

Renewable Energy Contingencies in Power Systems: Concept and Case Study

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Abstract-- This paper introduces the concept of renewable energy contingencies that represent long-term/extended variability of variable renewable energy (VRE) resources, namely, significant periods (e.g., days/weeks) of low wind/solar availability. These contingencies have not received much attention to date but are likely to emerge as a major issue in some countries such as India as the share of VRE increases. Using 38 years of climate model reanalysis data for wind over India, we demonstrate that low periods of wind contingency below long-term (Indian) national average of 5 m/s can extend for more than 100 days in several zones some of which are deploying large wind farms. Even in some of the best wind resource areas in India with long term average wind speed close to 7 m/s, low wind days (e.g., 5 m/s which is substantially below average) can extend up to 60 days. We propose a four-step methodology around a co-optimization based energy-ancillary services dispatch model to assess the impact of renewable contingency and implemented it for the state of Tamil Nadu, the most wind-rich state of India. We have estimated that annual renewable contingency cost impact of 5 GW additional wind in Tamil Nadu to be in the range of US\$27-76 million pa. Planning analysis should embrace the concept of renewable contingency to recognize these costs and put in place necessary spinning reserve and back-up generation resources.

Index Terms—Variable Renewable Energy, Interannual variability, Wind energy, Spinning Reserve, System planning.

I. INTRODUCTION

AS the penetration of large-scale grid-connected variable renewable energy (VRE) increases in power systems around the world, system operators, planners and energy regulators need to devise ways to accommodate not only the short-term (sub-hourly/intra-day) variability but also the longer-term extended variability (over the days, seasons and years) in planning and operation. A phenomenal body of research on modeling short-term variability and its impact analyses exists in the literature e.g., [1]. Technologies to cope with such variability including smart grid elements, demand response and battery storage have also developed over the years [2]. However, as we move into an uncharted territory of VRE taking on the dominant role, the longer-term variability must also receive more attention, than it has to date. International Renewable Energy Agency (IRENA) projects renewables to account for 38% of power generation worldwide by 2030, i.e., more than doubling the share in 2017. As the energy contribution of VRE in a system exceeds 20% of the energy requirements, substantially more care in planning such a system is needed. There is a natural smoothing effect of production of wind/solar often captured using the ‘diversity factor’ arising from wind/solar located over wide geography. Planning must ensure *inter alia* complementarity of all resources including wind and solar both in terms of temporal and spatial diversity factors over the longer term taking into consideration the renewable resource dynamics [1-4]. The latter may include variability in the longer term including *extreme* variability such as low wind/solar periods or high wind events that may render significant part of the VRE capacity in a particular location to be ineffectual over a long period. In general, the *inter-annual* variability of VRE is incompletely understood. Variability of renewable energy has, for example, been approximated using Typical Meteorological Year (TMY) [5-9] that represents typical annual weather pattern such as temperature, humidity, wind speeds and direction, radiation [6]. There are many variants of TMY [9-13] that try to capture multiple dimensions of variability. However, a comparison of alternative TMY methods by and large concludes that this is far from an easy task [12-18]. Some of the studies (e.g., [12-13], [14], [16]) have, for instance, indicated that having a low temporal resolution in a TMY can easily overestimate the volume of VRE. Pfenninger[14], in particular, has done an extensive generation planning study for the United Kingdom using 25 years of wind and solar data to conclude that TMY is unreliable and inter-annual variability is critical to determine the correct generation mix. Although the literature has

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progressed to identify the need for a better way to characterize inter-annual variability of VRE e.g., [18], it remains relatively quiet on the issue of renewable energy contingencies, i.e., what happens if several weeks of low VRE yield below mean level continues that lead to significant loss of energy production from this resource over a large geographical area. Although measures like a 3-day cloud cover and ‘worst week’ [4] have been used in planning, we explore the materiality of renewable contingencies that may include more persistent events focusing specifically on wind resource in India to illustrate it, and challenges these may pose for the power system.

This paper specifically discusses the issue of longer-term variability of renewables over months, years and decades in systems with relatively high penetration of VRE (namely, $> 20\%$ of energy). As the past studies [14,16] have shown, solar and wind generation may have significant dips well below their normal average. Depending on the geographical location such loss of production may last not just for hours but days and that too multiple times in some years. There is an added risk that climate change may considerably lower the average for wind power in some parts of the world which will also intensify these dips in wind production. These renewable contingencies are essentially the “generator outages” in a conventional power system. However, depending on renewable penetration level may potentially represent an order of magnitude larger outage event for a longer duration. We reiterate that complementarity of wind, solar and hydro – if all of these resources are available in a system – can offset major dips in one of these resources. Diversity of wind/solar resources over a wider geography can also offset the risk of the incumbent system is tightly interconnected with neighboring systems. Nevertheless, this is a risk that is incompletely understood and may pose a challenge in the longer term in many cases especially if a system goes too deep in one resource. As the remainder of this paper discusses and illustrates using the case for wind in India, longer term variability of this resource can be very significant even if we consider variability across the entire state which has relatively low share of hydro to balance such variability.

Consider for instance the southern state of Tamil Nadu in India that currently has over 9 GW of installed wind capacity that represents nearly a quarter of national wind capacity in that single state and accounts for 20% of the generation in the state. It is expected to have close to 21 GW of VRE capacity by 2021-22 – mostly in the form of wind – well in excess of its annual peak demand of 18 GW in the same year. Low availability of wind affects the entire state and hence a significant part of the generation in the state. Peak production of wind (and solar) on a bad day can dip by more than 50% from the average generation which may wipe out some 8 GW of generation or as much as 80% of the load in some low demand hours [19]. Worse - such events can:

1. last for days,
2. can occur multiple times in at least some years,
3. are intrinsically unpredictable, and
4. with climate change all of the above three might be getting worse in future.

Given the potential significance of renewable energy contingencies, it is paramount that we understand the challenges they entail for power system planning and operation. We use data for Indian wind resource wherever possible to illustrate the nature and magnitude of these challenges and undertake an assessment of the cost impact of these contingencies.

II. RENEWABLE CONTINGENCY CHALLENGES FACED BY POWER SYSTEMS

In this section, we present a few metrics such as frequency, depth and duration of low wind events that can be constructed from historic VRE resource data to characterize renewable contingencies. These are useful metrics synonymous to those used for reliability analysis in power systems. The discussion below uses these metrics to bring out the implications of renewable contingencies from a power system operation and planning perspective.

A. Challenge 1: Renewable contingency size (MW and GWh) and duration (days) can be far larger than the conventional (n-1) security standard followed in power systems planning

As we have alluded to before, a renewable contingency size and duration can be significantly bigger/longer than what power system operators and planners continue to use. A typical power system would be operated using the (n-1) contingency criterion that often equates to the largest online generating unit. As generating unit size grew over the last century to reach GW scale nuclear units, it became a seriously binding constraint in some systems especially if they were not part of a large interconnected system. Measures required to cover for a (n-1) contingency included back-up peaking generators and pumped-storage hydro to be in spinning mode that can be used to cover for the outage of the largest unit. The planned Kundakulam nuclear units (1 GW) in Tamil Nadu would become the largest single generator contingency that is considered to be difficult to cover. A typical generating unit outage has a (mean) repair time of a few days to three weeks. In comparison, a sharp decline in existing wind has been already in the order of 2-3 GW and has lasted for several weeks during the pre-monsoon months of March-May [19] and have caused major congestion on the transmission network leading to high prices in the southern region [20].

