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Risk constrained short-term scheduling with dynamic line ratings for Increased Penetration of Wind Power

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Abstract

Limited transmission capacity may lead to network congestion which results in wind curtailment during periods of high availability of wind. Conventional congestion management techniques usually involve generation management which may not always benefit large wind farms. This paper investigates the problem in detail and presents an improved methodology to quantify the latent scheduling capacity of a power system taking into account stochastic variation in line-thermal rating, intermittency of wind, and mitigating the risk of network congestion associated with high penetration of wind. The mathematical model converts conventional thermal constraints to dynamic constraints by using a discretized stochastic penalty function with quadratic approximation of constraint relaxation risk. The uniqueness of the approach is that it can limit the generation to be curtailed or re-dispatch by dynamically enhancing the network latent capacity as per the need. The approach is aimed at strategic planning of power systems in the context of power systems with short to medium length lines with a priori known unit commitment decisions and uses stochastic optimization with a two stage recourse action. Results suggest that a considerable level of wind penetration is possible with dynamic line ratings, without adversely affecting the risk of network congestion.

Keywords – Wind Power, Network congestion, dynamic line rating, power system optimisation

1. Introduction

Network congestion is a major factor hindering the large scale integration of renewable energy generators into the grid. It is an undesirable result of insufficient capacity being available on a network to transport electricity from generation to loads which leads to volatility in locational marginal prices (LMP) and inequitable allocation of available network capacity to market participants. A number of publications have used the volatility in LMP as an indicator of network congestion [1-3]. In systems with large amount of wind power, network congestion hinders effective integration and utilization of wind as extra wind generated has to be curtailed thereby leading to uncertainty in revenue for wind power producers and overall higher costs for customers. The dynamic nature of wind results in large variations in power output over a short period of time, which makes effective utilization of wind an even bigger challenge in congested networks.

Currently, line ratings are based on worst case assumptions of ambient weather conditions according to the process outlined in IEEE Std 738-2012 [4]. The IEEE standard also covers transient and dynamic rating methodologies and a number of publications [5-9] have applied this methodology to demonstrate that the true thermal capacity of a transmission line is usually considerably higher than the rated values. This is to be expected since conventional ratings are calculated under the worst case weather assumption although such operating conditions occurs rarely in practice. It is possible to exploit this property by using dynamic line ratings (DLR) which model the thermal limit of transmission lines as a stochastically varying function of internal and external real time operating conditions such as ambient temperature, cooling due to wind, level of loading, and sag.

To partially account for variation in ambient conditions, some ISOs (independent system operators) currently use normal and emergency ratings as well as separate ratings for hot and cold weather. While these ratings consider some variation in ambient conditions they still assume the worst case scenario for a shorter period of time. These ratings are an approximation at best and the actual thermal limit has a high likelihood of being significantly different. In modern power systems which consist of multiple competing entities and fast changing power flows due to presence of intermittent renewable generation, inaccurate estimation of real time ampacity can result in underutilization of network capacity and congestion. Any network investment requires strong economic justification and it may be viable to fully utilize existing network capacity prior to considering further investment in new assets. This is especially true for renewable generation which has to be competitive with conventional generation and cannot afford to add on the cost of increasing network capacity. Dynamic ratings can provide a significant increase in the normal and emergency operational flexibility of power transmission systems compared to the more traditional static rating and alleviate network congestion due to short periods of high wind power output. DLR is applicable for power systems with short to medium lines where thermal capacity as opposed to stability limit is the limiting factor to line capacity.

The benefit of DLR over conventional congestion management approaches is that it can potentially release latent capacity dynamically rather than relying on generation curtailment and demand reduction in congested parts of a network, thus improving the operational flexibility and deferring investments. Dynamic line ratings can exploit the advanced real time monitoring and control capabilities of smart grids to potentially alleviate network congestion, and ensure a more equitable allocation of costs between market participants.

