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Empirical Analysis of the Variability of Wind Generation in India: Implications for Grid Integration

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Contents

Abstract

We analyze variability in load and wind generation in India to assess its implications for grid integration of large scale wind projects using actual wind generation and load data from two states in India, Karnataka and Tamil Nadu. We compare the largest variations in load and net load (load –wind, i.e., load after integrating wind) that the generation fleet has to meet. In Tamil Nadu, where wind capacity is about 53% of the peak demand, we find that the additional variation added due to wind over the current variation in load is modest; if wind penetration reaches 15% and 30% by energy, the additional hourly variation is less than 0.5% and 4.5% of the peak demand respectively for 99% of the time. For wind penetration of 15% by energy, Tamil Nadu system is found to be capable of meeting the additional ramping requirement for 98.8% of the time. Potential higher uncertainty in net load compared to load is found to have limited impact on ramping capability requirements of the system if coal plants can me ramped down to 50% of their capacity. Load and wind aggregation in Tamil Nadu and Karnataka is found to lower the variation by at least 20% indicating the benefits geographic diversification. These findings suggest modest additional flexible capacity requirements and costs for absorbing variation in wind power and indicate that the potential capacity support (if wind does not generate enough during peak periods) may be the issue that has more bearing on the economics of integrating wind.

Executive Summary

India has about 20GW of installed wind capacity which is the fifth largest in the world (GWEC 2014). Integration of large-scale wind energy into the power system may introduce new challenges to system planning and operations. Operational integration challenges primarily include issues such as whether the system has enough flexible generation capacity to follow the net system load that the rest of the generation plants need to meet after wind generation is absorbed in the system. System planning challenges primarily include issues such as whether the system has enough capacity meet the net system peak demand considering the contributions by wind. While several studies have assessed the impacts of wind integration in the US and Europe, very few have assessed them in the Indian context (see for example, Soonee, Saxena and Rathour 2014; Chattopadhyay and Chattopadhyay 2012; George and Banerjee 2009; see Hummon et. al 2014 for analysis of variability of solar generation). In this study, we undertake empirical assessment of the variation in wind and load under different wind penetration scenarios and assess the incremental ramping requirements due to wind. The analysis focuses on the system operation issues and not system planning issues such as how much capacity support is needed, which we plan to cover in a separate paper.

Variability is the difference in the wind generation or load in two consecutive time periods. For assessing implications for integration, it is useful to estimate the additional variability added by wind to the existing variability in load. This can be achieved by comparing the variability in the system load with and without wind generation. We focus on variability in timeframes from 5-minute to 1-hour which determine the load following requirements of the power system. We did not cover within minute variability because studies have shown that the cost of providing regulation services (managing within minute variations) is a relatively minor component of the wind integration cost (B. K. Parsons et al. 2006); on several hours timeframe, thermal plants have enough time to ramp-up and down.

The analysis is conducted using the actual 5-minute wind generation and load data from two states in India viz. Karnataka or KA (peak load ~8GW) and Tamil Nadu or TN (peak load ~11GW) for the calendar year 2011 (>100,000 observations in each state). The data was shared with us by the National Load Dispatch Center of India. Tamil Nadu has the largest installed wind capacity in India (~6GW in 2011); the two states together cover over 50% of the wind capacity in the country in 2011. Note that we have data on wind generation integrated in the system and do not have data on wind curtailment. We believe that given the anecdotal evidence that wind curtailment is not likely to be significant given severe power shortages during peak wind periods; we argue that not having data on wind curtailment will not qualitatively change our results. However, having precise estimates about wind curtailment will increase the robustness of our results. Although we have data on load curtailment, these are only estimates by the utility. Hence we conduct our analysis using load met as well as estimates of total load (unrestricted demand).

We analyze the additional ramping capability requirements for integrating wind by assessing (1) whether the largest changes (variability) in load that the system has to meet increase after integrating wind generation, (2) whether these changes occur more often during times when the ramping capability is most constrained, (3) whether these changes are less predictable than those without integrating wind, leading to additional flexibility requirements, and (4) whether the magnitude of the changes reduces if load and wind from multiple states are aggregated.

1. Assessment of the Increase in Variability that the System Has to Meet after Integrating Wind

We estimate the variability in wind, load, and net-load (load minus wind generation) for 5 min, 15 min and 1-hr intervals. Net load is what the conventional generators like coal, gas, and hydro have to meet after wind generation has been integrated into the grid. Therefore, the incremental variability added by wind is the difference between load variability with net-load variability. We primarily use the 99th percentile value as the measure of variability. For example, if we find that the 99th percentile of the hourly variation in net load is 100 MW, it means that the variation in net load was 100 MW or lower for 99% of the time. This indicates that a ramping capability of 100 MW per hour may be sufficient. We undertake this analysis for three scenarios viz. current wind penetration (~10% by energy in TN; ~6GW installed capacity), 15% wind penetration by energy (~9GW installed capacity in TN), and 30% wind penetration by energy (~18GW installed capacity in TN).

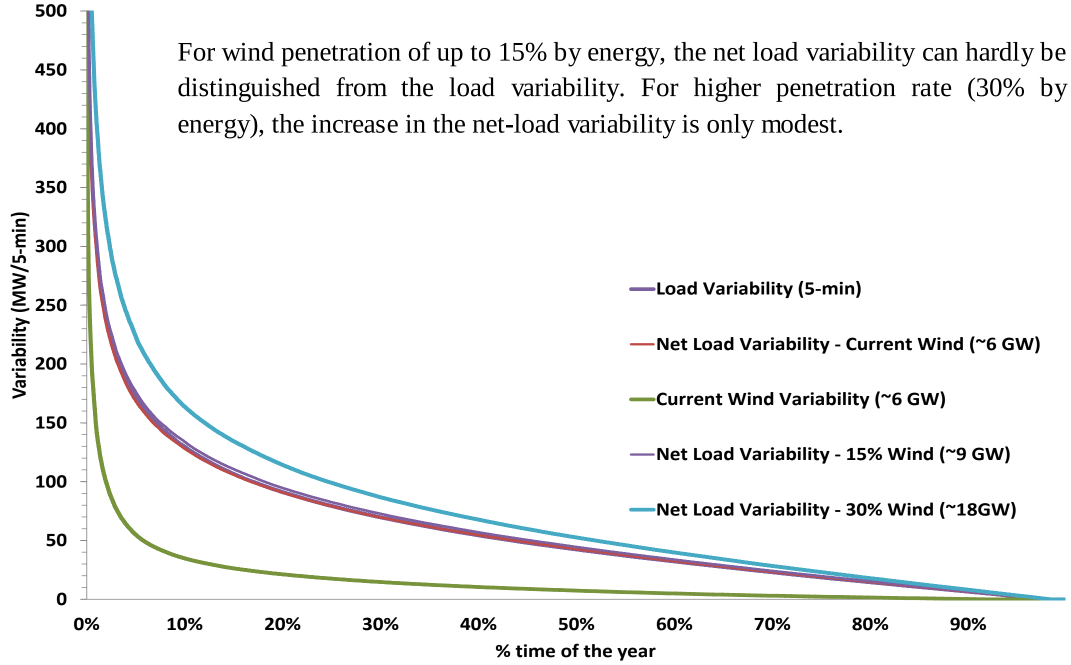

Figure ES-1: 5-min Load, Wind and Net Load Variability in Tamil Nadu (2011)

Figure ES-1 shows 5-min variability of current wind generation and load for Tamil Nadu; we have sorted the variability, i.e. changes over two consecutive 5-min intervals, from the highest to the lowest values. Existing variation in demand is significantly higher than that of wind. The figure also shows the 5-min net load variability for the current penetration, 15% penetration (by energy), and a 30% penetration (by energy). The net load variation increases noticeably only for 30% penetration by energy scenario and not for the other two scenarios.

Figure ES-2 shows the 99th percentile of the 5 min, 15 min, and hourly variability in Tamil Nadu load and net load (load minus wind) for the current wind penetration, 15% penetration, and 30% penetration (by energy). The variability in load, i.e. change in load over two consecutive periods for these intervals is lower than 2.7%, 3.8%, and 7.4% respectively of the peak demand for 99% of the time. For the same intervals, the variability in net load for current wind penetration is lower than 2.6%, 3.9%, and 7.4%, for 99% of the time indicating that the incremental variability added by wind is minor. For 15% and 30% wind penetration cases, the hourly net load variability is lower than 7.8% and 11.9% of the peak demand for 99% of the time indicating that even for aggressive wind penetration scenarios, the incremental variability added due to wind is only moderate.

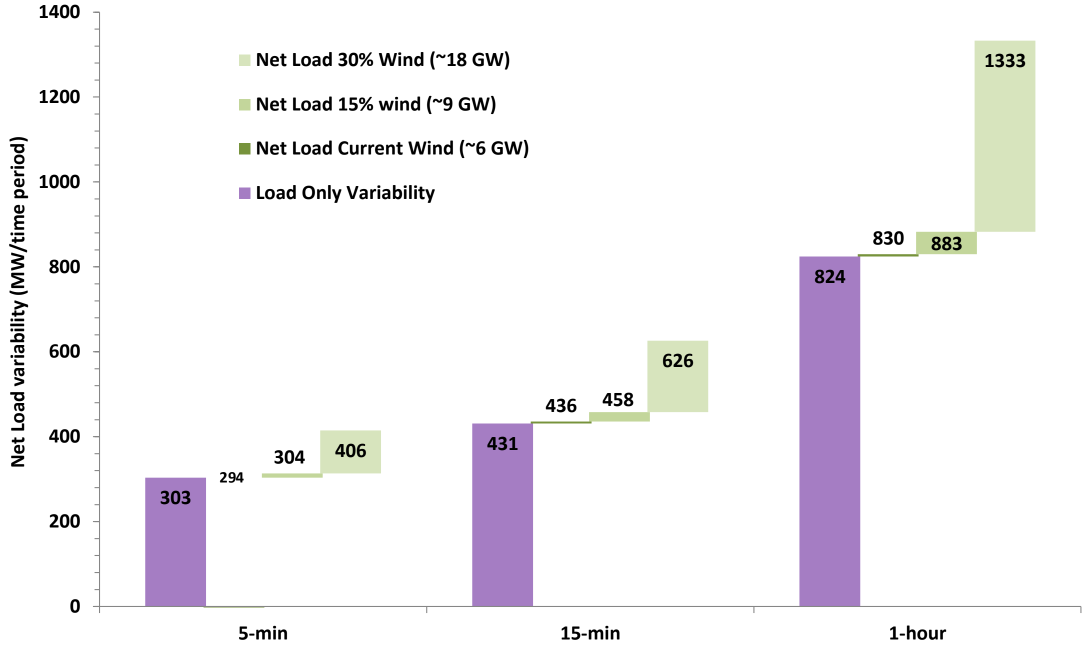

Figure ES-2: 99th percentile of the 5-min, 15-min and 1-hour variability in load and net load in Tamil Nadu (2011)

Wind generation in India is highly seasonal; it peaks during the monsoon (June-September). Wind generation and load (restricted demand) have a high linear correlation factor (0.75) during wind season (June-September); while it is low (0.1) during non-wind season (December-March). Moreover, the incremental net load variability during wind season is actually lower than that during the non-wind season.

2. Variability and Ramping Capability

Even though largest net load variation does not appear to be significantly higher than that already existing in the load itself, it could occur when ramping capacity is most constrained hence requiring additional ramping capacity. Ramp-up and ramp-down capacity is most constrained during low demand periods when any changes in load requirements are to be accommodated by relatively inflexible coal generation. Note that a situation where all generators are operating at full capacity and additional load needs to be met due to drop in wind generation is a system planning issue of lack of adequate capacity to meet demand and not an operations issue related to ramp capacity.