As countries rapidly expand VRE capacity across the length and the breadth of a country in all resource-rich areas this can potentially become a serious issue to render the system more prone to outages. The risk of outage would depend on several factors. The preceding discussion already touched upon some of them namely, complementarity of resources and spatio-temporal diversity factors of wind and solar in particular. It would depend as much on the mix of thermal generation. As wind/solar penetration increases, there may be significant thermal capacity that would continue to be available for some years. If the transition is planned well – these thermal resources can also offset the risk of energy shortage during major dips in wind/solar generation. However, these risks around long-term variability of wind/solar are lesser known than their short-term counterparts that need to be understood better and integrated into planning.

In this paper we use Modern Era Retrospective Analysis for Research and Application, Version 2 (MERRA-2) [21] to analyze wind energy. MERRA-2 system contains; Goddard Earth Observing System Model, version 5 (GEOS-5) [22-23] and finite volume dynamical core [24]. 3-dimensional Variation Assimilation (3dVar) technique using Grid-point Statistical Interpolation (GSI) [25-26] to assimilate data every 6 hours from conventional sources, such as, radiosonde, ships, buoys, aircraft and from other sources, such as, satellites. Approximately 5 million observations are assimilated every 6 hours and details of the observations can be found in McCarty et al [27]. We chose to use reanalysis data as it gives a continuous record of meteorological parameters from 1981 to 2018. Results from MERRA-2 and MERRA were used for wind generated power output analysis in Staffell and Pfenninger [28] and Olauson and Bergkvist [29].

Wind speed for this study is obtained at a resolution of $0.5^\circ \times 0.625^\circ$ every 3 hours at an altitude of 50m which are then interpolated to 120m for approximate hub-height wind speed. Daily mean wind speed is calculated for each year and a decadal mean wind speed is also obtained for the four decades or parts therein; 1981:1990, 1991:2000, 2001:2010 and 2010: 2018. Decadal wind speed from MERRA-2 is calculated to test whether inter-decadal wind speed vary significantly. We use two statistical parameters: (1) number of times the wind speed is lower than the decadal mean wind speed for at least 5 consecutive day i.e., the frequency of loss of wind energy production; and (2) maximum number of consecutive days that the wind speed is lower than the decadal mean wind speed which indicates the maximum duration of the loss of wind energy output. These indices are presented as a high-level measure of the long-term variability of wind. These indices are not intended to be a planning criterion for generation planning as there are indeed more dimensions of variability including seasonality of wind generation, locational variability and short-term variability. All these attributes are discussed and analyzed in subsequent parts of the paper and a dispatch analysis. Nevertheless, a high-level appreciation of variability using Fig 1-3 is useful as noted below:

- Fig. 1 shows wind resource in m/s at 120-meter hub height averaged across 1981-2018 at 50 kmX50 km resolution. It sets a reference for the next set of analyses. 3 hourly wind speed from MERRA-2 are used to calculate daily mean wind speed which in turn is used in the calculation of average wind speed for 1981 to 2018. Letters x, y and z in the figure show wind rich areas. **Location of z depicts the most wind rich area as identified from 38 years mean.** Given the low resolution of data, this yields on average a relatively low 5.04 m/s across the 38-year period and all grid points. Resource quality varies significantly and west and southern parts of the country are wind resource-rich areas. As the figures for four decades indicate, there is no discernible changes in wind speed over the four decades.
- Fig. 2 shows number of low wind events that last for at least five consecutive days, i.e., **frequency** of wind related contingencies. Frequency of contingencies is calculated by counting the number of 5 consecutive days that the wind speed is lower than the daily mean wind speed of each decade. The daily mean wind speed is variable for each decade. In spite of the variability in the daily mean wind speed, the spatial distribution of the frequency contingency remains similar for each decade. This is very prominent with 80-120 such events over each of the four decades (i.e., ~8-12 such events per year on average) including the wind-rich western and southern coasts. As India aspires to have 75 GW of wind capacity by 2022, each of these five-day low wind event can potentially mean loss of several GWs of capacity for *at least* five days for 8-12 times per year;
- Fig. 3 shows the **duration** or **intensity** of the wind contingency or the maximum consecutive number of low wind periods that fall below decadal mean threshold. Intensity of contingencies is calculated by counting the maximum number of consecutive days that the wind speed is lower than the daily mean wind speed of each decade. Although the spatial distribution of the high intensity contingencies remains similar, the values of intensity contingency show variability among the decades. This can be phenomenally high at 60-120+ *consecutive* days in some areas including relatively good wind areas that in fact contain some of the larger wind farms in the country. This may in fact mean low wind energy production lasting for months. We also find that this is a trend that has remained quite prominent since 1981 for each of the decades since then.

