential consumer commodity like power [6].
- **Need for integration and procurement planning:** Although the details of possible options of power procurement are available at the national and regional levels, the information may not be accessible to the states. Currently, there is no formal mechanism to monitor whether the demand is met by the state utilities through an optimal mix of available resources at a particular instant. Appropriate adequacy planning at the state/ regional level will ensure efficient utilization of reserves, thereby preventing undue surplus/ deficit situations [6].

2.2 Focus on Low-Carbon and Futuristic Energy Sources

Decarbonizing the electric power sector at a reasonable cost is pivotal to global climate mitigation efforts [23], [24]. Thus, finding an optimal mix of energy resources including firm low-carbon resources is essential to serve the larger goals of social welfare and climate mitigation is challenging. Firm resources are the technologies that can supply electricity reliably, especially covering the peak loads of the system. These form a reliable backbone of an electricity system. In the present scenario, this role is filled primarily by a coal-fired thermo-electric thermal power plant in India. In a zero-carbon power system, the challenge is to replace carbon-intensive technologies with other firm resources that can supply reliable power. Moreover, it should be able to pair with variable renewable resources like wind and solar, aided by the appropriate energy storage to enhance energy availability and reliability [25].

Low-carbon energy resources can be classified into three categories: firm low-carbon resources, fuel-saving resources, and fast-burst resources [23]. The 'firm low-carbon resources' are those that can reliably meet the electricity demand at different periods of the year. Conventional nuclear energy is considered globally as a prominent option in this category. Leading research institutes like MIT and Princeton University in the USA have studied pathways to achieve deep de-carbonization [26], [27]. Moreover, it is highlighted that in deeply decarbonized electricity systems with significant shares of VRE, the additional availability of at least one *low-carbon firm electricity generation technology* can overcome the reliability issues arising from the intermittencies of VRE sources [27]. The study also indicated that the presence of *low-carbon firm electricity generation* also substantially reduces the electricity costs [23], [27]. Looking at 2040 and 2050, there are many choices available for India that can potentially be considered as the '***additional firm electricity sourc***e'.

a) **Hydrogen** (although the production, storage, and distribution infrastructure will be capital intensive) and long-term **Pumped Hydro Storage** (PSH) systems.

b) **IGCC technology** aided by **carbon capture, utilization, and storage** (CCUS) technologies. (Economics needs to be worked out to examine the techno-economic viability of large-scale deployment)

c) **Nuclear Energy** (mainly **Small and Modular Reactors (SMR)**, since these are factory-built, use passive safety features leading to smaller Emergency Planning Zone (~ 1 km), and facilitate lesser lead-time)

Firm low-carbon energy resources are necessary for attaining a zero-carbon grid, that can withstand large penetration of intermittent renewable resources in the electricity generation mix, such as wind, solar, and hydropower. Fuel-saving resources which comprise mainly solar and wind in the Indian context, suffer from spatio-temporal variabilities across different regions in the country. These are termed '*fuel-saving*' since they are highly affordable during the period of availability and lead to reduced variable costs and lower fuel consumption from the other resources in the mix. Fast-burst resources refer mainly to energy storage batteries which provide a certain flexibility at the user end and can be used in conjunction with variable renewable energy resources to enhance reliability in the system [23].

3. Resource Adequacy (RA) fundamentals

Resource Adequacy (RA) programs can effectively utilize the various available energy resources, realizing a diversified electricity generation portfolio while using the transmission and distribution capacities in a sustainable way towards meeting the load-end demand cost-effectively. Essentially, the resource adequacy exercise aims to assess whether a system will achieve a desired level of reliability in terms of meeting the load-driven demand profiles by pooling in available resources. Earlier resource adequacy analysis used to be carried out in a rather simplistic way, where the main objective was to ensure enough installed capacity to meet peak load [5], [21]. System operators used a combination of technical or operating reserves, rescheduling, and load shedding to meet expected demand [3]. However, the increasing penetration of variable renewable energy (VRE) sources and the consideration for the energy-limited resources in the energy mix have necessitated a modification in this approach. The periods of risk (shortfall in electricity supply) are not necessarily periods of high load and hence all intervals matter for resource adequacy analysis and not just the peak demand period. Moreover, the problem of chronological operation (VRE, energy storage, load flexibility, hybrid resources) and its correlation with uncertainties such as marginal cost, weather events, climatic trends, combined outages, modular technology, etc. makes the selection of electricity mix a complex and interdisciplinary exercise [21].

3.1 A Shift from Planning Reserve Margin (PRM) to Adequacy Reserve Margin (ARM)

Planning Reserve Margin (PRM) is commonly used in resource planning to cover expected peak loads, aiming to compensate for future uncertainties. It uses a building block approach, where a specific percentage of peak load is attributed to significant events like forced generator outages, and weather events as well as for contingency reserves. **Figure 1** shows a 14% PRM, attributed to forced generator outages (2%), extreme weather events (5%), and contingency and emergency preparedness (7%). PRM is a deterministic method and often doesn't account for the uncertainties in variable renewable energy sources, and aspects of extreme weather events attributed to climate change.