We estimate ramping capacity of the system based on the typical ramp rate constraints of generators and whether these generators are online given the load, for every 15 minute interval. We compare the number of instances where ramping capacity is not sufficient to meet the ramping requirement given the variation load and net load (under different scenarios of wind penetration). Figure ES-3 shows the ramping requirement (net load variability) on X-axis and system ramping capacity (Y-axis) in Tamil Nadu for the 15% wind penetration case (~8680 MW installed capacity). Each point in the chart denotes the ramping requirement (X-axis) and ramping capacity (Y-axis) for a 15-min interval in 2011 (~34,500 observations). The figure also shows a 45 degree straight line; along that line, the ramping capability equals the ramping requirement. For 15% wind penetration (~8680 MW installed capacity), system ramping requirement is higher than the ramping capability for 1.2% of the time (428 instances out of ~34,500). In comparison, if we consider variation in load, the system ramping requirement is higher than ramping capability for 1.1% of the time (376 instances), which shows that during these periods, generators were ramping more than the constraints we have assumed for this analysis.

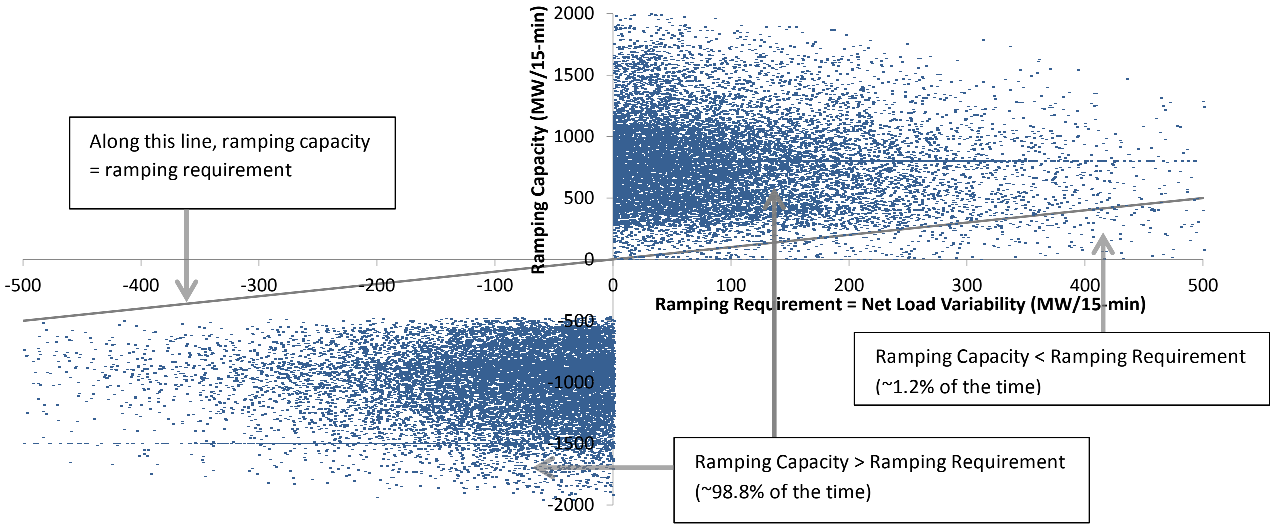

Figure ES-3: Ramping requirement & ramping capacity in TN for 15-min interval for 15% wind penetration scenario

3. Impact of Potentially Less Predictable Wind Variation on System's Ramping Capability

Typically, load variation is highly predictable, more so than wind. Hence, it is likely that the net load variation (after integrating wind) is less predictable than variation in load. Sufficient generation capacity needs to be committed and online (spinning) to meet ramp requirements. If ramp requirements are known in advance, appropriate level of units can be committed. Consider an extreme example where ramp requirements cannot be predicated at all, in such situation most generation units need to be committed and online. Alternatively, the system needs to have fast start units such as gas combustion turbines as they may be more cost effective than keeping all generation units online most of the time. Hence, higher predictability of variation will avoid costs associated with extra units being committed.

A preliminary analysis of the TN system suggests that because of the widespread shortage in the state, all thermal and gas units (including central allocations and IPPs) that were available on a given day were generating close to full load most of the time (98.9% of the time) i.e. all available thermal units were committed most of the time. Moreover, up to 25% wind penetration by energy (installed capacity ~15000MW), minimum stable generation of thermal plants is lower than net load most of the year. This means that even if wind generation is completely random, all thermal units can remain committed and provide the necessary ramping-up support. This will keep the integration costs limited to the loss of heat rate of thermal plants (typically 5-10% of the variable cost of thermal plants) and some wind curtailment (about 10%). However, with state of the art wind forecasting techniques, the forecast error can be significantly reduced over several hours ahead timeframe; this can help optimizing the unit commitments and minimizing wind curtailment even at high penetration rates. Moreover, if generation resources are shared across multiple states (through a real time energy or an ancillary services market), the system flexibility would improve and the need for wind curtailment can go down.

Informal conversations with the Indian system operators suggest that in 2013-14 wind season, sizable wind generation in Tamil Nadu had to be curtailed; although curtailment data is not available. In 2011, wind curtailment was only minor primarily because of more flexible deviation settlement mechanism (frequency based de-facto real-time market). It is expected that once the southern grid is fully integrated with the national grid, the deviation settlement will have more liquidity and the need for wind curtailment would go down significantly.

4. Effect of Load and Wind Aggregation

Note that the variability analysis conducted for various wind penetration rates in this study establishes the upper bound of variability, since it assumes that all future wind generation will be added in the same locations as the current wind sites. However, in reality, wind generation may be added in sites that are better dispersed geographically, and geographic diversity may significantly reduce the variability. So, next, we assess the effect of geographic diversity on wind variability. We repeated the same analysis for Karnataka. In 15% wind penetration case, the hourly wind variability of the aggregate system is less than 6.5% of the installed capacity, while it is less than 8.4% and 8.6% of the installed capacity in TamilNadu and Karnataka respectively. The following charts show the 99th percentile of the hourly net load variabilities in Tamil Nadu, Karnataka, and for TamilNadu+Karnataka combined system for the three wind penetration scenarios.

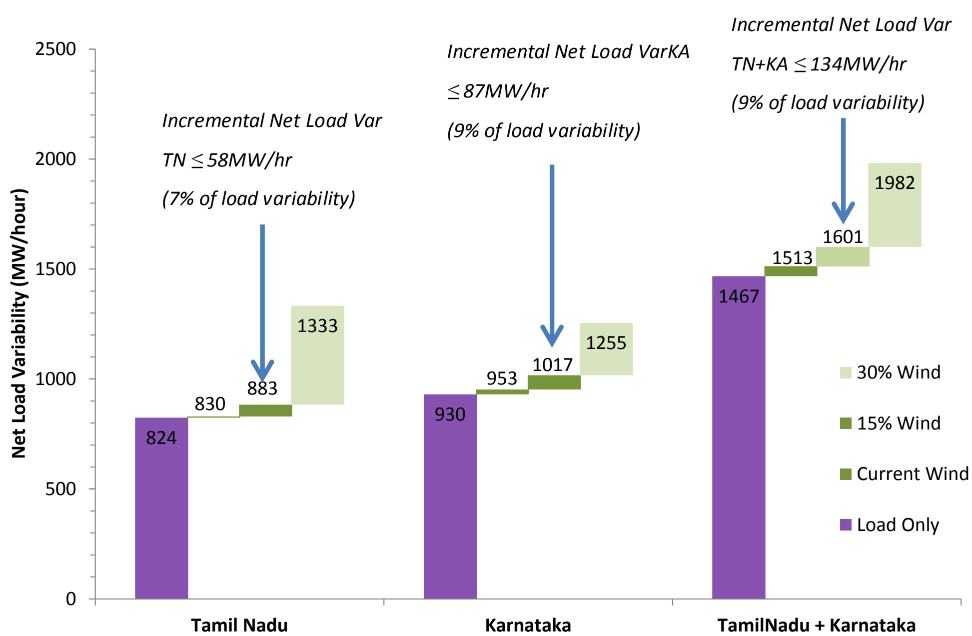

Figure ES-4: 99th Percentile Value of Hourly Net Load Variability TN, KA and Aggregate System (TN+KA)

As shown in Figure ES-4, in the aggregate system, the incremental variability added due to wind is only about 80% of the sum of incremental variabilities in each state.

In conclusion, it appears that given the limited contribution of wind energy to increasing variability of the net load that the systems needs to meet, requirements of additional flexible generation capacity may be modest and may not impose large integration costs. Our conclusions are similar to those by other integration studies in US and Europe which indicate a modest addition by wind to the total variability already existing in load. These findings indicate that the potential capacity support (if wind does not generate enough during peak periods) may be the issue that has more bearing on the economics of integrating wind. Accurate estimates of wind and load curtailment are needed to further improve the robustness of our findings.

1 Introduction

Electricity demand in India is expected to double by 2022 and increase fourfold by 2030 (CEA 2013). Wind energy is one of the cheapest forms of renewable energy available, with electricity costs comparable with those of imported coal–based plants (Abhyankar et al. 2013). With favorable regulatory framework and guaranteed feed-in tariffs, wind installed capacity in India has grown from 1.2 GW in 2000 to nearly 20.3 GW in 2013; India now ranks fifth globally in the installed wind capacity (GWEC 2014) and wind capacity additions are planned in the future. Hence, there is a need to assess the technical feasibility of the integration of large-scale wind generation into the Indian power system.

Since the power system typically sees significant variations in the electricity demand depending on the hour of the day and the season, the generation fleet needs to have the ability to increase and decrease generation fast enough to accommodate the variation in electricity demand and meet it for every instance. Integrating wind generation into the power system, in some instances, may increase the load-following requirements of the system and may introduce new challenges to system planning and operations. Operational integration challenges primarily include issues such as whether the system has enough flexible generation capacity to follow the net system load that the rest of the generation plants need to meet after wind generation is absorbed in the system. System planning challenges primarily include issues such as whether the system has enough capacity meet the net system peak demand considering the contributions by wind. To evaluate these challenges as well as assess the true cost of integrating wind power, it is necessary to develop an understanding of the nature and extent of variation in wind power generation. While several studies have assessed the impacts of wind integration in the US and Europe, very few have assessed them in the Indian context. In this study, we undertake empirical assessment of the variation in wind and load under different wind penetration scenarios and assess the incremental ramping requirements due to wind. The analysis is conducted using the actual wind generation and load data from the Indian states of Karnataka (peak load ~8GW) and Tamil Nadu (peak load ~11GW) for the calendar year 2011.

Typically, load variation is highly predictable, more so than wind. Hence, it is likely that the net load variation (after integrating wind) is less predictable than variation in load. Sufficient generation capacity needs to be committed and online (spinning) to meet ramp requirements. If ramp requirements are known in advance, appropriate level of units can be committed. A preliminary analysis of this topic is presented in the paper.

The rest of this paper is organized as follows. In section 2, we briefly review the available literature on wind variability. In section 3, we describe the methodology of the analysis, scenarios, and data. In section 4, we present the results of our analysis such as load and wind variability, incremental net load variability added by wind, ramping capacity in the system, impact of uncertainty in wind generation on unit commitment, and effect of load and wind aggregation. In section 5, we summarize our findings and provide recommendations for future analysis.

2 Literature Review

Most wind integration studies have looked at future power systems with wind (DeCesaro et al., 2009). Hence, forecasting and modeling techniques have played a key role in the creation of time-synchronized load and wind data sets used in these studies. Future load data are projected using historical load data, while future wind data have typically been derived using meteorological modeling methods that can recreate weather conditions that coincide temporally with the load data (DeCesaro et al., 2009).