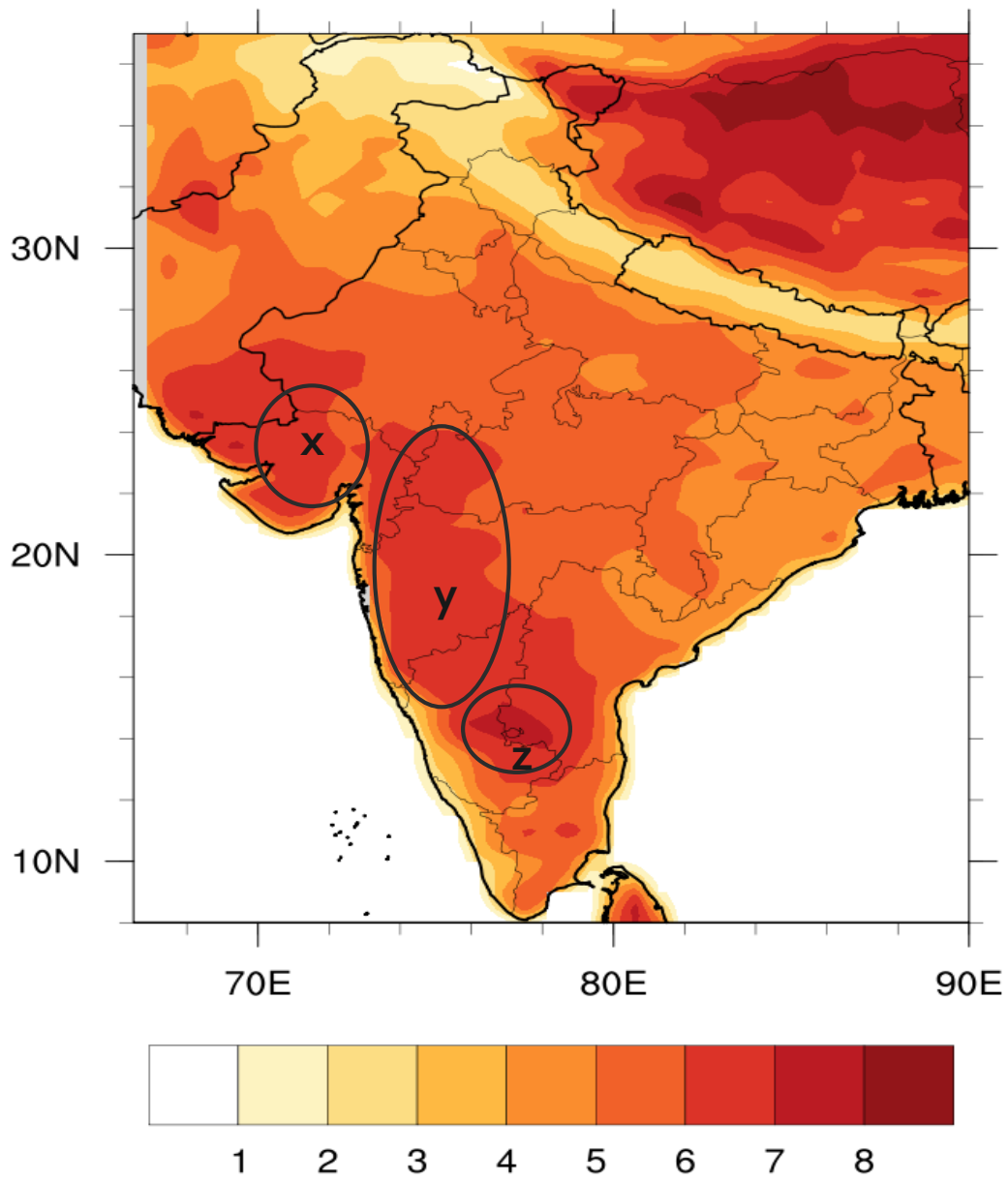


Fig 1| Daily mean wind speed (ms^{-1}) at 120m from 1981 to 2018 [X,Y,Z indicate wind-rich areas]

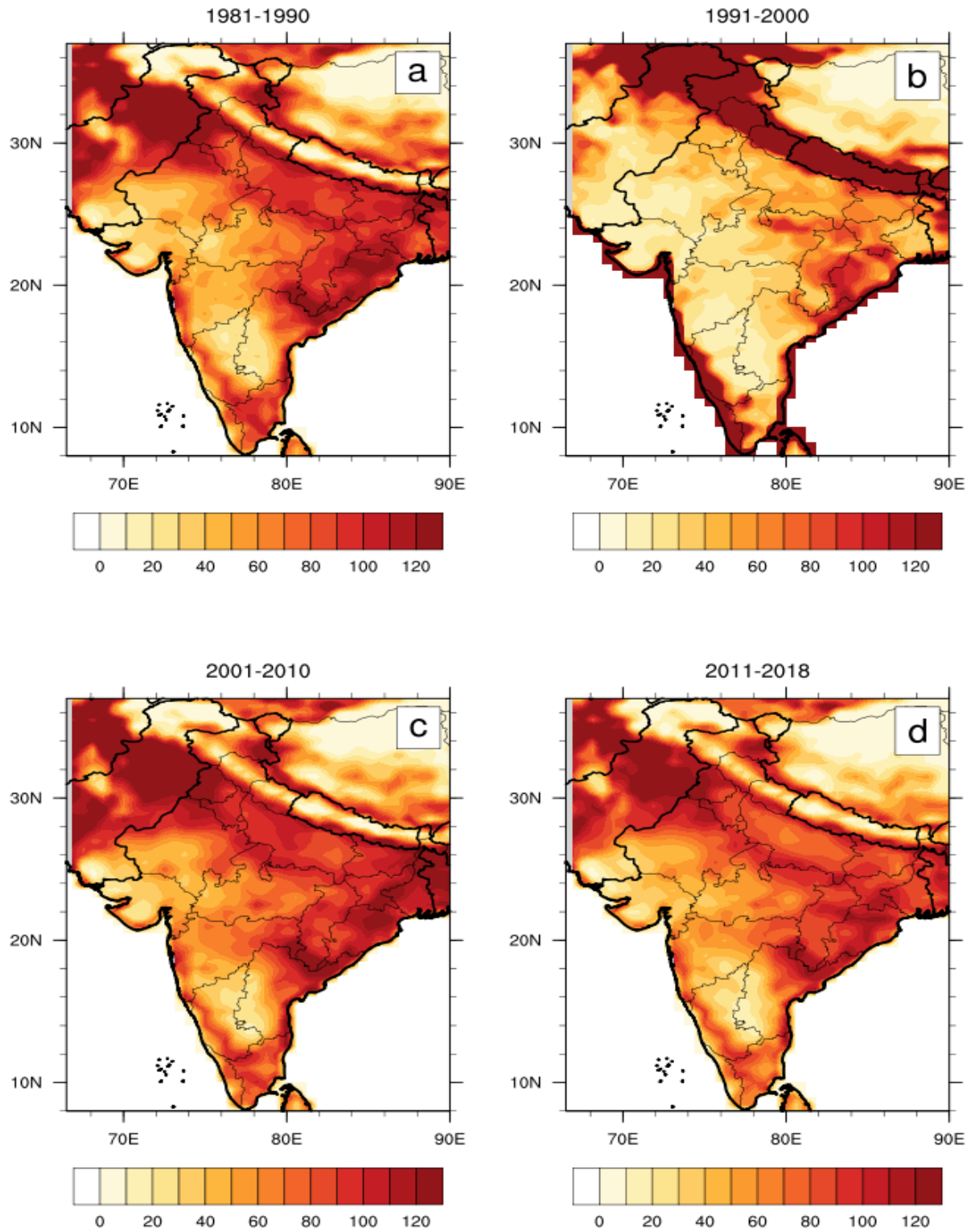


Fig 2| Frequency contingency for each decade (a) 1981:1990, (b) 1991:2000, (c) 2000:2010 and (d) 2011:2018.