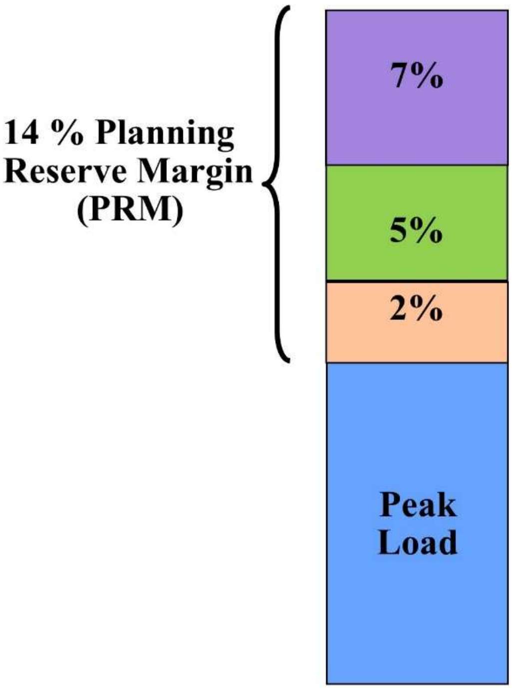

Figure 1. Planning Reserve Margin (PRM) for Resource Planning

Unlike PRM, Adequacy Reserve Margin (ARM) is based on the probabilistic method, wherein software simulations are used to study even the hourly operation of the power system, both the supply and the demand. The simulation is run for thousands of iterations based on the combination of future unknowns, such as solar irradiation, wind patterns, generator outages, river flow, etc., to find out the instances of insufficient generation. For instance, if the adequacy standard threshold is set to a limit of 5% in a year, the power system is deemed adequate if the likelihood of one or more shortfalls is less than or equal to 5% in a future year for which simulations are done. Different utilities set threshold limits based on their capacities, mostly based on economic and resource constraints.

Resource adequacy standards consist of a ***metric*** and a ***threshold*** for analyzing the resourcefulness of a system (see **Table 1)** [21]. The metric gives a measure of adequacy that can be calculated using deterministic or probabilistic methods. On the other hand, the threshold indicates the limit for the metric, depending on the discretion of individual utilities. If a utility is supplying power mostly to the essential loads, then the adequacy threshold will be more stringent. This indicates that the utility will reserve more buffer for emergencies in case of a deterministic approach, or the utility will opt for a 2-3% likelihood of risk events. **Section 3.2** discusses the probabilistic method/ metrics adopted in this study in detail.

Table 1. Metric and Threshold Considered for Resource Adequacy Study

Metric (Measure of Adequacy)	• Deterministic (e.g., reserve/ load planning) • Probabilistic (e.g., frequency, duration, and magnitude of potential curtailment events)
Threshold (Limit for the metric)	• Number of events per year (e.g., 1 shortfall in 1 year) • Percentage (e.g., % shortfall in terms of load unserved; or 10% of peak load as contingency reserves)

3.2 The Proposed Approach: Adequacy Assessment using Monte-Carlo Simulations and Probabilistic Risk Metrics

Monte Carlo simulations are used for evaluating resource adequacy since they consider the stochasticity of the power system, facilitating accurate probabilistic analysis. Monte Carlo techniques help simulate random events and model failure rates, which is useful for estimating the expected power deficits [28], [29]. The simulations allow for repetitive sampling for a specific time interval to evaluate the impact of uncertain factors such as fluctuations in the VRE resource profiles (e.g., wind, solar, and hydro generation). They are also instrumental in assessing the effects of random events, such as extreme weather events, generation outages, shortage in fuel (e.g., coal for Thermal power plants), water unavailability, maintenance shutdowns, and failures in power distribution networks on the overall performance of the power system. The Monte Carlo simulations utilize random sampling of the generation availability at any instance in connection with the demand profiles, and the iterative simulations help determine the number of instances of load loss [30].

Monte Carlo simulations can be of sequential and non-sequential types. Non-sequential simulation pivots around the state sampling approach, where the simulations are not chronologically added up and the system snapshots are considered at different instants. It requires fewer input parameters and is computationally efficient. In sequential Monte Carlo simulations, the process marches through time chronologically or sequentially since the status of generation of a particular type is dependent on the status during the previous hours. Sequential Monte Carlo simulates the failure rates, and generation deficits based on the probability distributions of unlikely random events (e.g. extreme weather events, shortage in inputs). For instance, the generation deficits due to maintenance shutdowns can be modelled by taking into account the meantime-to-maintenance statistics. Also, sequential Monte Carlo simulation is often used for hydroelectric systems since it addresses the availability of water at a particular instant [22], [30]. **Figure 2** schematically encapsulates the layers of operation embedded in the modelling framework.