(DeCesaro, Porter, and Milligan 2009) and (Ela et al. 2009) have reviewed and summarized the general approaches that have been used to estimate wind integration impacts in the US. The initial step in a typical wind integration study is to determine the incremental variability added by wind generation to a system using statistical methods under various scenarios such as increasing wind penetration rates and during critical periods when the system is most constrained with respect to its load-following or ramping capability. Results of such analyses are used to estimate the increase in ancillary services requirements imposed by wind generation. The statistical approaches typically adopted to calculate wind's impact on variability and reserve requirements are either based on standard deviation, or on exceedence level. In the standard deviation approach, the increase in standard deviation of netload σ_{NL} over the standard deviation of load σ_L is used to estimate the increase in variability due to wind generation, and the subsequent increase in operational reserve requirements (Holttinen et al. 2008).[1] Examples of the use of standard deviation as a measure of increased reserve requirements can be found in literature (Axelsson, Murray, and Neimane 2005; Holttinen 2005; Holttinen et al. 2008). In the exceedence level approach, an exceedence level for the probability of load exceeding generation is chosen beforehand. A given exceedence level (percentile) for the load alone, and the same exceedence level (percentile) for the netload are determined, and the difference between the two are used to determine the incremental reserve requirements (Holttinen et al. 2008).

To assess the impacts of wind integration, typically drawing on the results of the statistical analyses described above, most studies use one of the following three general approaches. The first approach estimates the cost of increased operating reserves required to balance the increased variability of the power system. This approach attempts to capture the impact and cost of wind's variability and uncertainty by comparing wind with a proxy resource that delivers a daily equivalent flat energy block based on wind energy. The flat block has no additional variability or uncertainty associated with it, so the operational differences can explicitly show the impacts. Examples of this widely-used approach can be found in (Acker, Tom et al. 2007). However,

[1] Netload equals Load minus Wind generation.

recent work has identified two problems with this approach. Firstly, the daily flat block tends to have more on-peak energy and less off-peak energy than wind, causing the daily flat block to be worth $1.50 - $2.00/MWh more than the actual wind energy, thus resulting in the overstating of wind integration costs (DeCesaro, Porter, and Milligan 2009; M. Milligan and Kirby 2009). Secondly, the daily flat blocks can have large step changes at midnight resulting in artificial ramping requirements that the real power system never sees (M. Milligan and Kirby 2009). Hence, Milligan and Kirby 2009, suggest the use of 24-hour rolling averages to provide certainty and near invariability while eliminating artificial ramps at midnights associated with the daily flat blocks, and also that the difference in energy value then be deducted from the calculated integration cost.

The second approach does not explicitly calculate the cost of wind integration, but examines the impact that wind has on unit commitment and dispatch, and calculates wind's net value to fuel and other variable cost reductions (Ela et al. 2009). This approach evaluates impacts of wind generation on issues such as system planning, operation, economics, load forecast accuracy, etc. Several examples of the use of this methodology can be found in literature (GE Energy 2005; GE Energy 2008; Holttinen 2008; Makarov and Lu 2008).

The third approach assesses the reliability impacts of wind on the power system, and estimates wind's contribution to system adequacy, or capacity value (Ela et al. 2009). A reliability-based method based on loss of load probability (LOLP) or a related metric is typically used to calculate effective load carrying capability (ELCC).[2,3]

In the Indian context, very few grid integration studies have been conducted so far. George and Banerjee 2009, have analyzed the impacts of wind integration in the Tamil Nadu grid in terms of capacity credit, and have proposed a new approach based on the annual load duration curve for generation expansion planning with higher penetration of wind.[4] Using this approach, they have quantified potential base and peak load savings achieved by the installation of wind power at various penetration levels. However, this study focuses mainly on capacity expansion planning issues, and does not assess the impact of wind variability in various timeframes and the resulting additional flexibility requirements imposed on the system.

The Report on Green Energy Corridors documents the analysis of the flexibility of the Indian power system for integrating a total of 72,400 MW of renewable energy by year 2022 (POWERGRID 2012). However, the variability analysis in this report is limited to the typical

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[2] ELCC – Effective Load Carrying Capacity. ELCC is the ability to augment system's firm generation capacity without increasing the LOLP.

[3] LOLP – Loss of Load Probability. Probability of load exceeding the available generation at a given point in time.

[4] Capacity credit is defined as the level of base load generation (i.e. firm power) that can be replaced with wind generation

day per month. Therefore, it does not capture the entire range of annual hourly load and wind generation variability.

Chattopadhyay and Chattopadhyay (2012) have conducted a study on the variability of wind generation in Tamil Nadu. However, they only analyze the inter-annual variability, using wind generation data derived from model-generated six-hourly wind speed; also, they study the variability of wind power density (W/sq. m) rather than wind power generation (MW) for January – December for years 1980-2000.

Soonee, Saxena and Rathour (2014) provide examples of how rapid changes in load and RE generation have been accommodated by the Indian power system and show the large ramping capability available. They also identify peculiar and drastic changes in load due to opening and closing of feeders on the hour as utilities are implementing rotating blackouts.

However, there is no study in the Indian context that has analyzed the actual variability in wind generation, load and netload for hourly or sub-hourly timeframes and assessed its impact on the power system. In this paper, we try to bridge this gap in the literature.

3 Methodology

We analyze the additional ramping capability requirements for integrating wind by assessing (1) whether the largest changes (variability) in load that the system has to meet increase after integrating wind generation, (2) whether these changes occur more often during times when the ramping capability is most constrained, (3) whether these changes are less predictable than those without integrating wind, leading to additional flexibility requirements, and (4) whether the magnitude of the changes reduces if load and wind from multiple states are aggregated. We first estimate the variability in wind and load to estimate the variability in net load that the system has to meet. We then estimate the system ramping capacity and compare it with variability in net load that it needs to meet.

3.1 Estimating the Wind and Load Variability

We first characterize the wind and load variability over 5-min, 15-min, and 1-hr timeframes. The approach we use is similar to that described in (Krich and Milligan 2005).

We define wind generation variability as the difference between wind energy generated in two consecutive time periods, and estimate the wind variability as follows:

$$V_{wt} = W_t - W_{t-1}$$

Where V_{wt} is the wind variability at time t, W_t is the wind generation at time t, and W_{t-1} is the wind generation at time t-1. Here, t and t-1 refer to consecutive 5-min, 15-min or 1-hr time periods. These differences are thus calculated for consecutive time periods throughout the year. Similarly, the following equation is used to determine the load variability:

$$V_{lt} = L_t - L_{t-1}$$

Where V_{lt} is the load variability at time t, L_t is the load at time period *t* (5-min, 15-min or 1-hr interval).

Net load (load minus wind) is the actual load that the conventional generators have to meet. Net load for time period *t* is defined as:

$$NetLoad_t = L_t - W_t$$

Where all symbols have their usual meaning.

Similar to the load variability, the netload variability is determined by the equation below:

$V_{netload\_t} = NetLoad_t - NetLoad_{t-1}$

i.e. $$V_{net\text{-}lt} = (L_t - W_t) - (L_{t-1} - W_{t-1})$$

Where $V_{net\text{-}lt}$ is netload variability at time period *t* and other symbols have usual meaning.

The difference in the net load variability and the load variability indicates the incremental variability added due to wind.

Note that we primarily use the 99th percentile of the variability as the measure of variability. It informs the load following capacity needed. For example, if we find that the 99th percentile of the hourly variation in net load is 100 MW, it means that the variation in net load was 100 MW or lower 99% of the time indicating that a ramping capability of 100 MW per hour may be sufficient 99% of the time to integrate wind. We compare the estimates of the 99th percentile of the variability to the ramping capabilities of the system to assess the level of additional ramping/load following capability needed to integrate wind generation.

3.2 Assessment of system ramping capability

To determine whether the power system will be capable of accommodating the variability introduced by increasing levels of wind penetration, we need to assess the instantaneous ramping capability of the system. The ramping capability of a unit during an hour depends on the actual generation from that unit during that hour, and the online capacity, which may be lower than the installed capacity. For example, if a unit is generating at its rated capacity, it has no capability for ramping up further, but it can ramp down. Similarly, if a unit is generating the minimum stable amount, it has no capability for ramping down further.

The rampdown and rampup capabilities of the system over a time interval are estimated using the available generation capacity and actual hourly generation as follows:

$$\mathrm{Rampdown\_Capability}_t = \sum_i \min(\mathrm{RF}_i.\, \mathrm{G}_{i,t}^{\mathrm{OLC}}, \mathrm{G}_{i,t}^{\mathrm{O}})$$

$$\text{Rampup\_Capability}_t = \sum_i \min\left(RF_i . G_{i,t}^{OLC}, \left(G_{i,t}^{OLC} - G_{i,t}^{O}\right)\right)$$

Where,

$G_{i,t}^{O}$ = Actual generation (MW) in time interval *t*; *i* represents the generation technology, such as coal, gas, hydro, etc.

$G_{i,t}^{OLC}$ = Online capacity (capacity of the units that are committed) of the generation technology *i* for time interval *t*.

RF_i = Ramping capability factor of the generation technology, which is its ramping capability expressed as a percentage of the available generation capacity (e.g. % of capacity/time period).

Scenarios for analysis

We estimate the hourly netload variability by developing three scenarios for the wind penetration rates for both states. We define wind penetration rates in terms of energy as shown below:

$$\text{Wind penetration rate} = \frac{\text{Total annual wind energy production (GWh)}}{\text{Gross annual electrical energy demand (GWh)}}$$

The scenarios are briefly described below:

i) Current penetration

This scenario uses the wind installed capacities in 2011. The installed wind capacity in Tamil Nadu in June 2011 was 6018MW, which translates to 10.4% contribution by energy; the peak load in 2011 in Tamil Nadu was 11,323MW. Wind installed capacity in Karnataka in 2011 was ~2200MW, which translates to ~6% contribution by energy; the peak load in Karnataka in 2011 was 8291MW.

ii) 15% penetration

In this scenario, we assume that wind energy supplies 15% of the total energy requirement in both states. Assuming the same wind generation profiles as the current ones, the installed wind capacity is 8,680MW and 5,218 MW in Tamil Nadu and Karnataka respectively.

iii) 30% penetration

In this scenario, we assume that wind energy supplies 30% of the total energy requirement in both states. Assuming the same wind generation profiles as the current ones, the installed wind capacity is 17,360 MW and 10,437 MW in Tamil Nadu and Karnataka respectively.

In this analysis, we have assumed that in the 15% and 30% penetration cases, the additional wind capacity is added at the exact same geographic locations as the current wind sites in each state; the wind generation profiles under these scenarios have been assumed to be the same as the current ones. However, in reality, the additional wind generation is likely to be added in locations other than the current wind generation sites; such geographic diversity is likely to reduce the variability in wind generation (DeCesaro, Porter, and Milligan 2009; Holttinen et al. 2008; Krich and Milligan 2005). This exercise therefore establishes the upper bound on the variation in wind generation and the resulting netload variability.

3.3 Data and Sources

For this study, we use actual 5-min load and wind generation data for 2011 in Tamil Nadu and Karnataka.[5] The data was shared with us by the National Load Dispatch Center of India. We believe that given the anecdotal evidence that wind curtailment is not likely to be significant given severe power shortages during peak wind periods; we argue that not having data on wind curtailment will not qualitatively change our results. However, having precise estimates about wind curtailment will increase the robustness of our results. Although we have data on load curtailment, these are only estimates by the utility. Hence we conduct our analysis using load met as well as estimates of total load (unrestricted demand).

The data for estimating the ramping capacity (online capacities i.e. unit commitments and plant level actual generation) was downloaded from Tamil Nadu state load dispatch center's website (www.tnebldc.org). Online capacity and plant level generation data was not available on Karnataka state load dispatch center's website; therefore, we have restricted the ramping capacity analysis to Tamil Nadu. The following charts present the 5-min load and wind generation data for Tamil Nadu and Karnataka.