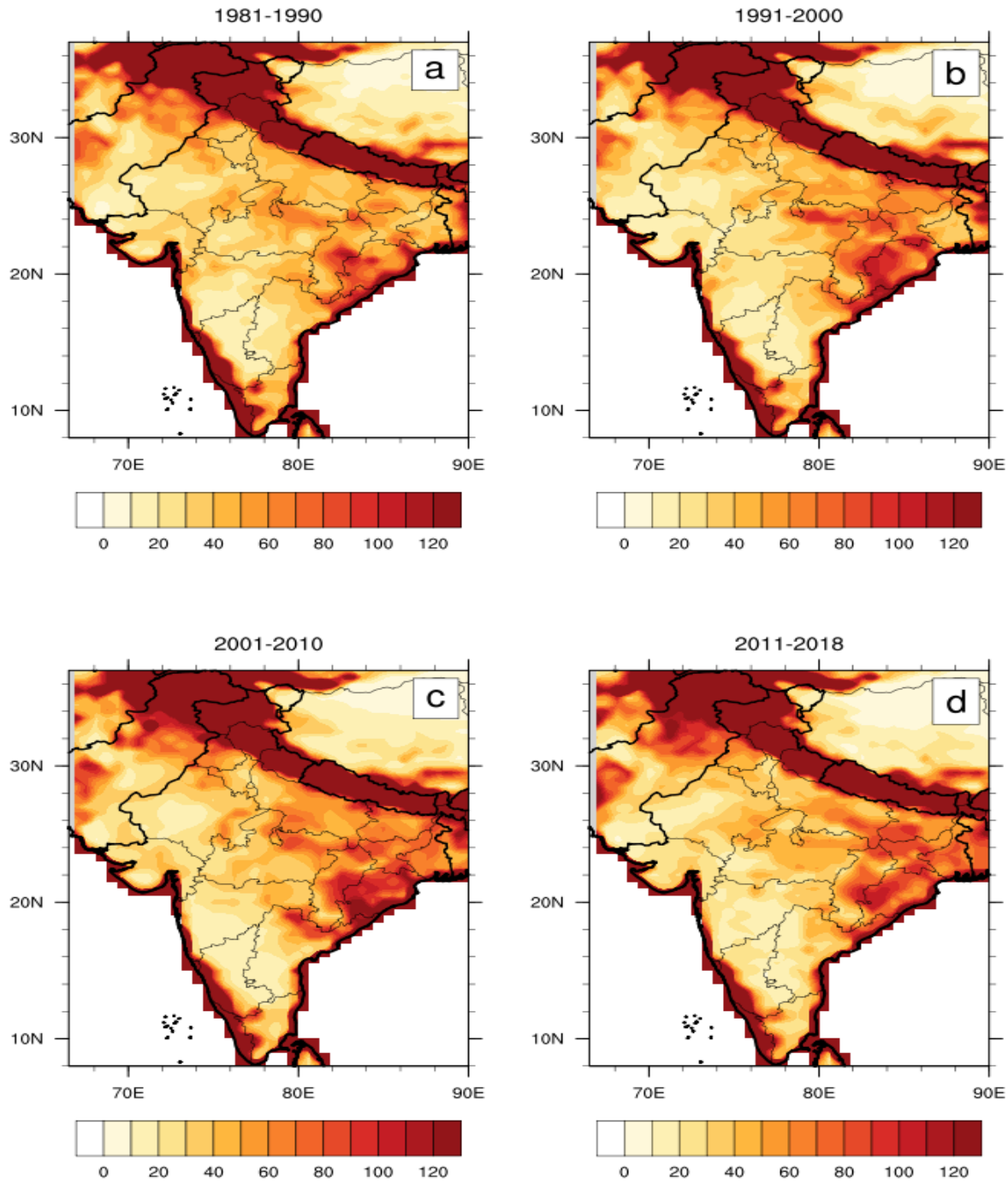


Fig 3| Duration/Intensity of contingency for each decade (a) 1981:1990, (b) 1991:2000, (c) 2000:2010 and (d) 2011:2018.

B. Challenge 2: As VRE penetration rises covering renewable contingencies may therefore require very significant back-up capacity and hence investments

Renewable contingencies, therefore, even after accounting for diversity of wind and solar over the entire state may be significantly larger and longer than a typical generator/line outage. There is of course an important distinction between a highly unpredictable failure of a generator vis-à-vis solar/wind output that are predictable with increasingly good accuracy of 90% or higher several hours, if not days, ahead. Nevertheless, there is an element of unpredictability as 50 Hertz, the German system operator, is beginning to experience in recent years with solar PV forecasts alone being out by several GWs on some days [30]. This capacity/energy shortfall or the size of the renewable contingency is the first significant challenge from a system operator perspective that is going to intensify over the years. A corollary of this observation is that resources need to be planned years

ahead to supplant for the gap including managing the transition well by keeping the existing fleet of flexible fuel-ready thermal generators that can pick up the generation during major wind/solar dips. Even with the utopian renewable system wherein we can build solar and wind farms at the best locations to diversify resources – we are looking at very significant back-up capacity (e.g., 50% of the VRE installed capacity) to manage the longer-term renewable contingencies alone. This is the second major challenge for the system that can be very expensive as we have demonstrated in a later part of this paper. This is perhaps also going to present significant logistical challenge for system operators to keep substantial back-up capacity in cold, warm or spinning state depending on the circumstances. Flexibility of demand will also be a critical resource that will need to be carefully developed as demand side management and demand response can to some extent counter the impact of wind/solar production dips. That said, it is important to note that longer term variability lasts for days and weeks and short-term demand response measures may not fully offset these risks.

Consider an example of the most wind-rich location (shown in Fig. 1). The mean wind speed for the decade in the location z, which is an area average of nine grid-points is 6.88 m/s. Three scenarios are created based on extreme (28% below mean), medium (12% below mean) and mean wind speed for the location z. We show in Fig. 4 and Fig. 5 the frequency (number of at least five consecutive day events) and depth or intensity (maximum number of consecutive days) of contingency. Both figures show the contingency parameters for a single decade:1991-2000:

- (a) 28% below mean of the area for the decade at 5 m/s cut-off (extreme contingency). This represents **extreme contingency events** with a severe drop in production of a wind farm in the range of 70%-90% (estimated using a standard wind power curve);
- (b) 12% below mean of the area for the decade at 6 m/s cut-off (**medium contingency**) which is indicative of a medium grade contingency with loss of production of 50%-60%; and
- (c) mean of the area for the decade at 6.88 m/s cut off (low-grade contingency) or a relatively **low-grade contingency** that may lead to 10%-30% loss in production.

The magnitude of frequency remains same for medium and low-grade contingencies while the spatial distribution remains the same for all three cases. We find that even in the best possible location:

- Extreme contingency events (below 5 m/s) can occur up to 80 times (consecutive five-day events over 1991-2000) some of which can last up to 30 days for a single event;
- Medium and low-grade contingencies can occur much more frequently (120 times) and last for up to 70 days.

A potential risk of losing up to 90% of the production for up to 30 days would be considered a very serious one in conventional planning. This will require serious planning to supplant for such outages that would require back-up capacity to be places with fuel stock to potentially carry for several weeks if not for more than 2 months (for low/medium grade contingencies). If the incumbent location were to develop a 1 GW wind farm (and Tamil Nadu in fact already has a 1.5 GW wind farm) – the amount of back-up capacity would more or less need to match the installed capacity.