Some of the common probabilistic metrics used to assess, measure, and monitor Resource adequacy are mentioned in **Table 2** [22], [30]. The criteria such as loss of loss expectation (LOLE), Loss of Load Events (LOLEV), Loss of Load Probability (LOLP), Loss of Load Hours (LOLH), and Expected Unserved Energy (EUE) are widely used. The LOLE refers to the average number of days within a predefined period on which the daily peak demand is expected to exceed the available generation capacity. Effectively, LOLE counts the number of days having loss of load events. But, in LOLE the severity of outages is not captured in terms of availability deficits (in MW or any other measurable unit). The LOLEV is a frequency metric, which records the number of events or shortfall events per year, wherein a shortfall event is defined as the instance where load exceeds generating capacity. The shortfall can be defined by the power utility based on either the extent or the duration of the deficit. The LOLP can be calculated based on daily loads or hourly loads. It is the probability of a system entering the state where the peak of electricity demands exceeds the available capacity during a given period. In other words, LOLP is the ratio of loss of load events to the number of possible Loss of Load events. The LOLH is a duration metric, that refers to the expected number of hours per time period (usually one year) when the hourly demand exceeds the generating capacity. This is usually calculated based on the hourly load extracted from the load duration curve. LOLH is calculated by counting the number of deficit hours in each iteration. The EUE is a magnitude metric that predicts the expected energy that the generating system fails to deliver when the load-side demand exceeds the generating capacity. This gives a measure of the intensity of the shortfall event (in terms of energy), and the capacity shortage associated with a specific source or group of energy sources. This provides the severity of deficiency rather than just the number of days or hours of discrepancies.

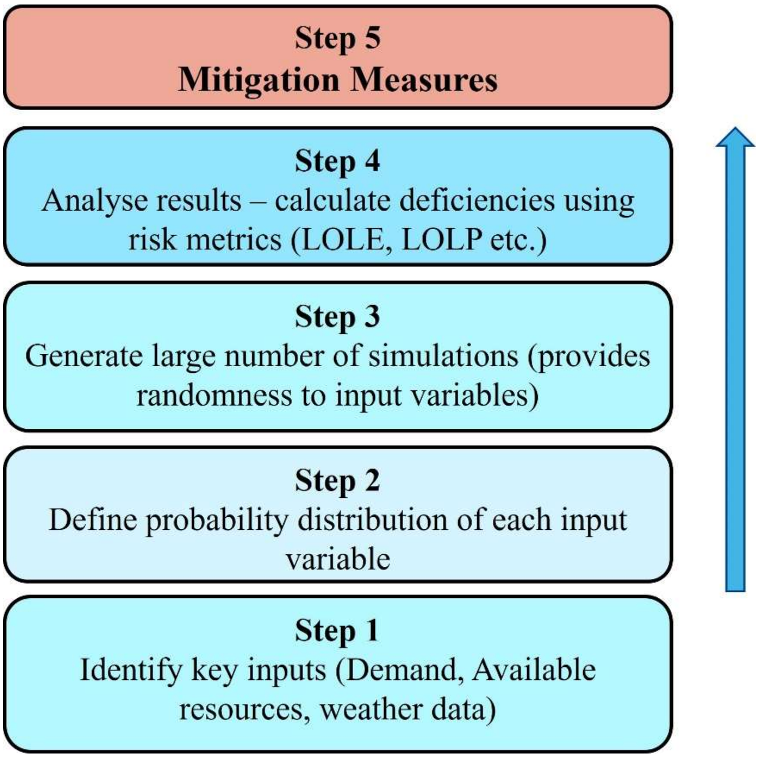

Figure 2. Flow Diagram for Adequacy Assessment using Monte-Carlo Simulations and Probabilistic Risk Metrics

Table 2. Common probabilistic metrics used to assess, measure, and monitor Resource Adequacy

Metric	Unit	Description
LOLE (Loss of load expectation)	Event -Days/ year	Expected (average) count of days experiencing shortfall over the study period. Expressed in terms of event-periods per year (e.g., event-hours per year, event-days per year)
LOLEV (Loss of Load Events)	Events/ year	Number of events or shortfall events per year
LOLP (Loss of Load Probability)	%	Probability of loss of load event during a given period. Doesn't indicate the magnitude, and frequency of the significant outage events.
LOLH (Loss of Load Hours)	Hour/ year	Expected number of hours per year when the load exceeds the generating supply [22].
EUE (Expected Unserved Energy)	MWh/ year	Expected (average) total energy shortfall over the study period. Expressed in energy units (e.g., MWh/year or GWh/ year)