[5] Note that the load data does not include load shedding. We chose not to consider load shedding because the load shedding claims of the utility are not measured or independently validated.

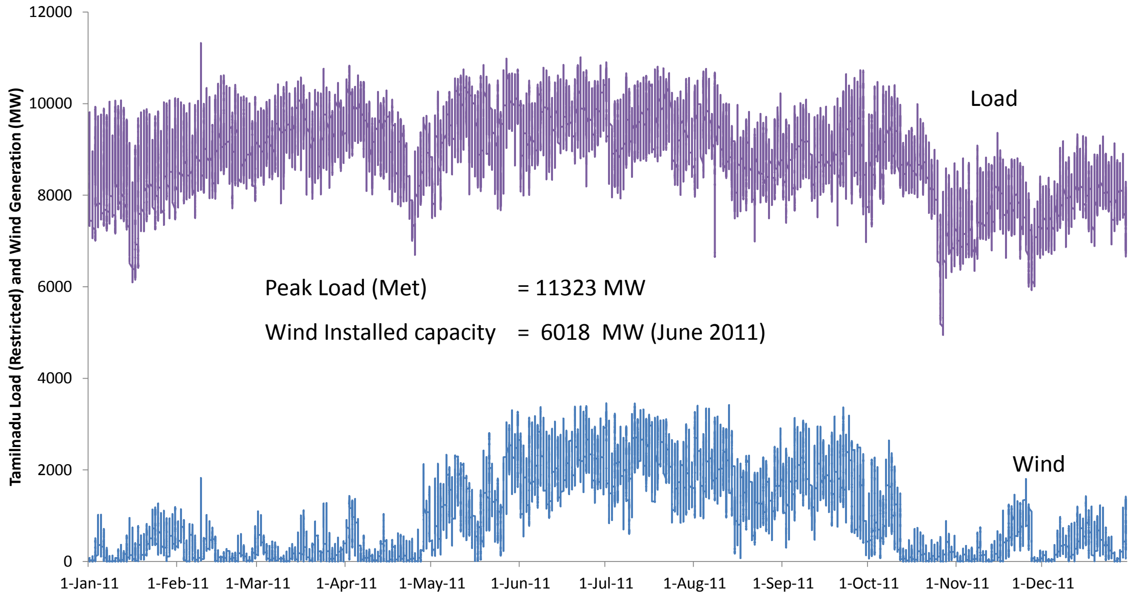


Figure 1: 5-min Load and Wind generation data for Tamil Nadu (2011)

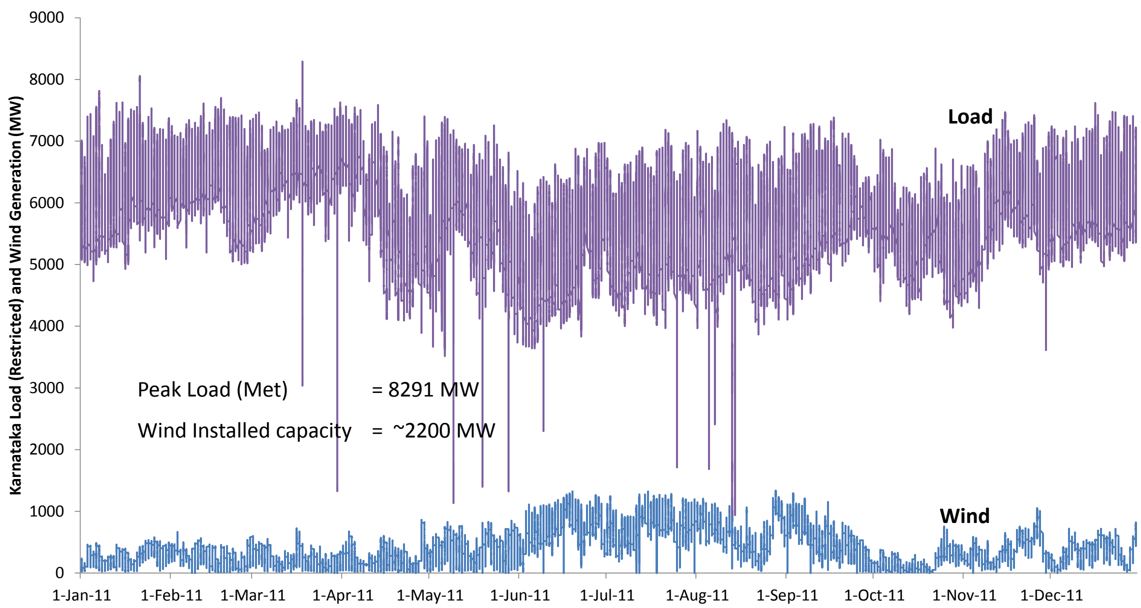


Figure 2: 5-min Load and Wind generation data for Karnataka (2011)

The data outliers, seen in Karnataka charts (Figure 2) have been excluded from the analysis.

Ramping Capacity Data

Ramping capabilities and startup times can vary widely between technologies. Coal plants and combined cycle gas plants can change their output by about ~20-30% of their capacity per hour (Mills and Wiser 2013). The start-up time for combined cycle gas plants is 30-60 minutes, while the startup time for steam turbine plants is 60-600 minutes (Vuorinen 2007). Hydropower plants can typically ramp up to their full capacity in about 10 minutes (EPRI 2011). Most other plants (including thermal) are able to ramp up from their minimum stable generating level to maximum output within a span of 6 hours. Hence, we focus our analysis on the 1-hr timeframe.

Table 1 shows the theoretical ramping capability, actual ramps achieved by Tamilnadu state generating stations, and the total installed capacity of each type of generation technology in the state of Tamil Nadu. While Tamil Nadu meets large portions of their power demand from in-state generation, they also receive some of their power from the central sector and private entities. The table below shows the total installed capacity of coal, combined cycle gas, hydropower, diesel, nuclear and pumped storage allocated for the two states.

Table 1: Summary of ramping capabilities and installed capacities –Tamil Nadu

Generation type	**Theoretical ramp rate – % of the online capacity per hour**		**Actual ramp rate achieved by Tamilnadu state generating stations – % of the online capacity per hour[e]**				**Tamil Nadu**
	Ramp up	**Ramp down**	**Ramp up**		**Ramp down**		**Installed Capacity[d] (MW)**
			Maximum	**99th percentile**	**Maximum**	**99th percentile**	
Coal	22%[a]	22%[a]	49%	6%	49%	5%	8,212
CCGT	24%[a]	24%[a]	87%	19%	100%	18%	523
Hydro	100%[b]	100%[b]	100%	73%	100%	44%	1,722
Diesel	100%[a, c]	100%[a, c]	NA	NA	NA	NA	412
Nuclear	1%[a]	1%[a]	NA	NA	NA	NA	524
Pumped storage	100%[b]	100%[b]	100%	50%	75%	29%	400
Total							11,793

Notes:
[a] Source: (Mills and Wiser 2013)
[b] Source: (EPRI 2011)
[c] Source: (Mills and Wiser 2013). We assumed ramp rates for diesel generators to be the same as that for Gas CTs.
[d] Source: (CEA 2012). The installed capacity numbers include generation plants owned by the state generation utilities, contracted capacities with IPPs and allocations from the central sector plants (like National Thermal Power Corporation etc.).
e: The actual ramps are calculated only for the Tamilnadu state generation stations based on the 15-min generation data

4 Results

In this section, we present the results of our analysis

4.1 Current variability in load and wind

The following chart shows the load variability for 5-min, 15-min and 1-hour intervals in Tamil Nadu in a descending order. The chart also shows the 99th percentile load variability value (inset).

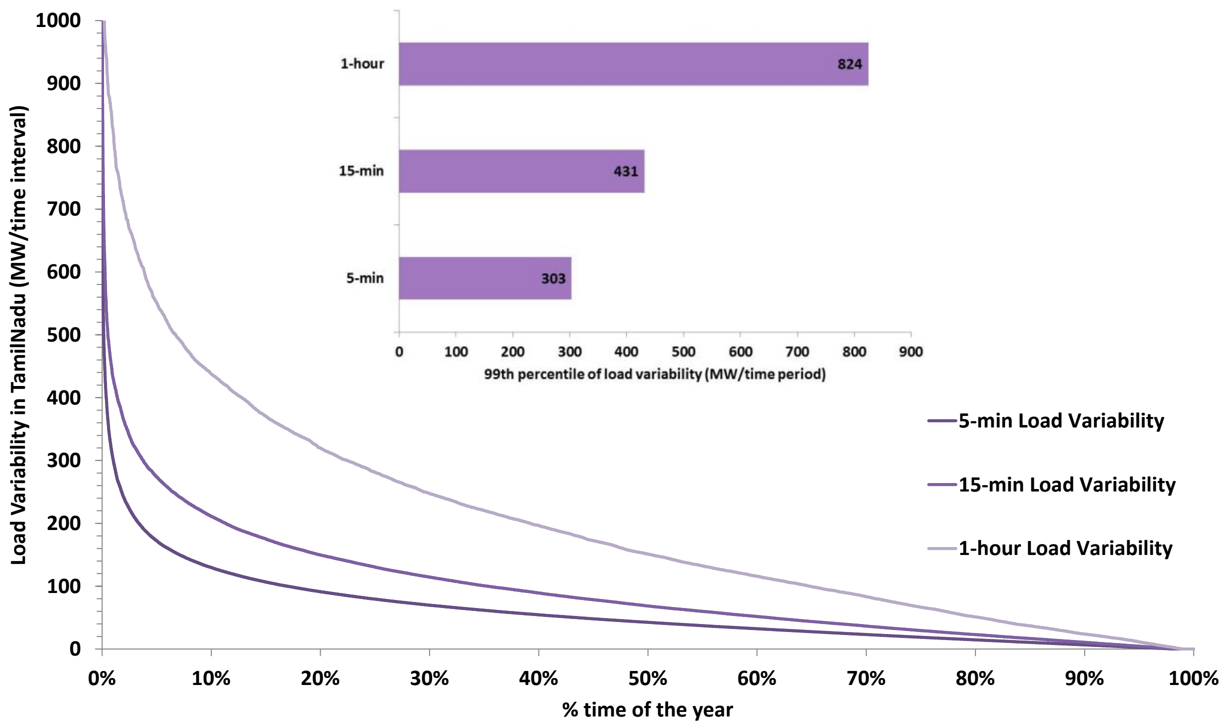


Figure 3: Load variability in Tamil Nadu (2011)

It can be seen from the charts that for 99th percent of the time the load variability is less than 2.7% (303 MW), 3.8% (431 MW) and 7.3% (824 MW) of the peak demand for 5-min, 15-min and 1-hour time intervals respectively. The following charts show the wind variability (in a descending order) in Tamil Nadu for these time intervals. The figure also shows the 99th percentile value of the wind variability (inset).