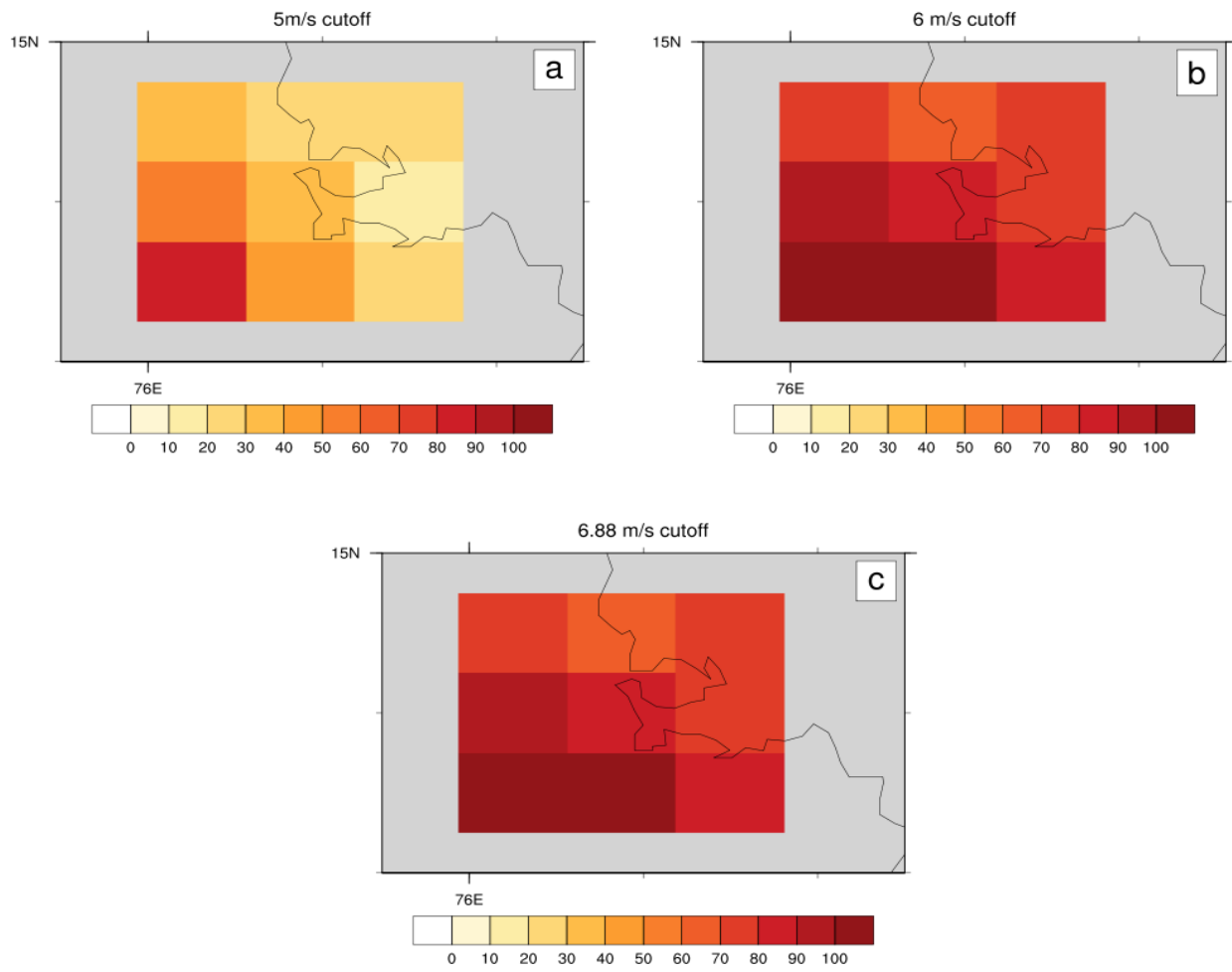


Fig 4| Frequency of contingency for the area 'z' (shown in Fig 1) for 1991:2000

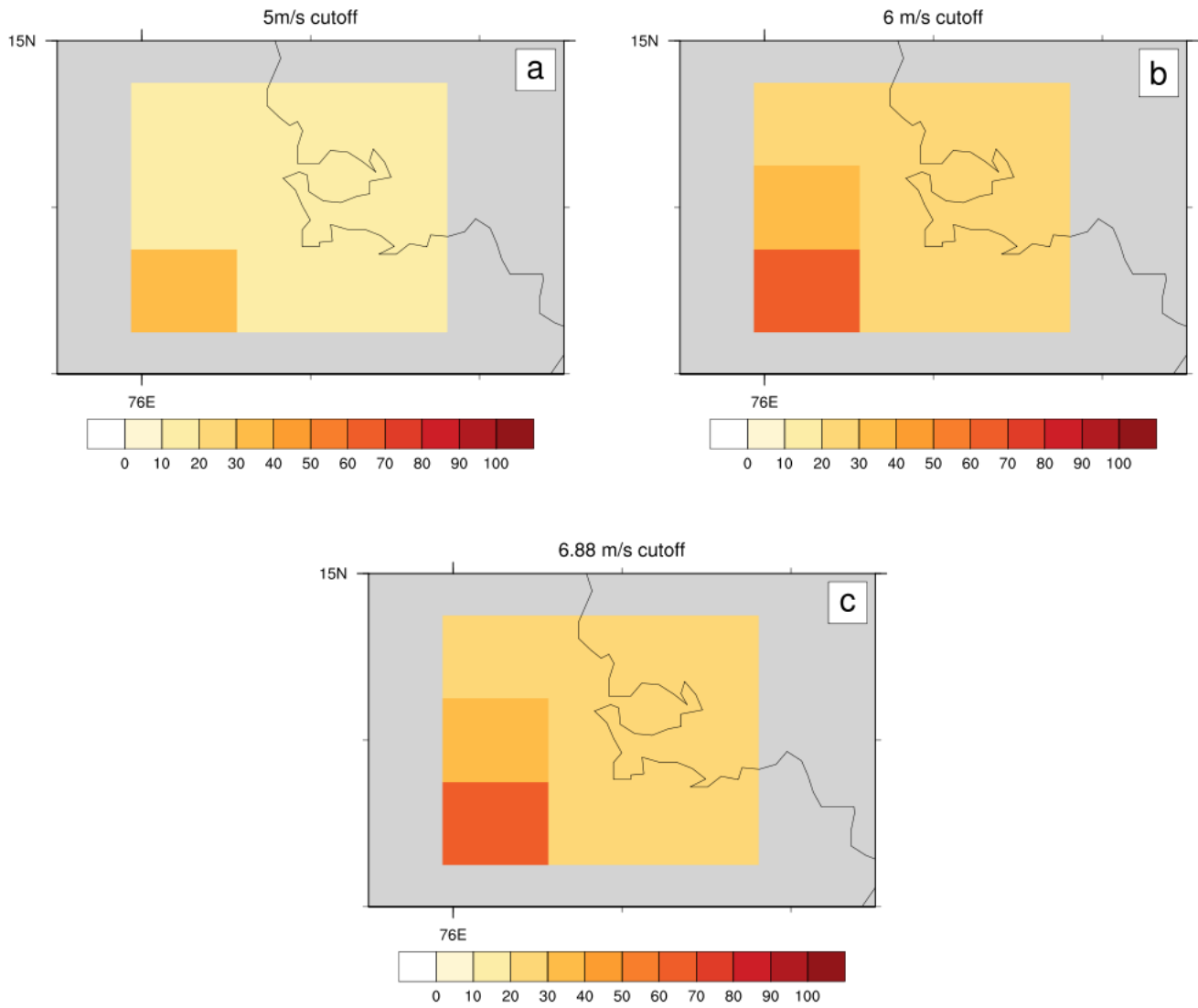


Fig 5| Intensity of contingency for the area 'z' (shown in Fig 1) for 1991:2000

Next, we look at two more attributes on how the (extreme) wind contingency events may unfold over the years (inter-annual) and within a year (intra-annual). Fig. 6 shows the maximum consecutive number of low wind days can vary anywhere between 8 (in 1994) to close to 14 days (in 2000) for area 'z' shown in Fig 1. The values are calculated with 5 m/s⁻ cut-off wind speed and averaged over the area for all grid points. Frequency and intensity of contingencies are lowest for 1994 and highest for 2000. Fig. 7 further reveals their occurrence within a year can be very unpredictable albeit the wind speed for 1994 and 2000 both clearly show these events are more likely to be clustered around Jan-Jun and Sep-Nov period. The key point is that these events are highly unpredictable. Even for the potentially best wind farm location in the country a serious low wind event (below 5 m/s) can last for up to 14 days with very little production and may occur for up to 6 times in a year.