4. Results and Discussion

A representative test case is simulated using XL Risk, an open-source MS Excel plug-in with Python script at the back end. XL Risk provides extensive simulation statistics and user-friendly graphical output [31], [32]. A total of 10000 iterations are run for a specific temporal block (~ 15 minutes). Sample sequences among the iterations are shown in **Tables 3, 4,** and **5**. It should be noted that, as the number of discrete risk events increases, the available capacity decreases, thereby limiting the capability of the power system to meet the demand at any given instant. Representative data has been used for Capacity (MW) and Demand (MW) to illustrate the working of Monte Carlo simulations. Each generation source is assigned the *Monitored Capacity* (the aggregate nameplate capacity in MW), *Conservative Availability* (MW), *Realistic Availability* (MW), and *Optimistic Availability* (MW). Conservative availability refers to the lowest possible generation output, whereas optimistic availability refers to the highest possible generation output. Based on the Monte-Carlo algorithm, a representative '*Available Capacity in MW*' based on a given Plant Load Factor (PLF) (between the lowest and the highest possible values) is forecasted for the given instant of time. The availability can be better predicted if accurate data on the probability distributions of different input variables are available. To further address the random nature of generation, discrete risk events are considered (each with a certain percentage of likelihood). These events include Generator Outages, Maintenance Shutdowns, and Water unavailability. More than one event may occur at the same instance, leading to larger generation deficits as compared to that observed during a single risk event. The discrete events are modelled using the Bernoulli distribution with two possible levels, Likely (1) or Unlikely (0). In the representative XL Risk simulations (10,000 simulations were run), the mean Available Capacity came out as 62025.04 MW. **Figure 3** shows the range of outcomes that can be used to find a probabilistic estimate for the *Available Capacity* at any given instant of time. Though the maximum value changes over each iteration, the most probable output lies in the range of 60,823 - 67,823 MW.

In addition to the resultant distribution, the Tornado Chart, a horizontal bar graph that ranks the correlation between each random input variable and the outcome, is provided to highlight the significance of each random variable (see **Figure 4)**. The bar length in either direction reflects the negative or the positive strength of the correlation. After one cycle of simulation (i.e., 10,000 iterations), the Tornado Chart shows that water unavailability emerges as a major deciding factor for the deficit in Available Capacity (MW). The available capacity predicted through Monte Carlo simulations for a specific interval (15 minutes each) needs to match the electricity demand profiles. For example, if the RA for the upcoming 5 days needs to be evaluated, then 96 number of time slices need to be considered for computation for each day.

Table 3. A test case template of Monte-Carlo Simulation using XL Risk with ONE discrete risk event

<table>
<tr><th>Generation Sources</th><th>Monitored Capacity (MW)</th><th>Conservative Availability (MW)</th><th>Realistic Availability (MW)</th><th>Optimistic Availability (MW)</th><th colspan="3" rowspan="10">Based on the Monte-Carlo algorithm, a representative 'Available Capacity in MW' based on a given PLF (between the lowest and the highest possible values) is forecasted for the given period.</th><th>Total available capacity (MW)</th></tr>
<tr><td>Hydro</td><td>25791</td><td>6,448</td><td>8,511</td><td>10,316</td><td>7,566</td></tr>
<tr><td>PSP</td><td>1000</td><td>250</td><td>330</td><td>400</td><td>343</td></tr>
<tr><td>Small Hydro</td><td>1680</td><td>420</td><td>554</td><td>672</td><td>610</td></tr>
<tr><td>Solar PV</td><td>87171</td><td>10,461</td><td>13,076</td><td>15,691</td><td>14,899</td></tr>
<tr><td>Wind</td><td>12327</td><td>1,479</td><td>1,849</td><td>2,219</td><td>1,976</td></tr>
<tr><td>Biomass</td><td>3984</td><td>558</td><td>677</td><td>797</td><td>753</td></tr>
<tr><td>Nuclear</td><td>3720</td><td>2,790</td><td>3,162</td><td>3,422</td><td>3,120</td></tr>
<tr><td>Coal + Lignite</td><td>52420</td><td>28,831</td><td>37,742</td><td>44,557</td><td>41,369</td></tr>
<tr><td>Gas</td><td>5781</td><td>1,445</td><td>2,023</td><td>2,601</td><td>2,227</td></tr>
<tr><td colspan="8">Available capacity (in MW) based on assumed PLF without considering discrete risk events</td><td>72,862</td></tr>
<tr><th>Discrete "Risk Events"</th><th colspan="2">Likelihood</th><th>Conservative reduction (in MW)</th><th>Median value reduction (in MW)</th><th>High-level reduction (in MW)</th><th>Likelihood (Yes/No Consideration)</th><th>Risked Impact (MW)</th><th>Reduction in Available Capacity (MW)</th></tr>
<tr><td>Generator Outages (1% to 5% of Total Installed Capacities)</td><td colspan="2">20%</td><td>1,841</td><td>3,762</td><td>9,405</td><td>1</td><td>2,466</td><td>2,466</td></tr>
<tr><td>Maintenance Shutdowns (1% to 5% of Total Installed Capacities))</td><td colspan="2">10%</td><td>1,902</td><td>3,877</td><td>9,694</td><td>0</td><td>5,699</td><td>0</td></tr>
<tr><td>Water unavailability (20% to 60% of Total Hydro Installed Capacities)</td><td colspan="2">20%</td><td>5,694</td><td>11,388</td><td>17,083</td><td>0</td><td>7,854</td><td>0</td></tr>
<tr><td colspan="8">Reduction in Available Capacity due to Discrete Risk Events (MW)</td><td>2466</td></tr>
<tr><td colspan="8">Total Available Capacity considering the assumed PLF and discrete shortfall events (in MW)</td><td>70396</td></tr>
</table>