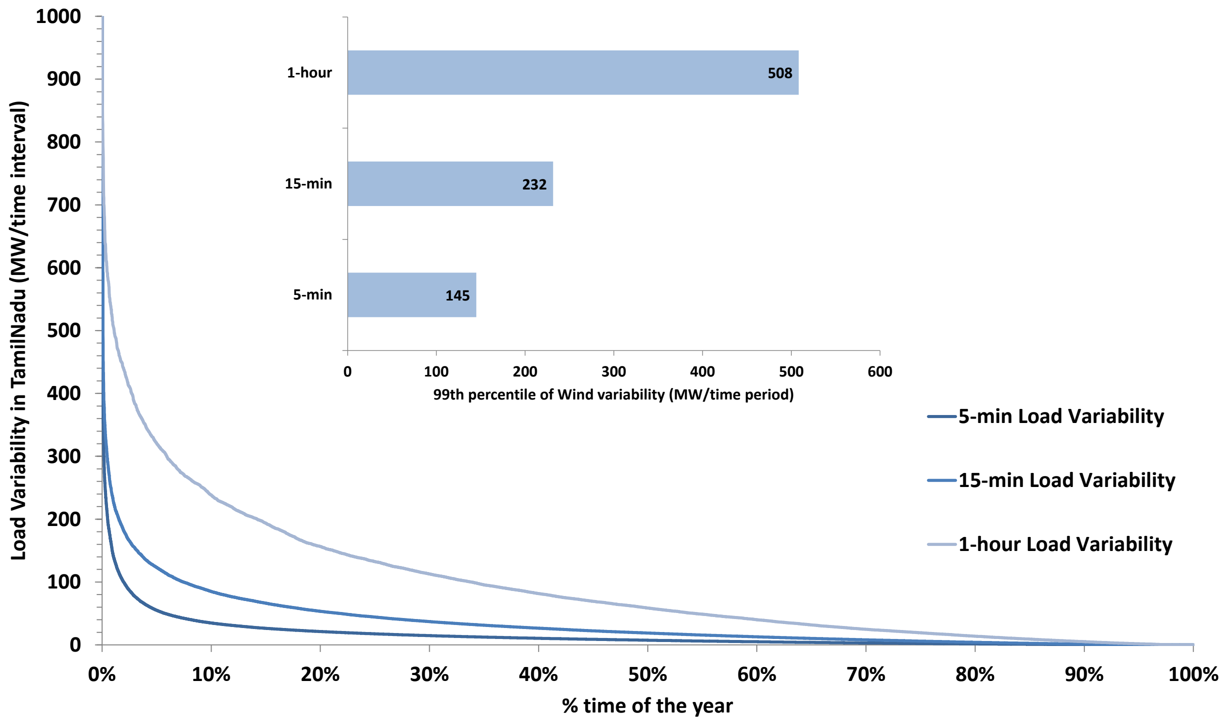


Figure 4: Wind variability in TamilNadu (2011)

As seen from the charts, wind variability is significantly lower than the load variability in all timeframes. For 99th of the time, wind variability is lower than 1.3%, 2.0% and 4.5% of the peak demand or 2.4% (145 MW), 3.8% (232 MW) and 8.4% (508 MW) of the wind installed capacity for 5-min, 15-min and 1-hour time intervals respectively. For both load and wind generation, the 99th percentile variability is significantly lower than the maximum variability.

The following chart shows wind variability for different levels of wind penetration – current penetration, 15% by energy and 30% of energy for 5-min, 15-min and 1-hour timeframes.

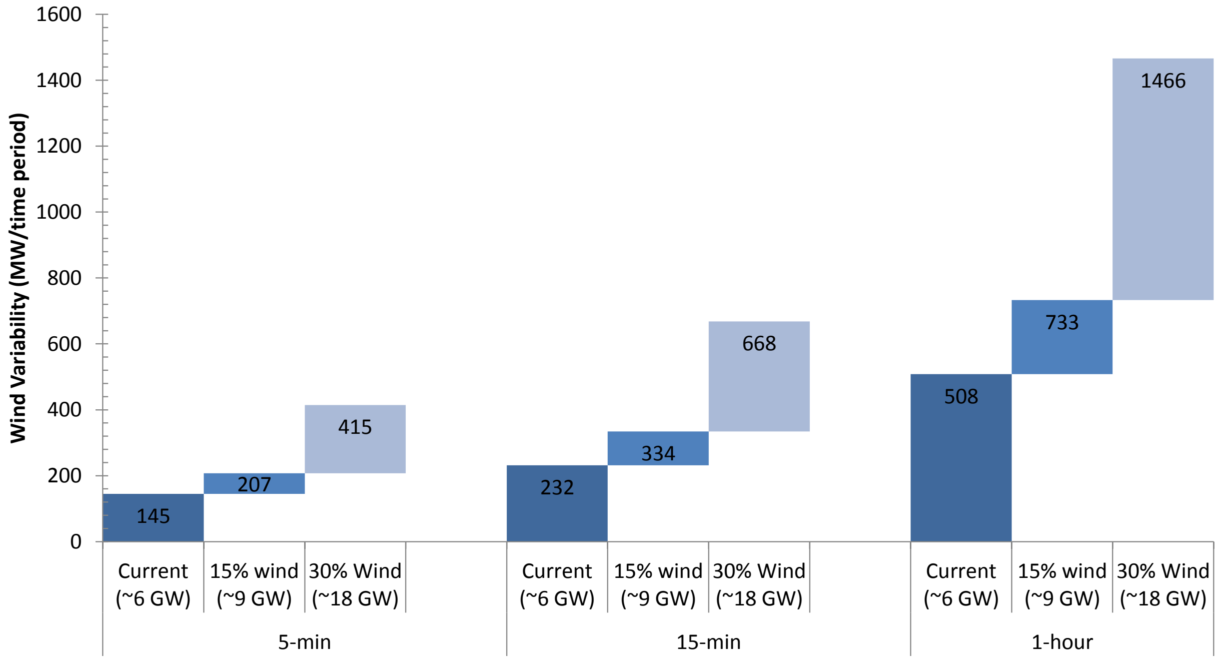


Figure 5: Tamil Nadu wind variability for different penetrations (2011)

As can be seen from the chart, wind variation would be less than 508MW/hour, 733MW/hour, and 1466MW/hour for 99% of the time for current wind penetration level (6018MW installed capacity), 15% by energy (~9,000 MW installed capacity) and 30% by energy (~18000 MW installed capacity) i.e. less than 8.4% of the installed capacity for all penetration levels.

These results are in agreement with other studies that have looked at the characteristics of variability over different time scales in other regions. Cappers et al., (2011) show that the wind variability as a percentage of nameplate capacity increases over increasing time scales. According to Michael Milligan et al. (2011), there is less diversity among individual wind plants or loads in the load-following (minutes-to-hours) timeframe than in the regulation (minute-to-minute) timeframe and therefore, aggregation does more to reduce regulation requirements than it does to reduce load-following requirements.

4.2 Incremental variability added by wind at varying penetration levels

The key issue regarding wind energy integration is the incremental variability it adds to the system. This can be estimated by comparing the load variability with the netload variability.

The following chart shows the 5-min load variability and the net load variability in Tamil Nadu. Note that the difference between the load variability and the net load variability is the incremental variability added due to wind generation.

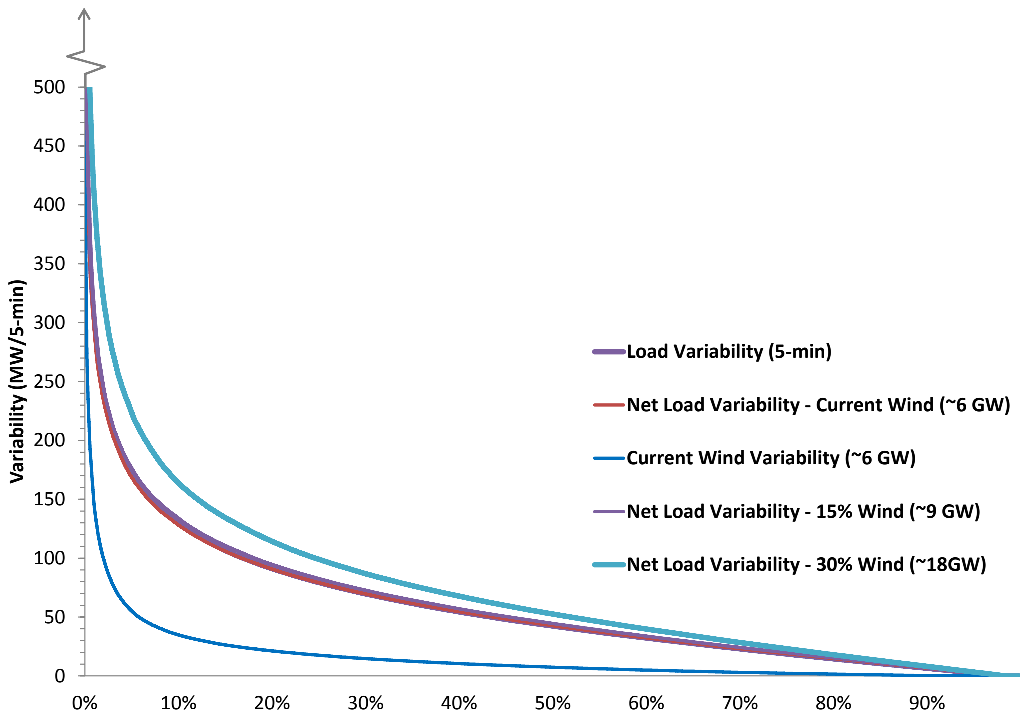


Figure 6: 5-min load and net load variability for different wind penetration levels in Tamil Nadu (2011)

The figure shows 5-min variability of current wind generation and load for Tamil Nadu where we have sorted the variability from the highest to the lowest value. This figure indicates that the existing variation in demand is significantly higher than that of wind. The figure also shows the 5-min net load variability for the current penetration, 15% penetration (by energy), and a 30% penetration (by energy). For wind penetration of up to 15% by energy, the net load variability can hardly be distinguished from the load variability. For higher penetration rate (30% by energy), the increase in the net-load variability is only modest. The following chart shows the 99th percentile values of the load variability and net load variability for the three wind penetration levels for 5-min, 15-min and 1-hour timeframes.

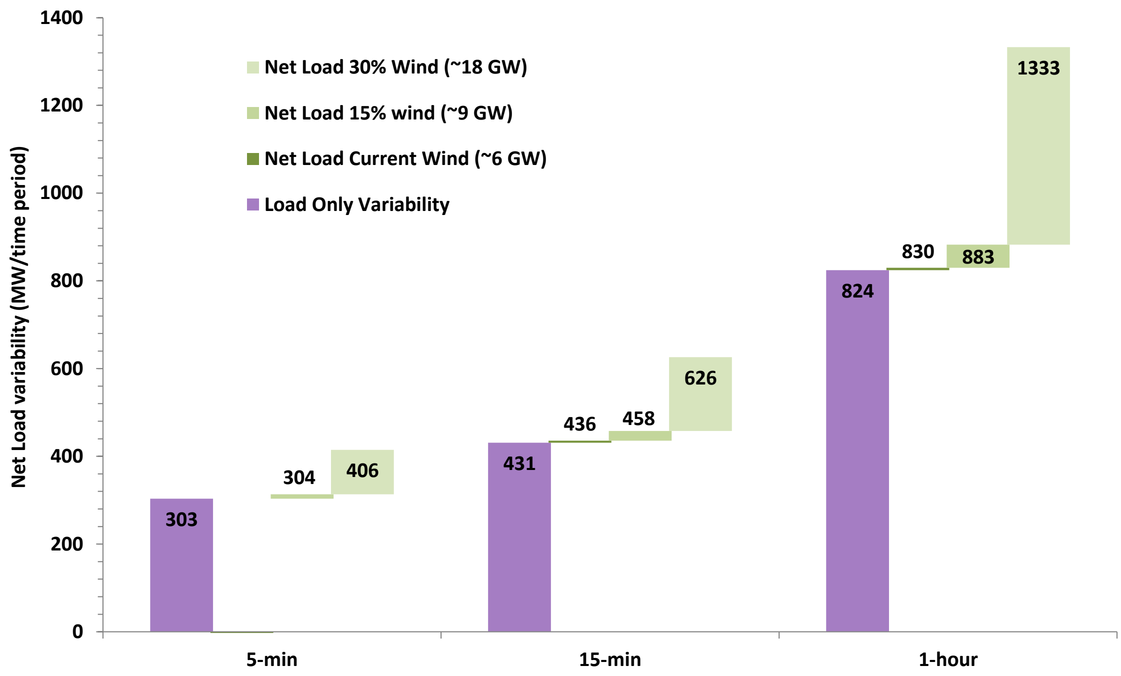


Figure 7: 99th Percentile Load and Net Load variability in Tamil Nadu for different wind penetration levels

Note that the net load variability (the variability that the conventional generators have to meet by ramping up or down) for 15% wind penetration scenario (~8680MW wind installed capacity) is lower than 2.7%, 4.0% and 7.8% of the Tamil Nadu peak load for 5-min, 15-min and 1 hour interval respectively for 99% of the time. This means that for 15% penetration by energy, the incremental variability added due to wind is less than 0.3% (1 MW), 6.3% (27MW), and 7.2% (59MW) of the load variability for 5-min, 15-min and 1 hour interval respectively for 99% of the time. For aggressive wind penetration rate (30% by energy – wind installed capacity of ~18GW), the incremental variability added due to wind is significant i.e. less than 62% (509MW/hr) of the current load variability for the 1-hour interval. For smaller timeframes, this number is significantly smaller i.e. 34% (103MW) for 5-min interval and 48% for the 15-min interval.