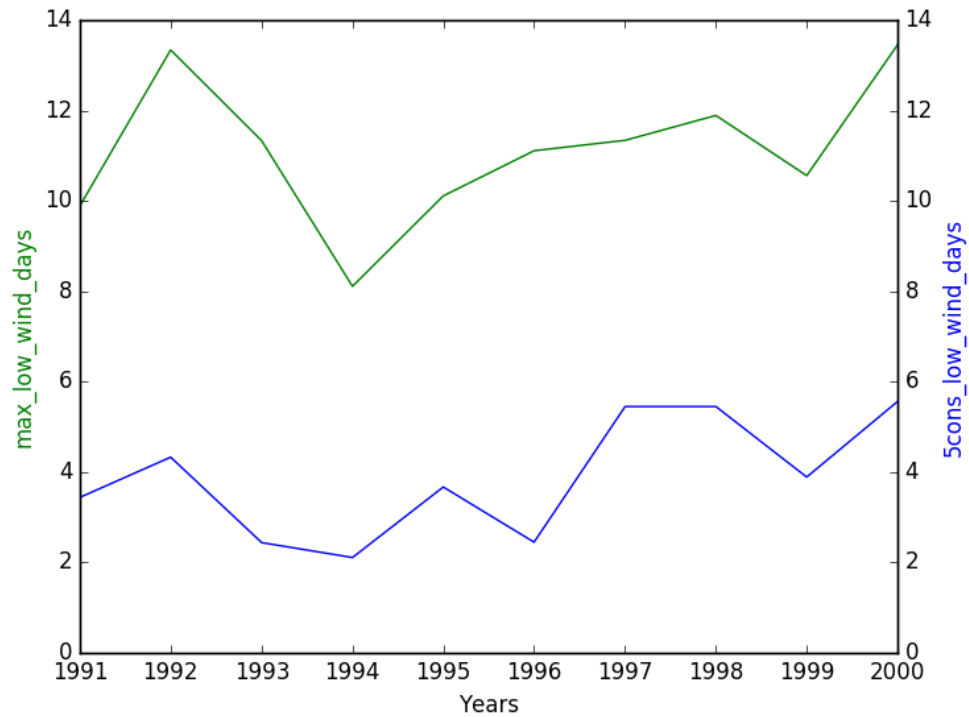


Fig 6| Timeseries of frequency of contingency (blue) and intensity of contingency (green) from 1991 to 2000 for area 'z'

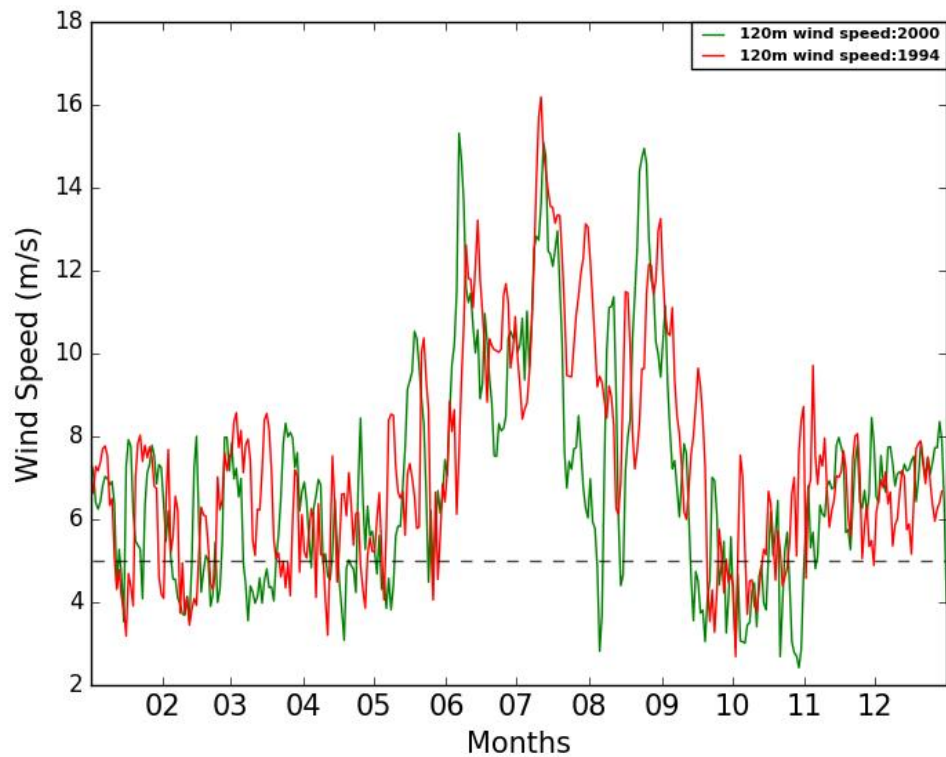


Fig 7| Timeseries of wind speed at 120m for 1994 (red) which has the lowest and 2000 (green) which has the highest frequency and intensity contingencies for the area 'z'

Further, we extend these conclusions on severity of the contingency events to the entire state of Tamil Nadu. As noted before, this state is gearing to take its stock of VRE capacity to 21 GW by 2022. This will require a very significant level of increase in spinning reserve allocation, associated dispatch adjustments, demand response, investments in sophisticated controls and back-

up that is fuel-ready throughout the year, and import from neighboring states to provide this capacity through enhanced interconnection with the state. We have presented a case study in section III using a dispatch analysis using a dispatch model even for a much lower 5 GW wind capacity addition and shows the cost imposed by renewable contingency can be quite significant. Hard measures such as back-up thermal capacity is likely to increase as the renewable capacity addition increases from 5 GW to 21 GW. This is a real challenge as we move in the domain of high VRE systems. These investments and costs have not been discussed in the renewable energy literature or as far as we are aware feature in any “VRE integration cost”. Power system reliability centric investments are notoriously difficult to recover through a market-based system even for the more regular (n-1) contingencies. It is difficult to imagine that private investment in the order of billions of dollars in Tamil Nadu will eventuate to cover for renewable energy contingencies. Such investments are intrinsically highly risky. There are also difficult market design issues e.g., high capacity payments or to allow for super-high price caps on spot energy prices to recover such investments even if they were to be built.

C. Challenge 3: There is very little resource data analysis conducted to date on contingency, let alone develop methodology and criteria to incorporate them in power systems planning models

Although climate model data has been around for a long time and the numerical analysis using this data is not difficult to do – there is surprisingly little literature on inter-annual variability and contingency analysis conducted for power systems. We should draw some parallels to the problems faced by hydro-dominated systems wherein contingencies around dry year risk is well established [31]. The costs associated with managing such risks has been significant – Brazil being the case in point, but of course those systems have in one form or another learnt to cope with it through diversification of resources. Interestingly, VRE has been put forward as part of diversification strategies for hydro dominated system although the inherent vulnerability of VRE itself has not been discussed much less analyzed systematically. The experience of hydro-dominated systems is useful to put in place improved data, planning and operation methodology and technologies to do the same for VRE-dominated counterparts. This brings us to the third challenge on planning for VRE-dominated systems because the power system community is yet to embrace even the concept of renewable contingencies let alone translate it into planning criterion. Once renewable contingency is embedded in the planning framework, it needs to be implemented with renewable and power system data, and methodology development to assess the risks faced by system and associated costs.

It should be noted that the scale and scope for the latter is vastly greater than hydro-dominated and the nature of the contingency is more severe in several respects, namely: (i) the quantum may become far greater, e.g., India is aiming to have 175 GW of VRE (including 75 GW of wind) by 2022 and potentially 275 GW by 2027; (ii) the contingency events may be more frequent; and (iii) they may also occur at a faster pace. A dry year is not easy to predict either, but it unfolds much more gradually over a course of months and weeks compared to a low wind/solar events. The latter events leave little room for preparation and presents great logistical challenge to have significant generation capacity to be fuel and grid ready to roll into action – at least part of it being perpetually in spinning state. It may also be worthwhile pointing out that both hydro and VRE are affected by climate change [32-33]. In countries like India that relies heavily on monsoon for both hydro, solar and wind energy to pick up to get through the summer months, increased uncertainties including significant delays in onset of monsoon may mean both of these resources are not available for days and weeks. As Tamil Nadu, which historically had its exposure to hydro risks from delayed monsoon, also became reliant on wind energy, the composite effect has been severe as our previous analysis in 2012 [19-20] had demonstrated. The expected unserved energy as a share of demand was projected to double from 4.95% in the base plan for 2017 to over 10% if 5 GW of baseload coal/gas/nuclear were to be replaced with wind and solar. Significant outages in 2009-11 did see addition of baseload capacity that has since reduced the impact of wind variability [34], but beyond reaction to major outages, planning is yet to recognize the role of renewable contingencies.