The two immediate challenges of implementing the dynamic line rating methods presented in [5-8] are the need for an online, smart monitoring system to capture real time variation and the modelling of uncertainty in constraints in optimal scheduling. While uncertainty in optimization variables can be accounted for by stochastic optimization techniques, uncertainty in constraints is more challenging to model since analytical constrained optimization techniques only allow fixed constraints. Most of the power system applications of optimal scheduling problems model line power transfer limits as deterministic values and place less emphasis on dynamic variation in line capacity. Exceeding thermal limits for a short period of time results in an increased level of risk and it is important to account for this when modelling dynamic ratings. An alternative to this is chance constrained optimization which allows some flexibility in the constraint satisfaction by allowing constraint violation, provided their probability is limited to a specified value [10, 11].

This paper proposes a new mathematical framework and a methodology to incorporate benefits of real time variation in line ratings to temporarily relax constrained capacity of a network and to vary reinforcement thresholds. The technique allows the stochastically estimated real time ampacity to be included in scheduling decisions by allowing a degree of flexibility to satisfy dynamic thermal limit constraints. The uniqueness of the proposed approach is that it replaces the current deterministic constraints (normal and emergency) in the optimal scheduling problem, with dynamic constraints. The approach dynamically quantifies the extent to which capacity could be relaxed by utilizing a discrete stochastic penalty function to model the risk associated with relaxing thermal limits. This method also incorporates the benefits of smart grid environments where real time data of system parameters such as sag and ambient temperature is available. The proposed approach could potentially provide considerable advantage over traditional approaches of using deterministic ratings due to the use of real time extraction of latent capacities during the optimization process. The proposed technique indicates the extent of congestion in a power network by weighting LMP at each node with respect to demand and finding the difference in the weighted LMP from the uncongested base case. The extended conic quadratic (ECQ) approach presented in [12] is used for optimization. It is modified to include dynamic line ratings.

2. Dynamic Asset Rating

2.1 Stochastic Optimisation with Dynamic Asset Ratings

The maximum thermal capacity of a line depends on the maximum allowable temperature of the line at which the conductors start to lose structural integrity or undergo annealing. IEEE Std 738 2012 outlines the process for calculating the maximum ampacity based on weather conditions for steady state, transient and dynamic scenarios. A number of models [5, 6, 8] apply the concepts in IEEE Std. 738 to determine dynamic line ratings which use weather data as an input. Kazerooni et al [7] have shown that when all the stochastic variations in weather are accounted for, the thermal capacity of the line can be modelled by the generalized extreme value probability distribution and in most cases the rated line capacity is on the lower end of the possible range of thermal capacities.

The correlation between wind speed and the cooling of the line was considered negligible in for this study, due the variation in weather conditions in different parts of a line [8]. While it is expected that weather conditions will mostly be favourable compared to the worst case assumptions for conventional line ratings, it is unlikely that all parts of the line will be exposed to high wind speeds which coincide with periods of high wind at the single location of the wind farm. It is assumed that the dynamic capacity is limited by regions where cooling due to wind is low and this provides a conservative estimate of the benefit due to DLR on wind integration. Typical parameters for the probability distribution of line capacity are provided in [7]. To determine the probability distribution of line ampacity historical weather data across the line will be necessary as per the procedure outlined in [7]. If correlation between wind speed and dynamic thermal ratings are to be accounted for, a different approach is required where the probability distribution of line capacity is conditional based on the probability of the wind speed distribution. A range of probability distributions for line capacity would be necessary for different wind speeds. Such an approach should be used with caution as it may overestimate the benefit of DLR.