The analysis presented so far presented annual wind and load data. As shown in Figure 1 and Figure 2, the wind generation in India is highly seasonal. The wind generation peaks in the monsoon months (June through September) while it is significantly lower in other months – especially after November. The largest swings in wind generation are more likely to occur when the generation is high i.e. during monsoon. The following table shows simple correlation between Tamil Nadu wind generation and load (restricted as well as unrestricted) during wind months (June through September) and non-wind months (December through March - when wind generation is very low and so is the absolute variability in wind generation).

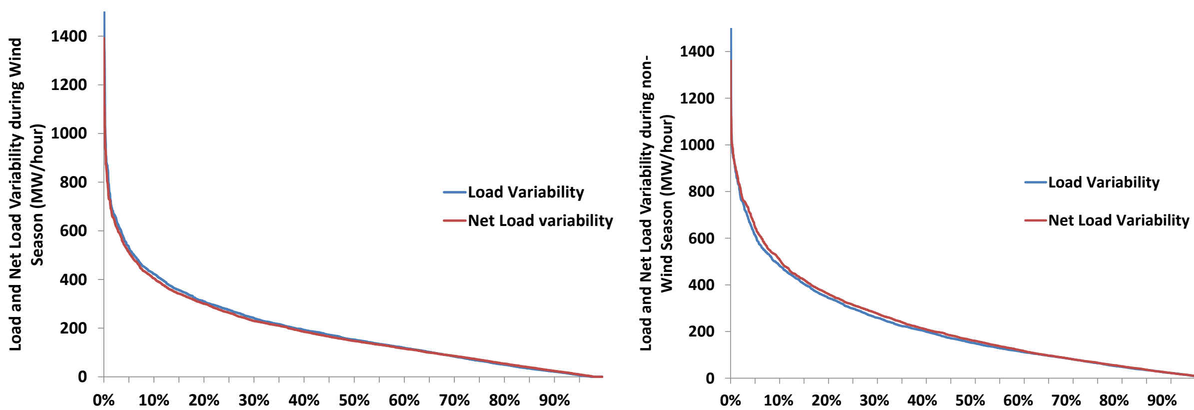
Table 2: Simple Correlation Factors between Wind Generation and Load by Season in Tamil Nadu

	Wind Months (June-Sep)	Non-Wind Months (Dec-Mar)	Annual Average

Wind Generation and Load (Restricted Demand)	0.75	-0.02	0.55
Wind Generation and Unrestricted Demand (i.e. total demand including power cuts)	0.48	0.03	0.26

The correlation between wind generation and load is much higher during wind months, while it is almost zero during non-wind months. If the electricity shortage is included in the demand, the correlation during wind months drops – but it is still significantly higher than that during the non-wind months. This suggests that in 2011, wind generation contributed significantly towards meeting the load during wind-months.

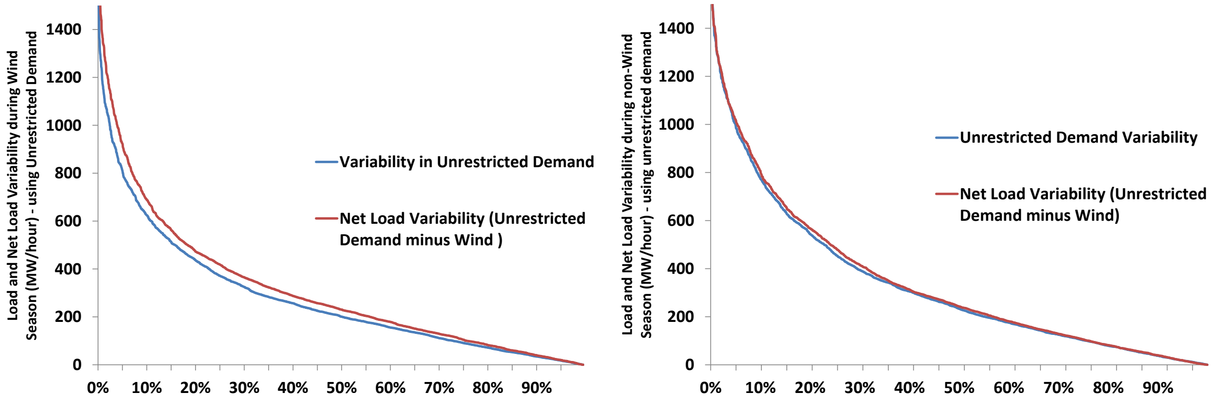
Although the variability analysis presented so far has captured all the extreme variability events in the year, in order to assess the seasonal impacts of wind variability, it is instructive to compare the net load variability during wind and non-wind months as shown in the following charts.



(a) Wind Season (June- September) **(b) Non-wind season (December – March)**

Figure 8: Load and Net Load Variability (MW/hour) during Wind and Non-Wind Months in Tamil Nadu (Current Wind Penetration)

The net load variability for current wind penetration during wind season is almost the same as the load only variability; it can hardly be distinguished on the chart. During non-wind months, when wind generation and variability is expected to be much smaller, the net load variability is somewhat higher than the load only variability. This corroborates the key finding from Table 2 that the wind generation (especially during wind season i.e. monsoon) is significantly correlated with the load. Note that load indicates the demand that is met by the supply. In 2011, Tamil Nadu faced significant peak as well as energy shortage even during the monsoon months; wind energy, being highly seasonal, would therefore have a strong correlation with the load (restricted demand). In the following charts, we repeat the seasonal analysis using the unrestricted demand (including power shortages).



(a) Wind Season (June- September)

(b) Non-wind season (December – March)

Figure 9: Load and Net Load Variability with Unrestricted Demand (MW/hour) during Wind and Non-Wind Months

During wind season, the net load variability (with unrestricted demand) is slightly higher than the load variability in unrestricted demand; during non-wind months, this difference is very small. However, the incremental variability added due to wind even during wind season is only marginal.

4.3 System ramping capacity

The netload variability of the system drives its ramping requirements; in order to ensure reliable grid operation, the system needs to accommodate the netload variability by ramping other generators (such as coal, gas, hydro, etc.) up or down. Even though largest net load variability does not appear to be significantly more than that already existing in the load itself, it could occur when ramping capacity is most constrained hence requiring additional ramping capacity. Ramp-up and ramp-down capacity is most constrained during low demand periods when any changes in load requirements are to be accommodated by relatively inflexible coal generation. Note that a situation where all generators are operating at full capacity and additional load needs to be met due to drop in wind generation is a system planning issue of lack of adequate capacity to meet demand and not an operations issue related to ramp capacity.

We estimate ramping capacity of the system based on the typical ramp rate constraints of generators and whether these generators are online given the load, for every 15 minute interval. We compare the number of instances where ramping capacity is not sufficient to meet the ramping requirement given the variation load and net load (under different scenarios of wind penetration). Figure 10 shows the ramping requirement (net load variability) on X-axis and system ramping capacity (Y-axis) in Tamilnadu for the 15% wind penetration case (~8680 MW installed capacity). Each point in the chart denotes the ramping requirement (X-axis) and ramping capacity (Y-axis) for a 15-min interval in 2011 (~34,500 observations).

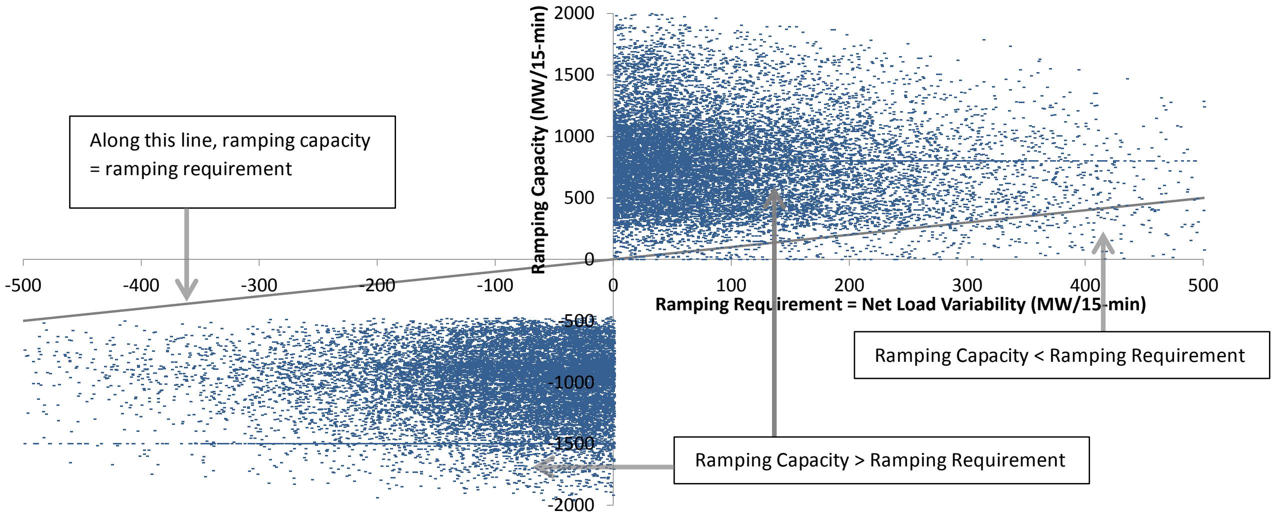


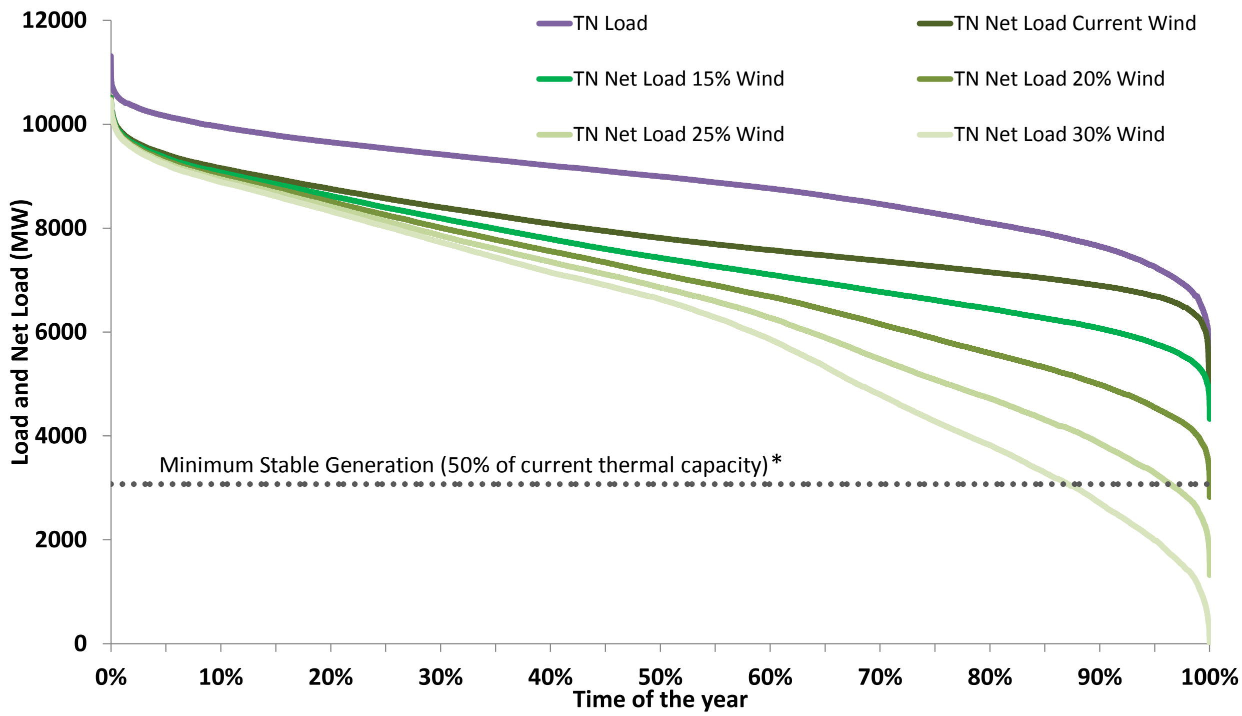
Figure 10: Ramping requirement and ramping capacity in Tamil Nadu for every 15-min interval for 15% wind penetration scenario