Table 4. A test case template of Monte-Carlo Simulation using XL Risk with TWO discrete risk events

Generation Sources	**Monitored Capacity (MW)**	**Conservative Availability (MW)**	**Realistic Availability** (MW)	**Optimistic Availability** (MW)	**Based on the Monte-Carlo algorithm, a representative 'Available Capacity in MW' based on a given PLF (between the lowest and the highest possible values) is forecasted for the given period.**	**Total available capacity (MW)**
Hydro	25791	6,448	8,511	10,316		8,582
PSP	1000	250	330	400		240
Small Hydro	1680	420	554	672		520
Solar PV	87171	10,461	13,076	15,691		13,789
Wind	12327	1,479	1,849	2,219		1,238
Biomass	3984	558	677	797		562
Nuclear	3720	2,790	3,162	3,422		2,235
Coal + Lignite	52420	28,831	37,742	44,557		39,968
Gas	5781	1,445	2,023	2,601		1,125
Available capacity (in MW) based on assumed PLF without considering discrete risk events						**68,259**

Discrete "Risk Events"	**Likelihood**	**Conservative reduction (in MW)**	**Median value reduction (in MW)**	**High-level reduction (in MW)**	**Likelihood (Yes/No Consideration)**	**Risked Impact (MW)**	**Reduction in Available Capacity (MW)**
Generator Outages (1% to 5% of Total Installed Capacities)	20%	1,841	3,762	9,405	**1**	2,466	**4,623**
Maintenance Shutdowns (1% to 5% of Total Installed Capacities))	10%	1,902	3,877	9,694	**0**	2,599	**0**
Water unavailability (20% to 60% of Total Hydro Installed Capacities)	20%	5,694	11,388	17,083	**1**	7,854	**9,235**
Reduction in Available Capacity due to Discrete Risk Events (MW)							**13858**
Total Available Capacity considering the assumed PLF and discrete shortfall events (in MW)							**54401**

Table 5. A test case template of Monte-Carlo Simulation using XL Risk with THREE discrete risk events

<table>
<tr><th>Generation Sources</th><th>Monitored Capacity (MW)</th><th>Conservative Availability (MW)</th><th>Realistic Availability (MW)</th><th>Optimistic Availability (MW)</th><td colspan="3" rowspan="10">Based on the Monte-Carlo algorithm, a representative 'Available Capacity in MW' based on a given PLF (between the lowest and the highest possible values) is forecasted for the given period.</td><th>Total available capacity (MW)</th></tr>
<tr><td>Hydro</td><td>25791</td><td>6,448</td><td>8,511</td><td>10,316</td><td>7,256</td></tr>
<tr><td>PSP</td><td>1000</td><td>250</td><td>330</td><td>400</td><td>293</td></tr>
<tr><td>Small Hydro</td><td>1680</td><td>420</td><td>554</td><td>672</td><td>623</td></tr>
<tr><td>Solar PV</td><td>87171</td><td>10,461</td><td>13,076</td><td>15,691</td><td>12,126</td></tr>
<tr><td>Wind</td><td>12327</td><td>1,479</td><td>1,849</td><td>2,219</td><td>2,103</td></tr>
<tr><td>Biomass</td><td>3984</td><td>558</td><td>677</td><td>797</td><td>635</td></tr>
<tr><td>Nuclear</td><td>3720</td><td>2,790</td><td>3,162</td><td>3,422</td><td>2,920</td></tr>
<tr><td>Coal + Lignite</td><td>52420</td><td>28,831</td><td>37,742</td><td>44,557</td><td>37,023</td></tr>
<tr><td>Gas</td><td>5781</td><td>1,445</td><td>2,023</td><td>2,601</td><td>1,936</td></tr>
<tr><td colspan="8">Available capacity (in MW) based on assumed PLF without considering discrete risk events</td><td>64,915</td></tr>
<tr><th>Discrete "Risk Events"</th><th colspan="2">Likelihood</th><th>Conservative reduction (in MW)</th><th>Median value reduction (in MW)</th><th>High-level reduction (in MW)</th><th>Likelihood (Yes/No Consideration)</th><th>Risked Impact</th><th>Reduction in Available Capacity (MW)</th></tr>
<tr><td>Generator Outages (1% to 5% of Total Installed Capacities)</td><td colspan="2">20%</td><td>1,841</td><td>3,762</td><td>9,405</td><td>1</td><td>2,466</td><td>1,926</td></tr>
<tr><td>Maintenance Shutdowns (1% to 5% of Total Installed Capacities))</td><td colspan="2">10%</td><td>1,902</td><td>3,877</td><td>9,694</td><td>1</td><td>4,506</td><td>5,239</td></tr>
<tr><td>Water unavailability (20% to 60% of Total Hydro Installed Capacities)</td><td colspan="2">20%</td><td>5,694</td><td>11,388</td><td>17,083</td><td>1</td><td>7,854</td><td>9,257</td></tr>
<tr><td colspan="8">Reduction in Available Capacity due to Discrete Risk Events (MW)</td><td>16422</td></tr>
<tr><td colspan="8">Total Available Capacity considering the assumed PLF and discrete shortfall events (in MW)</td><td>48493</td></tr>
</table>