The parameters of the probability distribution are determined according to the rated maximum limit on transmission lines. Based on the analysis in [5] most utilities load their lines such that the probability of exceeding the rated capacity ranges from 20 – 30%, depending on the season. Thus it was assumed that the probability of exceeding the rated capacity was 25% and an inverse distribution was used to determine the parameters for the probability distribution. The probability distribution was discretised by considering ten frequency and value pairs to represent the probability distribution. The actual probability can vary depending on the utility but it is straightforward to perform the analysis with a different value. A more detailed study might treat this as a random variable. The objective function incorporating DLR as a penalty function with stochastic elements is shown in (1)

$$f(x) = C_g(P_g) + C_W(P_W) + C_{DLR} + C_{congestion} \tag{1}$$

where $C_g(P_g)$, $C_w(P_w)$, C_{DLR} and $C_{congestion}$ represent cost of conventional generation, cost of wind (including reserves), cost of dynamic ratings, and cost of congestion respectively. $C_g(P_g)$ and associated constraints of conventional OPF (optimal power flow) problems are given in [12-15]. $C_w(P_w)$ is the cost of uncertainty due to wind, which can be incorporated into OPF by using stochastic optimization and is given in [12]. The problem is solved by transforming to a conic quadratic optimization problem and using an interior point method [12, 16]. This has the advantage that the objective function becomes quadratic and almost all the constraints become linear. These transformations are not system dependent and hence can be applied directly without a modification.

2.2 Formulation

The total cost of DLR (C_{DLR}) in (1) is determined stochastically and represents the penalty for temporarily relaxing the line thermal constraint. The stochastic penalty function enables substitution of the static line thermal constraint with a dynamic constraint. The cost of DLR is partly due to the long term cost of derating due to repeatedly overloading lines and the short term risk of causing damage by severe overloading which causes line temperature to exceed the maximum allowable value. It is assumed that when implementing DLR, the short term risk and expected cost of thermal overload is considered much more significant than long term derating costs. Separate studies by Wang [17] and Zhang [18] describe the variation of thermal overload risk with line current and demonstrate that for low levels of current overloading the risk of thermal overload is low but this increases rapidly for higher levels of DLR. Thus, the sensitivity of the penalty function to dynamic overloading must increase with increasing levels of DLR, thus suggesting an exponential penalty function. Instead it is modelled using a quadratic function as given in (2) since it can approximate the exponential function accurately for low levels of DLR, and the relative ease of calculating the Jacobian and Hessian matrices for quadratic functions.

$$C_{DLR} = \sum_{p=1}^{N_L} \sum_{q=1}^{N_L} \left[c_{OLp} \left(\sum_{k=1}^{N_k} h_{pq,k} a_{pq,k} \right)^2 \right] \tag{2}$$

where *p*-*q* represents a line from bus *p* to bus *q*. The cost of violating the constraint is proportional to the magnitude by which the actual line flow exceeds the line capacity. The constraints in (3) complement the expression for C_{DLR} in (2) to account for the cost of uncertainty in stochastic line rating.

$$\begin{aligned} a_{pq,k} &\geq s_{\max,pq,k} - S_{sch,pq} \\ a_{pq,k} &\geq 0 \end{aligned} \tag{3}$$

The thermal capacity of line *p*-*q* is approximated by a discrete random variable where each discrete value (represented by index *k*) of $s_{max,pq,k}$ has corresponding probability $h_{pq,k}$. The term $a_{pq,k}$ (with per unit cost c_{OLp}) represents the amount by which the actual line flow exceeds the discrete line capacity in the k^{th} ordered pair and it corrects any violation in the constraint $S_{sch,pq} > s_{max,pq,k}$. Thus ($h_{pq,k}$, $a_{pq,k}$) represents the probability distribution of dynamic line rating and the average value of $a_{pq,k}$ for all *k* represents the expected dynamic line rating.

The cost of DLR is based on the expected value of dynamic line rating which includes both the amount of DLR (a_{pq}) and the time for which it is implemented (h_{pq}). h_{pq} is an array of relative frequencies associated with each value of a_{pq}. If the time for which DLR is implemented varies, the value of $h_{pq,k}$ will change so that the probability distribution of a_{pq} changes. If the time for a specific amount of DLR is varied, it will change the probability distribution (specifically a change in probability for that level of DLR) and hence the expected value of DLR.