The figure also shows a 45 degree straight line; along the straight line, the ramping capability equals the ramping requirement. The points that fall below the straight line in the first quadrant and the points that fall above the line in the third quadrant indicate the occurrences where ramping capability cannot meet the ramping requirement. For 15% wind penetration (~8680 MW installed capacity), system ramping capacity is higher than the ramping requirement for 98.8% of the time. There are 428 occurrences (1.2 % time) when the ramping capacity is lower than the ramping requirement. Note that for meeting the current load variability, system ramping capacity is lower than the ramping requirement for ~1.1% of the time (376 occurrences), which shows that during these periods, generators were ramping more than the constraints we have assumed for this analysis. This implies that the additional ramp-up capability imposed by Tamil Nadu wind is minor.

4.4 Predictability, Unit Commitment, and Wind Curtailment

Typically, load variation is highly predictable, more so than wind. Hence, it is likely that the net load variation (after integrating wind) is less predictable than variation in load Sufficient generation capacity needs to be committed and online (spinning) to meet ramp requirements. If ramp requirements are known in advance, appropriate level of units can be committed. Consider an extreme example where ramp requirements cannot be predicated at all, in such situation most generation units need to be committed and online. Alternatively, the system needs to have fast start units such as gas combustion turbines as they may be more cost effective than keeping all generation units online most of the time. Hence, higher predictability of variation will avoid costs associated with extra units being committed.

In order to assess this problem, we looked at unit commitments of Tamil Nadu's generation plants including central sector allocations. A preliminary analysis suggests that because of the widespread shortage in the state, all thermal and gas units (including central allocations and IPPs) that were available on a given day were generating close to full load most of the time (98.9% of the time) i.e. all available thermal units were committed most of the time. This means that the current wind generation did not influence the unit commitment decisions in TamilNadu. Note that once the thermal units have been committed, they can be backed down up to the minimum stable level, and still be available for ramp-up support. Therefore, uncertainty in wind generation would have a limited impact on the ramping capability, as shown in section 4.3. The following chart shows the TamilNadu load and net load duration curves for a range of wind penetration levels (current penetration to 30% by energy). The chart also shows the minimum stable generation of the thermal plants (including central sector allocations) supplying the state.



* Note: For thermal power plants, minimum stable generation of 50% of the rated capacity has been a widely cited value in the literature. Few informal conversations with the systems operators, however, suggest that in India, minimum generation for thermal (mainly coal) units is typically used as 70%.

Figure 11: TamilNadu net load for various wind penetration levels and minimum stable generation

Figure 11 shows that up to 25% wind penetration by energy (installed capacity ~15000MW), minimum stable generation is lower than net load most of the year. This means that even if wind generation is completely random, all thermal units can remain committed and provide the necessary ramping-up support. For higher wind penetration levels (30% by energy), the net load is higher than the minimum stable generation level for about 90% of the time. This implies that wind curtailment or additional ramping support (more flexible generation) may be necessary, albeit their magnitudes would be relatively small. Note that this analysis presents the limiting case assuming wind generation is a random variable and cannot be predicted. However, with state of the art wind forecasting techniques, the forecast error can be significantly reduced over several hours ahead timeframe (Hodge and Milligan 2011); this can help optimizing the unit commitments and minimizing wind curtailment even at high penetration rates.[6] Moreover, if generation resources could be shared across states (through a real time or an ancillary services market), the system flexibility would improve and the need for wind curtailment can go down.

In India, deviations from the day-ahead schedules are settled in a frequency based de-facto real time market, called Unscheduled Interchange (UI). In 2011, operational grid frequency band was 49.5Hz to 50.2Hz (CERC 2010).[7] In February 2014, the Central Electricity Regulatory Commission tightened the grid operation norms by limiting the operational grid frequency band to 49.7 Hz to 50.05Hz (CERC 2014). This has significantly reduced the volume of energy available as UI. Informal conversations with the Indian system operators suggest that wind curtailment was not a big problem in 2011 primarily because of more flexible settlement mechanism (UI). However, with increased penetration and tighter grid frequency bands, wind generation in Tamil Nadu had to be curtailed in the 2013-14 wind season; unfortunately, data on curtailment is not available. The robustness and accuracy of our findings would increase significantly with reliable load and wind curtailment data.

4.5 Benefits of Load and Wind Aggregation

Note that the variability analysis conducted for various wind penetration rates in this study establishes the upper bound of variability, since it assumes that all future wind generation will be added in the same locations as the current wind sites. However, in reality, wind generation may be added in sites that are better dispersed geographically, and geographic diversity may significantly reduce the variability. So, in this section, we analyze the effect of aggregating wind generation. Unfortunately, we do not have site level wind generation data for Tamil Nadu. Therefore, we aggregated Tamil Nadu system with that of the neighboring state of Karnataka.

First, we repeated the variability analysis for Karnataka. The following charts show the 99th percentile values of wind and net load variability in Karnataka for the three wind penetration levels over 5-min, 15-min and 1-hour time intervals.

[6] Informal conversations with the Indian system operators suggest that rigorous forecasting techniques are not yet practiced in India.

[7] Indian electricity grid operates on a frequency of 50 Hz.

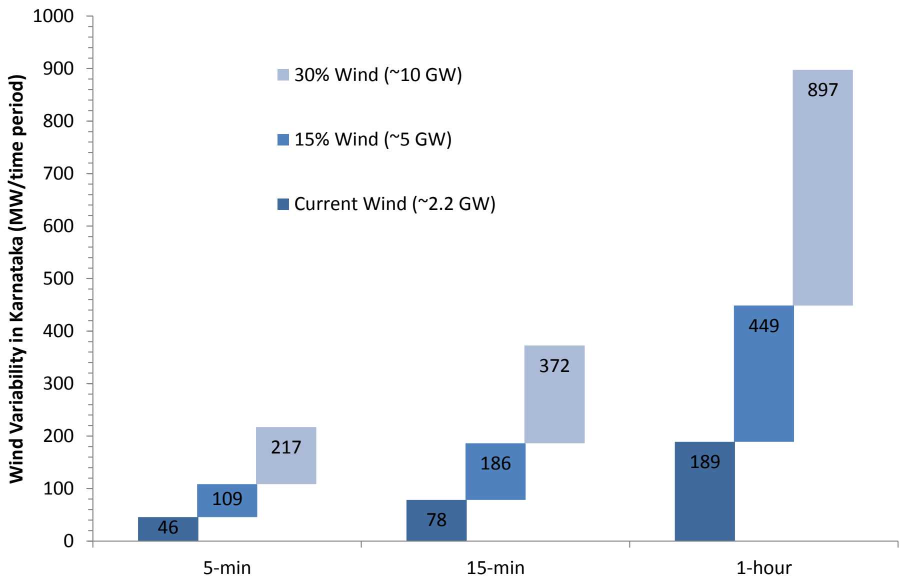


Figure 12: 99th Percentile Values of Wind Variability in Karnataka (2011)

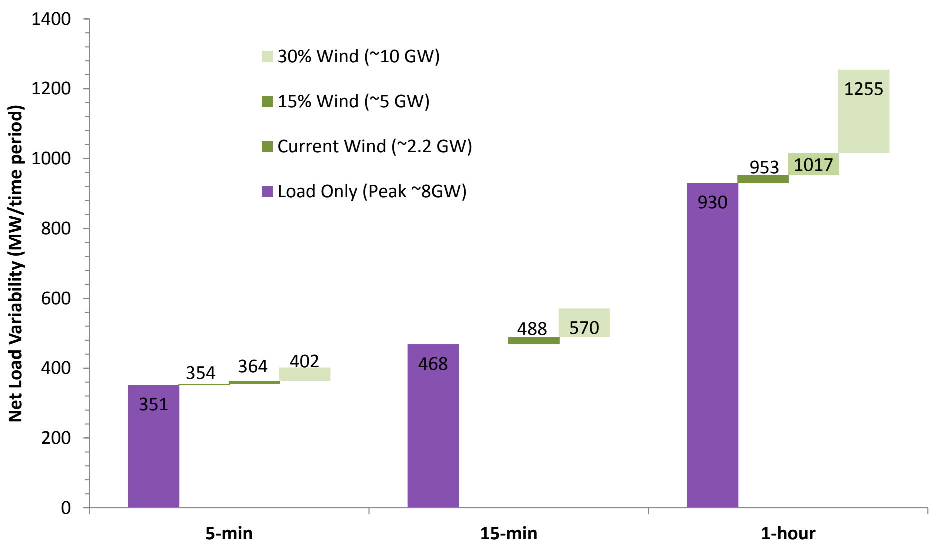


Figure 13: 99th Percentile Values of Net Load Variability in Karnataka (2011)

As shown in Figure 12 and Figure 13, similar to TamilNadu, the incremental variability added due to wind in Karnataka is small. For example, in 15% wind penetration case (installed capacity of ~5000 MW, peak load of 8291MW), the wind variability is less than 9% of the installed capacity per hour (~450MW/hr) for 99% of the time. The incremental net load variability added due to 5,000 MW of wind (~15% by energy) is less than 87MW/hour (1.1% of the peak demand) for 99% of the time.

Next, we aggregated Tamil Nadu (TN) and Karnataka (KA) systems and performed the same analysis. The following chart shows the 99th percentile value of the hourly wind variability in the individual states as well as in the aggregate system.