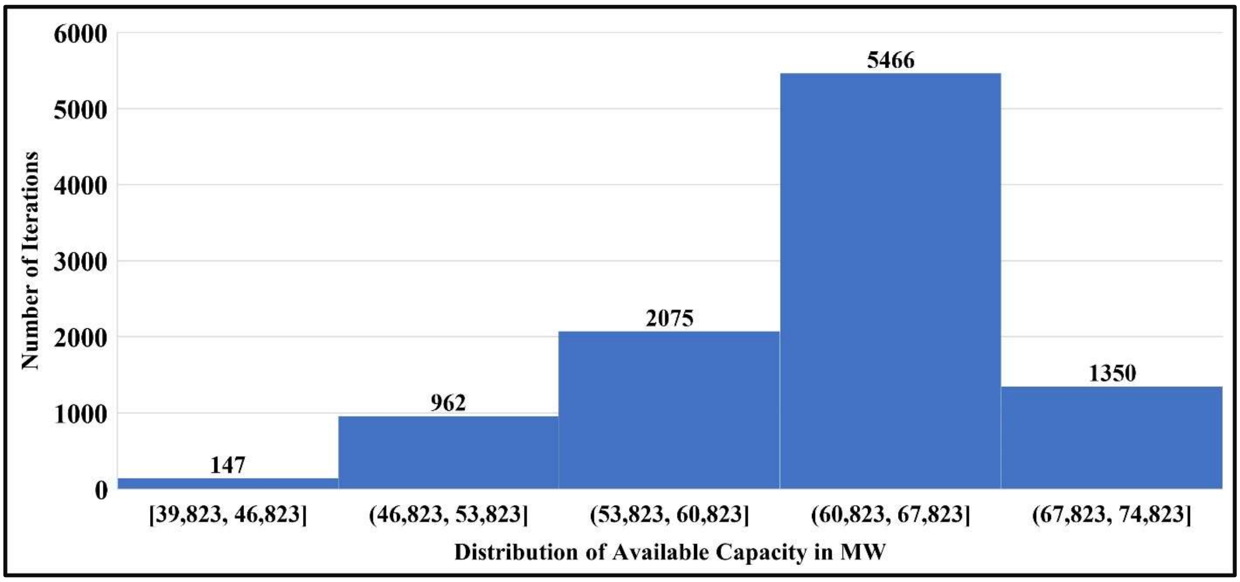

Figure 3. Statistics from simulation output showing the distribution of Available Capacity (MW) with uncertainty ranges

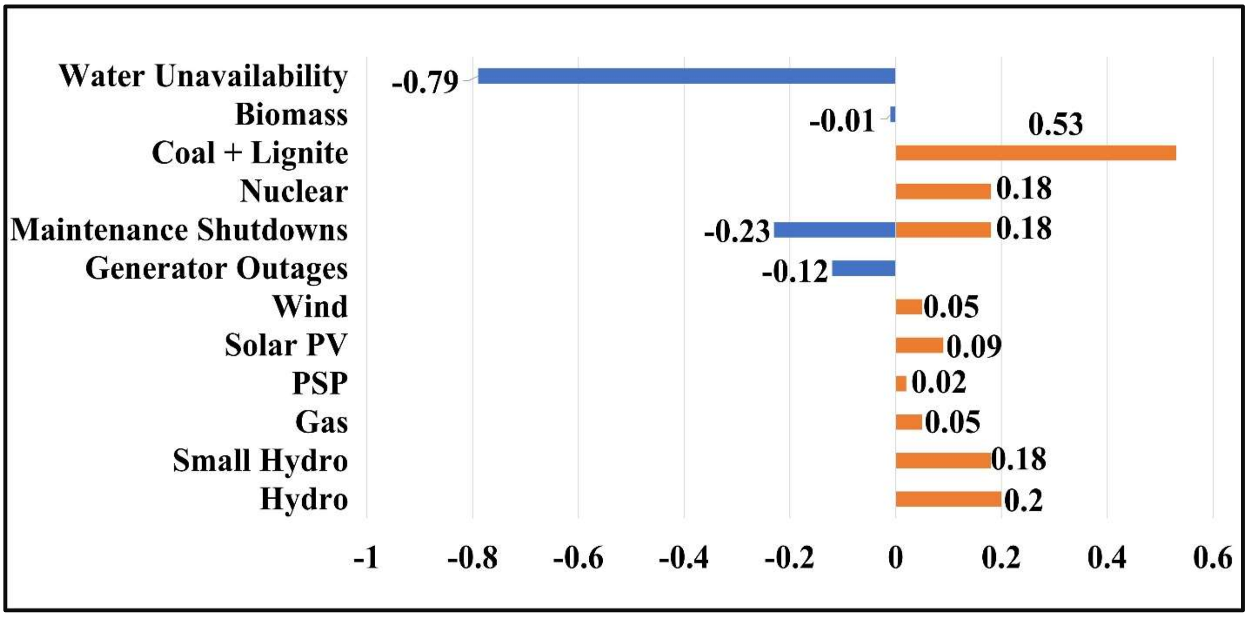

Figure 4. Tornado Diagram showing the relative importance of the variables influencing Available Capacity (MW)