D. Challenge 4: Renewable contingencies can lead to catastrophic power system events

The fourth and the final challenge related to renewable contingencies is associated with catastrophic events that may result from extreme weather events such as a storm that may knock out distribution lines (or even transmission towers) and lead to shutting down a major part of the wind turbines. These generation/T&D outages may cascade into other problems with more generator/lines tripping leading to potentially a catastrophic power system event with part/all of the grid collapsing. Grid failures have of course occurred in the past in all parts of the world even without renewables. Absent sufficient planning and good operational practices in place however, renewable contingencies increase the vulnerability of the system all other things being equal. Consider the case of South Australia that did not have a grid failure for several decades before it had a significant share of wind. However, it had *three* such events connected to wind production over a period of 18 months. Power systems with high share of VRE is less resilient although this statement must be qualified to say that the degree of resilience would vary greatly depending on the nature of the transmission system, power system controls in place and operator capacity and discipline. It is also true that with better planning and appropriate investments – resilience of these systems can be enhanced. The 50Hertz [30] experience not only showed the challenges around renewable contingencies, but also demonstrated that systems can continue without necessarily diminishing reliability. The introduction of the largest battery storage system in South Australia since December 2017 has also contained the risk exposure of the system and averted potential catastrophic events. Although we do not

present any analysis here, extreme wind speed events that will also render wind production potentially over a large area to drop sharply over several decades also need to be carefully analyzed to understand the nature of system security risks.

III. IMPACT OF RENEWABLE CONTINGENCY

In this section, we bring together the discussions in the preceding section to present a formal analysis of the impact of renewable contingency. As we have alluded to – the impact of wind generation dip persisting over days and weeks can potentially present a significant challenge. A part of this risk can be offset depending on availability of back-up capacity that may be in the form of existing thermal generation, the ability to operate any available hydro capacity differently to preserve hydro energy and demand response. We will continue with the example for the state of Tamil Nadu for 2022 for a targeted addition of 5 GW of wind (which will still leave the total wind capacity at 14 GW well below the policy target of 21 GW). The analysis uses an hourly dispatch optimization model for 2022 that considers co-optimization of spinning reserve. Spinning reserve is needed in the system to guard against sudden outage of thermal generation as well as short and long-term dips in solar/wind production. Absent sufficient spinning reserve provided by generators, there will be outages that has a high cost. **Put differently, we do assume all possible options that can counter the risk of outages from supply side flexibility with thermal and hydro generation providing spinning reserve, and demand response.** There would however be additional cost imposed on the system to provide such reserve especially as the requirement of such services would grow disproportionately. As wind variability in Tamil Nadu is already a significant issue that will become even more prominent with wind capacity increasing to 14 GW – we need to pay special attention to the cost of spinning reserve. There is currently no spot market for spinning reserve or even an appropriate “merit order” curve for spinning reserve provision that reflects increasing cost of providing spinning reserve (SR) as the requirement for it increases. In the discussion that follows:

1. We have first shown how low SR condition is indirectly reflected in energy spot prices using data from the Indian Energy Exchange;
2. We have calculated SR requirement for Tamil Nadu using forced outage probability of thermal generation. Additional SR required for different grades of wind contingency is calculated and added to the requirement for the thermal system;
3. Finally, we have used the dispatch model to assess the cost of spinning reserve. As already noted, this is the major component of the additional cost imposed to counter long term variability; and
4. In addition, as long-term variability of wind would also require back-up generation to not only provide SR but also meet part of the lost wind generation, there would also be fuel costs incurred.

Let us first look at the characteristics of the energy spot market that in itself implicitly reflects the high cost of energy spot prices during low SR conditions. The state which is part of zone ‘S2’ of the Indian Energy Exchange (IEX) has experienced considerable price volatility over the last 6 years as shown in Fig 8. A significant part of it has been shown to be associated with drop in wind speed Jan-Jun and Sep-Nov (Fig 7) especially during the pre-monsoon months of April/May as discussed in [19]. Prices above INR 5000/MWh (or USD 71/MWh) which is considered high (relative to an average of Rs 3000/MWh) account for 38% of the time over the last 6 years and very high INR 10,000/MWh (\$142/MWh) for 5.2% of the time. High price events are typically associated with spinning reserve in the state dipping below 500 MW. This foreshadows the high cost of spinning reserve obtained using the dispatch model in step-3 below.

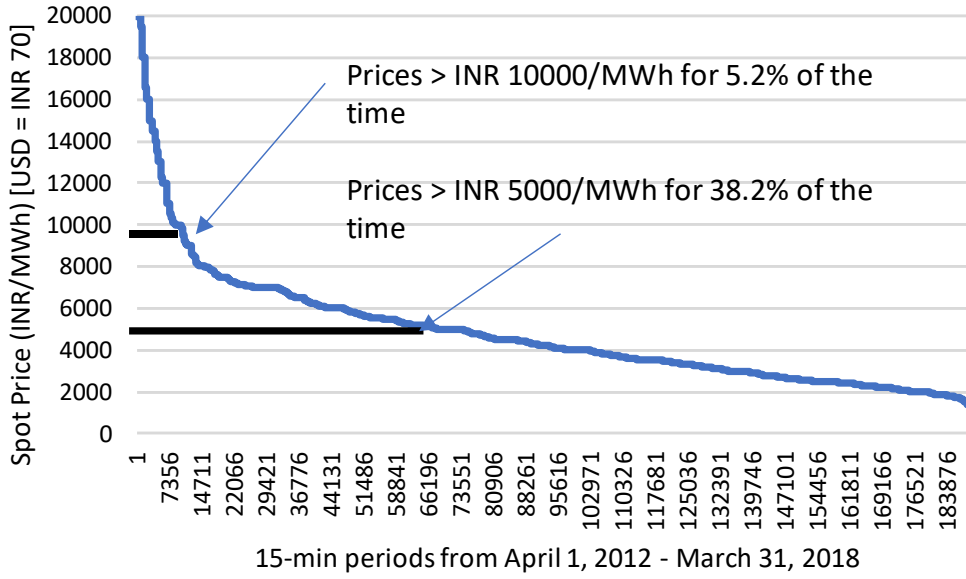


Fig 8| Tamil Nadu 15-minute spot prices over 1 Apr'12-31 Mar'18
[Source: Indian Energy Exchange, <http://www.iexindia.com>]

The following steps are used to assess the cost impact.

Step-1 - Reliability of the thermal system: Probability of outage $P(x)$ of x MW can be expressed by the following relationship [36] that can be approximated from the capacity outage table by estimating parameters a and M :

$$P(x) = ae^{-x/M}$$

Step-2- Spinning reserve implication: Spinning reserve for the thermal system can be expressed using the estimated parameters a , M and the required level of Loss of Load Probability (LOLP) [36] which is dominated by the forced outage of thermal generators:

$$SR_{thermal} \geq \text{Max}[\{M[\ln(a) - \ln(LOLP)]\}, K]$$

Where, LOLP is the reliability standard for the system and K is the largest online generator (assumed to be 1000 MW for 2022). $SR_{thermal}$ is calculated for Tamil Nadu system as 1123 MW for a LOLP of 0.2% following the CEA standard [34].