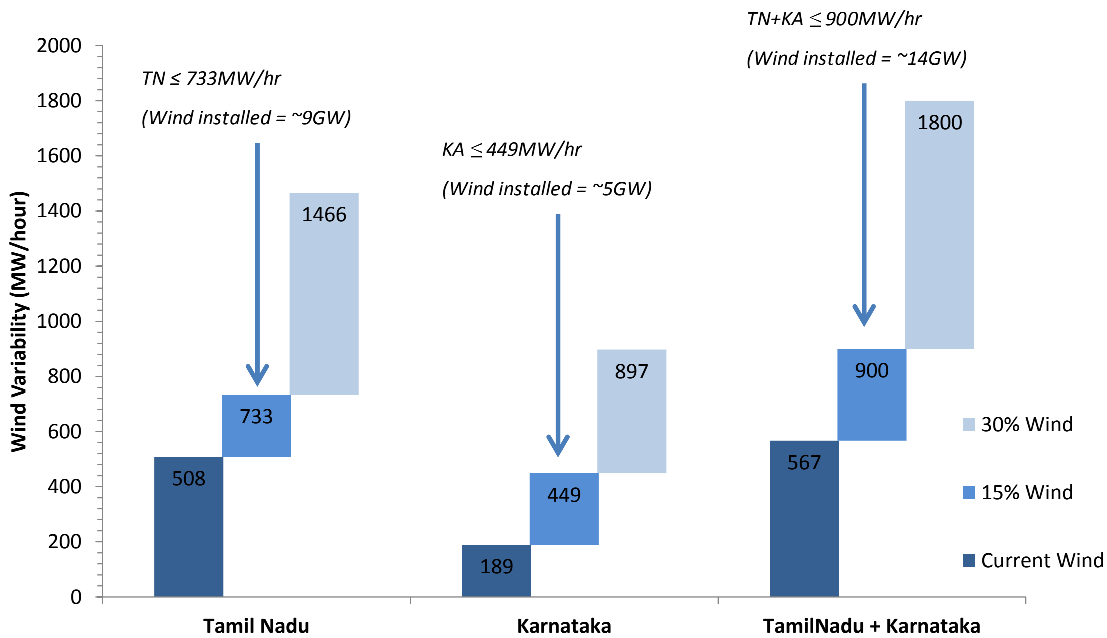


Figure 14: 99th Percentile Value of Hourly Wind Variability in TamilNadu, Karnataka and Aggregate System (TamilNadu + Karnataka)

As shown in Figure 14, wind variability in the aggregate system reduces significantly. For example, in 15% wind penetration case, the hourly wind variability of the aggregate system is less than 6.5% of the installed capacity, while it is less than 8.4% and 8.6% of the installed capacity in TamilNadu and Karnataka respectively.

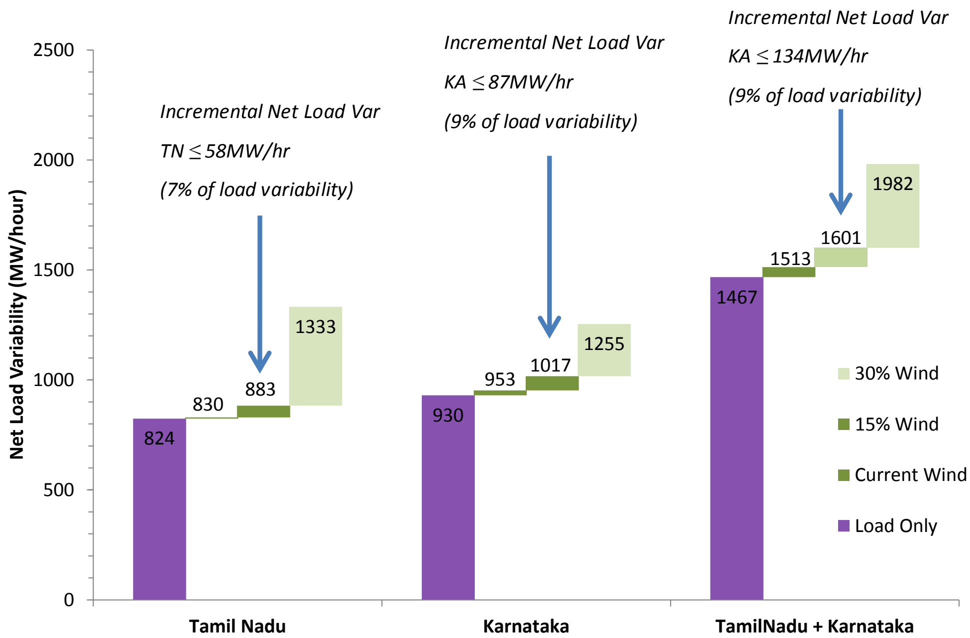


Figure 15: 99th Percentile Value of the Hourly Net Load Variability TamilNadu, Karnataka and Aggregate System (TamilNadu + Karnataka)

As shown in Figure 15, in the aggregate system, the incremental hourly net load variability due to 15% wind penetration is less than 134MW/hr (9.1% of the load only variability) for 99% of the time; the same numbers are 58MW/hr (7.1% of the load only variability) and 87MW/hr (9.3% of the load only variability). In other words, the incremental variability added due to wind in the aggregate system is only about 80% of the sum of incremental variabilities in each state. These results are in agreement with the variability literature that has shown that load and wind aggregation (combining multiple systems) reduces the variability significantly (Michael Milligan et al. 2009; B. Parsons et al. 2004; Smith et al. 2007).

4.6 Comparison with Variability in US and Europe

In this section, we compare the variability numbers in Tamil Nadu and Karnataka with those of some North American and European wind projects. Most studies analyzing the variability in American and European systems estimate the incremental variability by taking differences of standard deviations of system load and netload variabilities. Therefore, in the following table, we present the incremental variability of the Indian wind projects in terms of differences in standard deviations to facilitate the comparison.

Table 3: Comparison of incremental variability (standard deviations) added due to wind in US, Europe and India

	USA			North Europe					India (Current penetration)		
	Iowa Case A*,[a]	Iowa Case B*,[a]	Grant County PUD (WA)[b]	Finland (2001)[b]	Denmark (2000-02)[b]	Nordic (2000-02)[b]	Sweden (70% offshore)[b]	Sweden (50% offshore)[b]	Karnataka[c]	Tamil Nadu[c]	Aggregate (Karnataka + TamilNadu)[c]
Peak demand (MW)	NA	NA	610	11,696	6,349	68,476	25,800	25,800	8,291	11,323	18,438
Nameplate capacity (MW)	1,600	1,600	64	4,000	2,000	19091-19375	4,000	4,000	2,200	6,018	8,218
Wind penetration rate (as % of total energy requirement)	NA	NA	NA	10.0%	10.0%	10.0%	6.6%	6.6%	6%	10%	9%
Standard deviation of system load-only variability (MW). (mean ≈ 0)	188	188	12.1	269	273	1,438	575	575	314	269	476
Standard deviation of netload variability (MW) (mean ≈ 0)	206	220	12.9	288	279	1,485	579	578	318	272	477
Increase in standard deviation of variability due to wind (MW)	18	32	0.8	19	6	47	4	3	4	3	2
Increase in standard deviation (%)	***9.6%***	***17.1%***	***6.7%***	***7.1%***	***2.2%***	***3.3%***	***0.7%***	***0.5%***	***1.3%***	***1.2%***	***0.4%***

* Case A represents the combination of wind projects that are the most geographically dispersed and has the least impact on load following demands. Case B represents the least geographically dispersed wind generation projects with the highest impacts on load following demands (Krich and Milligan 2005).

[a] Source: (Krich and Milligan 2005)

[b] Source: (Holttinen, Milligan et al. 2008)

[c] Source: Authors' estimates. Please note that these values refer to the current penetration of wind projects.

The incremental variability added due to current wind penetration in TamilNadu and Karnataka is significantly lower than that in US, and is comparable to that in North Europe. If the two Indian systems are aggregated (TamilNadu+Karnataka), the variability drops even further and is lower than the North European wind.[8]

Conclusions

In this study, we empirically assess the variability in load and wind generation in India and their impact on grid integration using actual 5-minute data from two Indian states of Karnataka (KA) and Tamil Nadu (TN) - together accounting for more than 50% of the existing wind capacity in the country. We first estimate the variability in wind, load, and net-load (load minus wind generation) for 5 min, 15 min and 1-hr intervals. Net load is what the conventional generators like coal and gas have to meet after wind generation has been integrated into the grid. Therefore, the incremental variability added by wind is the difference between load variability with net-load variability. We primarily use the 99th percentile value as the measure of variability. We then assess the level of additional ramping/load following capability needed to integrate wind by estimating the difference in the net load variability and the current ramping capability of the system. We undertake this analysis for three scenarios viz. current wind penetration, 15% wind penetration by energy, and 30% wind penetration by energy.

We find that the existing variation in demand is significantly higher than that in wind. In TamilNadu, for 5-min, 15-min and 1-hour time intervals, the variability in load is lower than 2.7%, 3.8%, and 7.4% of the peak demand respectively for 99% of the time. For the same intervals, the net load variability for current wind penetration is lower than 2.6%, 3.9%, and 7.4%, for 99% of the time indicating that the incremental variability added by wind is minor. For 15% and 30% wind penetration cases, the hourly net load variability is lower than 7.8% and 11.9% of the peak demand for 99% of the time indicating that even for aggressive wind penetration scenarios, the incremental variability added due to wind is only moderate. The net load variability determines the system ramping requirement. We estimate ramping capacity of the TN system based on the typical ramp rate constraints of generators and whether these generators are online given the load, for every 15 minute interval. We find that for 15% wind penetration (~8680 MW installed capacity), system ramping requirement is higher than the ramping capability for 1.2% of the time (428 instances out of ~34,500). In comparison, if we consider variation in load, the system ramping requirement is higher than ramping capability for 1.1% of the time (376 instances), which shows that during these periods, generators were ramping more than the constraints we have assumed for this analysis.

Typically, load variation is highly predictable, more so than wind. Hence, it is likely that the net load variation (after integrating wind) is less predictable than variation in load. Sufficient

[8] It is to be noted that this comparison is only illustrative, as the incremental variability numbers are not directly comparable across regions / countries since the wind penetration rates may vary.

generation capacity needs to be committed and online (spinning) to meet ramp requirements. If ramp requirements are known in advance, appropriate level of units can be committed. A preliminary analysis of the TN system suggests that because of the widespread shortage in the state, all thermal and gas units (including central allocations and IPPs) that were available on a given day were generating close to full load most of the time (98.9% of the time) i.e. all available thermal units were committed most of the time. Moreover, up to 25% wind penetration by energy (installed capacity ~15000MW), minimum stable generation of thermal plants is lower than net load most of the year. This means that even if wind generation is completely random, all thermal units can remain committed and provide the necessary ramping-up support. This will keep the integration costs limited to the loss of heat rate of thermal plants (typically 5-10% of the variable cost of thermal plants) plus some wind curtailment (about 10%). However, with state of the art wind forecasting techniques, the forecast error can be significantly reduced even several hours ahead; this can help optimizing the unit commitments and minimizing wind curtailment even at high penetration rates. Moreover, if generation resources are shared across multiple states (through a real time energy or an ancillary services market), the system flexibility would improve and the need for wind curtailment can go down.

Note that the variability analysis conducted for various wind penetration rates in this study establishes the upper bound of variability, since it assumes that all future wind generation will be added in the same locations as the current wind sites. However, in reality, wind generation may be added in sites that are better dispersed geographically, and wind aggregation may significantly reduce the variability. So, next, we assess the effect of geographic diversity on wind variability by aggregating the TamilNadu and Karnataka systems. We find that in 15% wind penetration case, the hourly wind variability of the aggregate system is less than 6.5% of the installed capacity, while it is less than 8.4% and 8.6% of the installed capacity in TamilNadu and Karnataka respectively. Similarly, the incremental variability added due to wind in the aggregate system is only about 80% of the sum of incremental variabilities in each state. In short, aggregation of geographically diverse load and wind resources is found to lower the variability significantly. Overall, the incremental variability added by wind generation in India is found to be lower than that in the US, and is comparable to that seen in the North European projects.

In conclusion, it appears that given the limited contribution of wind energy to increasing variability of the net load that the systems needs to meet, requirements of additional flexible generation capacity may be modest and may not impose large integration costs. Our conclusion are similar to those by other integration studies in US and Europe which indicate a modest addition by wind to the total variability already existing in load for up to 30% wind penetration levels. Accurate estimates of wind and load curtailment are needed to further improve the robustness of our findings. These findings indicate that the potential capacity support (if wind does not generate enough during peak periods) may be the issue that has more bearing on the economics of integrating wind.

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