An illustrative representation of probabilistic metrics for 2 days, showing supply and demand comparison is presented in **Figure 5.** Four blocks of 15 minutes each can be averaged out to get the hourly peak supply versus demand graph. For the sample illustration shown, LOLE is 2 events-days, LOLEV is 4 events and EUE is 1400 MWh for the given period of two days.

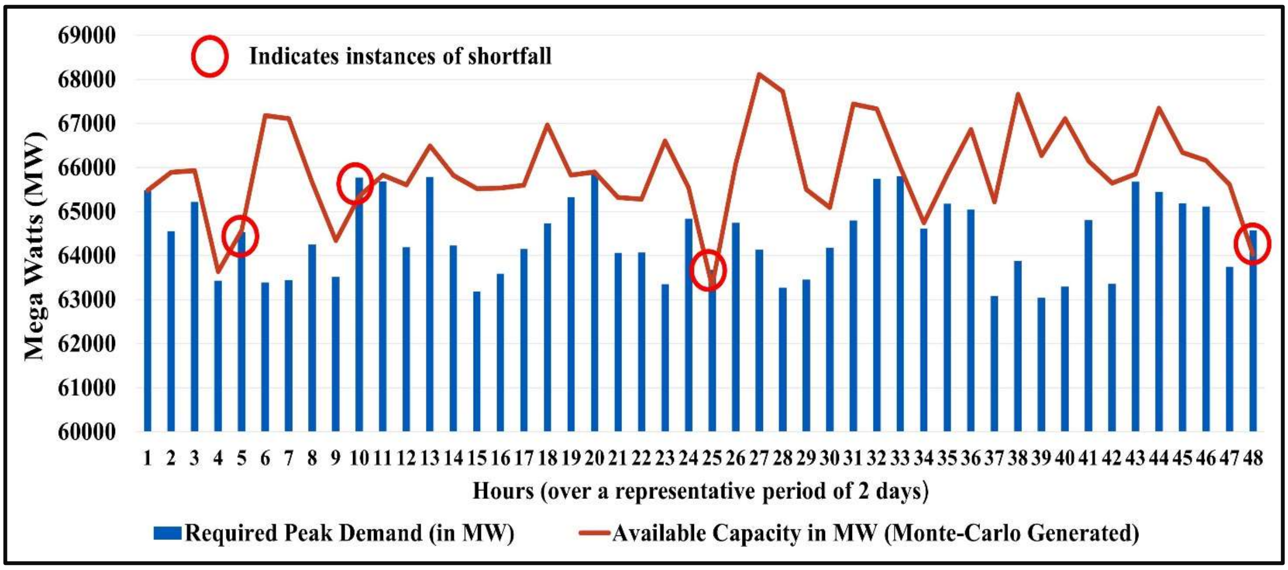

Figure 5. An illustrative graph of Peak Demand Requirement (MW) vs. Available Capacity (MW) based on assumed levels of risk events

5. Salient Outcome - A Conceptual Framework for Resource Adequacy Studies in India

As evident from **Figure 6**, the key components of typical strategic resource adequacy planning for reliable electricity generation are as follows:

1. Forecasting of the electricity demand and projection of capacity requirements for the near-to-medium term.
2. Analysis of the capabilities of the utilities to cater to the fluctuating demand profiles and to ensure operational flexibility.
3. Evaluation of the various cost components for the incumbent and emerging electricity generation sources.
4. Evaluation of sustainable and optimal electricity mix for the near-to-medium term future, considering reliability attributes, cost assumptions, risk factors, and the environmental impact (in terms of emissions).
5. Formulation of probability metrics for assessing resource adequacy.
6. Formulation of actionable recommendations.

The methodology discussed in this study can be used to create a range of power generation source scenarios considering different indicators such as fixed and variable costs for electricity generation, greenhouse emissions associated with power generation from different types of sources, risks associated with the transmission network, climate change preparedness, extent of electrification, and probability-based adequacy metrics. While building the scenarios, varying contributions from the VREs as well as low-carbon firm energy sources must be considered. The electricity demand can be projected by looking at the economic as well as industrial growth trends in the country in conjunction with the recent demand profiles. The diversification of energy sources can be considered based on the plans rolled out by the Government and capacity expansions envisaged by the Generation Companies (GENCOs) and the transmission and distribution (T & D) companies. Resource Adequacy (RA) studies in India would be pivotal for various interventions that can be segregated into five distinct levels, as follows:

1. Export – Import requirements can be assessed to meet regional demands in 2026, 2030, and 2040.

2. Regional adequacy in terms of transmission System can be planned considering both inter-regional and intraregional transmission adequacy.
    a. *One needs to assess whether existing transmission lines are sufficient to load the requirements.*
    b. *Transmission lines/ substation adequacy (especially, 220 kV lines) need to be strengthened/ augmented for intra-regional adequacy.*
    c. *Transmission lines/ substation adequacy (especially, 765 kV (AC/ DC) and 440 kV lines) need to be strengthened/augmented for inter-regional adequacy.*
3. Generation adequacy can be planned at the regional level, based on existing and upcoming energy sources.
4. Generation portfolio can be strategically created based on physical and operational constraints by creating an Adequacy reserve margin (ARM) using probabilistic risk metrics.
5. Expected future shortfalls in generation can be addressed by:
    a. *Optimizing operating parameters (PLF, ramping rate) for thermal power plants (Coal, Gas, IGCC)*
    b. *Reducing RE curtailment.*
    c. *Aligning regional adequacy plans with regional potential for new energy sources.*

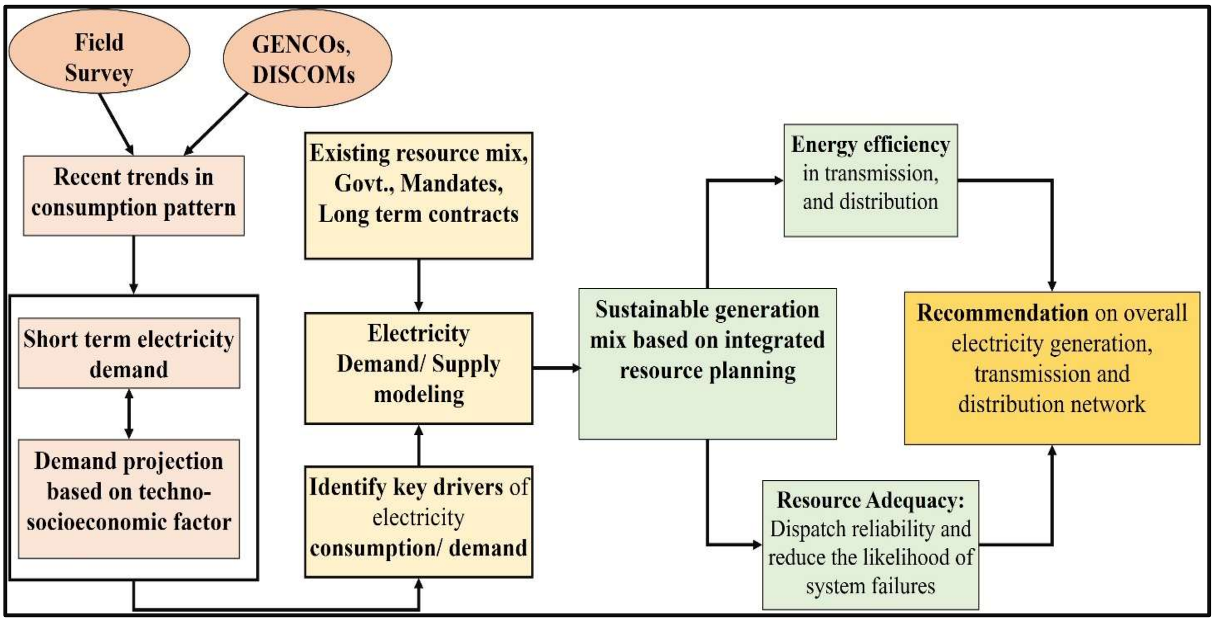

Figure 6. Conceptual Template for Resource Adequacy Study in India

6. Conclusion

A reliable power system should remain unfazed by the fluctuations emanating from the perturbations in the generation, transmission, and distribution stages. This necessitates an assessment of current and future adequacy to mitigate the supply-demand mismatch in the short term as well as the long term while ensuring the operational reliability of the power system. These assessments would help the policymakers and regulators address potential concerns in the power system and even pre-empt some of the imminent risks. The variabilities in the generation side associated with increasing penetration of VRE have necessitated the use the probabilistic approaches in measuring the resource adequacy of a system. For a developing country like India, it is essential to periodically assess the resource adequacy with the evolving electricity mix, changing peak and off-peak demands, and aspirational developments in the country. Monte Carlo simulation serves as a useful tool to estimate the discrepancies between the effective electricity generation capacity and the demand. The results indicate that the available capacity decreases with an increasing number of discrete risk events, thereby limiting the capability of the power system to meet the demand at any given instant. For an illustrative probabilistic simulation considering a loss of load expectation (LOLE) value of 2 events-days, loss of load event (LOLEV) is found to be 4 events, and the expected unreserved energy (EUE) is estimated as 1400 MWh for the representative period of two days. The study shows that different probability risk metrics have the potential to inform the severity of various risk events toward creating deficit scenarios and such metrics would help enhance the resilience of the power systems as a progressive transition happens from legacy devices to modern, digital grid management infrastructure.

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