SR will also be needed to cover for variability in wind/solar $\varphi|_c$ where φ represents the total variability of VRE under renewable contingency c .

$$SR_{VRE|c} \geq \sum_{g \in VRE} \varphi_g|_c$$

Selection of contingency would depend on the reliability standard sought for the system, e.g., cover for some or all of low, medium and extreme variations below mean wind speed as discussed in the preceding section. $SR_{VRE|c}$ for 2022 with 5 GW of additional wind scenario is calculated as follows: (a) Low-grade contingency (mean wind speed below 6.88 m/s): 560 MW; (b) Medium-grade contingency (below 6.0m/s): 670 MW; and (c) Extreme contingency (below 5.0 m/s): 978 MW.

Total SR requirement for the system is given by:

$$SR_{total} = SR_{thermal} + SR_{VRE|c}$$

Total SR requirements ranges from 1863-2101 MW for 2022 which is obtained by directly adding the thermal and VRE related requirement. This may be an overestimate of the SR requirements but reflects well the total back-up capacity ideally needed for the state to cover both forms of contingency.

Step-3– Cost of spinning reserve: High energy spot prices are associated with low spinning reserve conditions in the system. We have used an energy and ancillary services dispatch co-optimization model for Tamil Nadu [19] for a typical week to calculate an SR supply curve shown in Fig.9. The model also allows top 5% of the demand to be price responsive and the costs for demand response are imputed from the energy spot prices shown in Fig 8.

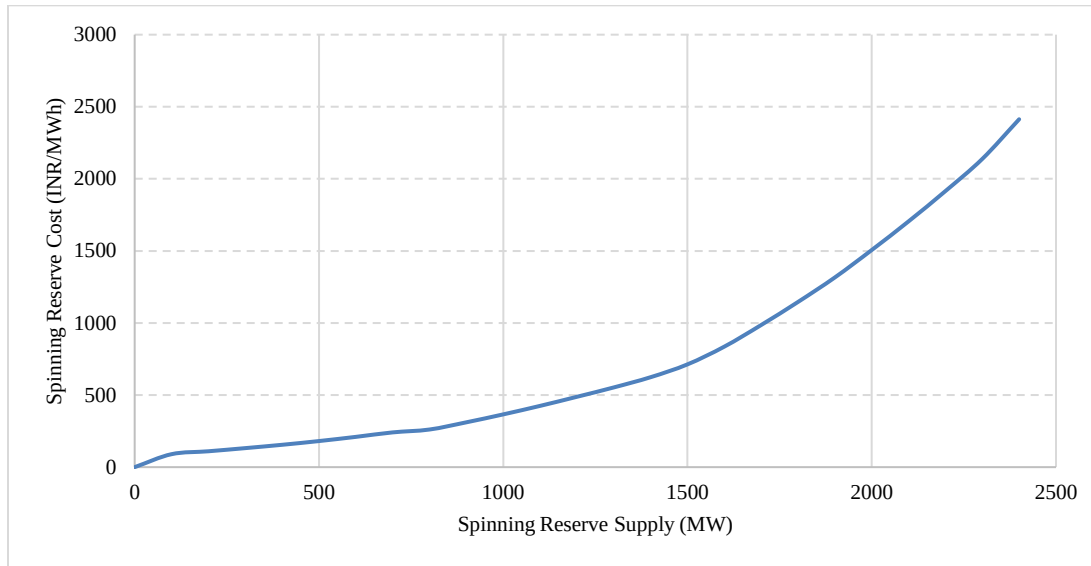


Fig 9|Spining reserve supply curve for Tamil Nadu in 2022

SR costs largely reflect opportunity cost of generation especially as generation from cheaper hydro/coal/lignite needs to be withheld to meet generation from more expensive part of the coal or gas/diesel units or interstate import. Spinning reserve marginal costs rise sharply beyond the first 500 MW. **The high end of the supply curve is consistent with the price duration curve that shows energy prices rising sharply as demand-supply conditions tighten.** This is also reflected in the planning authority's (CEA) projection that showed small negative reserve of (-)0.2% [37] for most months in 2018/19. In reality, securing spinning reserve of more than 700-800 MW for a single state will be indeed a very expensive proposition. In other words, notwithstanding the high cost of SR, we have in fact overestimated the ability of the system to provide more than 2,000 MW of SR. Nevertheless, we use the supply curve (Fig.9) to assess the additional cost burden of wind capacity addition to cover for different contingency condition, rather than assume that the system will face rolling outages with much higher costs associated with it.

Step-4- Energy cost impact of low wind: Additional energy costs incurred because of extended periods of low wind has been approximated using a simple average cost measure of INR 1300/MWh to reflect the fact that a dip in wind MWh will be supplanted by spare coal/gas capacity or inter-state import.

Table-1 summarizes the renewable energy contingency cost impact of 5 GW additional addition in Tamil Nadu by 2022 in terms of spinning reserve and energy costs. The more significant part of the cost arises from ensuring there is back-up capacity in place to provide the necessary spinning reserve to absorb the variability. High SR costs, especially for the extreme contingency, is an artefact of limited SR availability in the Indian states with marginal costs increasing rapidly as the requirement goes above 500 MW. Energy costs can also be significant for medium grade contingency that can lead to ~70% loss of wind energy on average for 40 days in a typical year. Overall, RE contingency costs can range from INR 1984-5358 million (USD 27-76 million) for 2022. This represents a 0.5%-1.5% increase in system cost with an average increment of Rs 48/MWh (\$0.7/MWh). While the benefits of low-cost clean energy development in a coal dominated system can far outweigh these costs, we note that the traditional RE integration costs do not currently consider these costs arising from sustained wind energy variability.

TABLE 1: RE contingency cost impact (in Rs million*) of 5 GW of wind addition by 2022

RE contingency	SR cost	Energy Cost	Total cost
Low contingency	1,785	109	1,894
Medium contingency	2,540	390	2,930
Extreme contingency	4,812	546	5,358

* All costs in INR million (assuming 1 USD = INR 70) for 2022.

IV. CONCLUDING REMARKS

All four power system challenges discussed above can be addressed as long as these are recognized, accepted and analyzed in a scientific and technology neutral way. The size of the contingency, in itself, is not a problem as long as there are measures to manage it and it is economic to deploy these. Building massive peaking power plant is certainly not the only solution and almost certainly not the cheapest one. It is possible to extract significant flexibility in the existing capacity. There are many options, e.g. interconnect systems, deploy storage, encourage demand response and innovative weather-dependent pricing systems to encourage participation, and enhance solar and wind technologies themselves for them to provide ancillary services, to name a few. However, it is important to recognize there are trade-offs as variability imposes costs and not all of these costs are hitherto integrated in planning and operation.

Renewable contingencies also present us a strong reason to systematically analyze the trade-offs involved in increasing the level of VRE penetration. As developing countries are rapidly adopting higher and higher targets, it would appear that more the better is the norm. Even if the renewable contingencies are surfacing in reality, they are being patched up through ad-hoc investments and rules including limiting the VRE generation only up to certain share of load and rejecting the rest, or worse leading to load shed and grid failures. The innovations around VRE including the massive cost reduction is probably the best development for the power system over the last several decades. The part of the energy community that truly cares for it should be very objective and scientific about defining how it is adopted for it to be put to the best use – renewable contingencies to date is a missing element that should be recognized to meet this end.

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