The DLR scheduling framework is to be used for a fixed scheduling period. This will typically be in the order of 15 – 30 minutes as longer periods of DLR will result in substantial risk of thermal overload. For the scheduling period under consideration, DLR is implemented at all times or not at all and the risk of implementing DLR for that time is captured by the cost function. In practice, smart monitoring systems will record the line temperature at the start of the scheduling period and simulate the final line temperature at the end of the scheduling period including the uncertainty based on the method in IEEE Std. 738. Based on this, the probability of exceeding the maximum line temperature can be determined. The line capacity probability distribution for the given scheduling period can be determined by the generalized extreme value distribution and based on this capacity, current is scheduled to minimize the time for which the line is overloaded. The severity associated with an outage in the event that the risk of thermal overload is realized can be determined by the number of customers affected by the outage and the total energy not supplied.

The risk associated with thermal overload includes both the likelihood of exceeding line maximum temperature and the cost of an outage in the line under consideration. The value of c_{OLp} is chosen so that the quadratic function in (2) best fits the variation of risk of thermal overload with current. Thus the risk of thermal overload is described by the expected cost of outage in a particular line which is considered the cost/penalty of DLR. In the case studies, a number of different values of c_{OLp} are used to determine the effect that the cost of DLR has on the effectiveness of DLR.

The proposed approach assumes cost of congestion ($C_{congestion}$) to increase linearly with the extent of congestion in the system. The main contributor to $C_{congestion}$ is the cost of dispatching expensive reserve generation after lower cost generation has been curtailed. It is assumed that these rapid response reserve generators have minimal startup cost and a much smaller output range compared to large generators. They are distributed in the network and the operating cost over the small range of output is approximated by linear cost functions. Alternatively, load may have to be shed if redispatch cannot supply load. The penalty associated with shedding load is also assumed to be linearly related to the load curtailed as shown in (4).

$$C_{congestion} = \sum_{n=1}^{N} c_D P_{local,n} \tag{4}$$

s.t.

$$P_{local,n} \le P_{D,n},\ P_{local,n} \ge 0,$$

where $P_{local,n}$ represents any adjustment of load (by calling on local reserves or load shedding) at bus n (where the total number of buses is N). $P_{local,n}$ is required to balance the system when congestion has occurred but it has a high cost per unit (c_D). Cost of network congestion can also represent the loss of revenue for generators since they cannot sell energy. This increased cost required to balance the system under congestion is allocated unevenly among customers which results in the volatility in nodal pricing that is observed during congestion.

For low levels of DLR, cost of congestion is higher relative to the risk of thermal overload from dynamically overloading lines. The optimization algorithm prefers to use DLR than call on expensive reserves after redispatch due to the lower cost of DLR. However, there is a maximum amount of DLR indicated by the intersection of the two functions in (2) and (4) beyond which, risk of DLR is greater than cost of congestion. Beyond the threshold point C_{DLR} is greater than $C_{congestion}$ thus forcing the optimization to not allow DLR beyond this limit as the risk associated with further overloading would not be justifiable. The DLR limit point represents both the maximum extent to which thermal limits can be relaxed and the time for which it can be relaxed

In addition to C_{DLR} and $C_{congestion}$ the basic OPF formulation includes generator fuel cost ($C_g(P_g)$) and constraints including real and reactive power balance, voltage limits, generator limits, and minimum generator up and down time. Line thermal constraints are replaced by the dynamic line rating formulation. The proposed approach modelled wind power intermittency cost ($C_w(P_w)$) using stochastic optimization by discretizing the probability distribution of wind power and balancing probabilistic reserve cost with cost of wasted wind [12] as shown in (5).

$$C_w(P_w) = \sum_{j=1}^{N_W} \left[e_j P_{Wj} + c_{Wj} \sum_{k=1}^{M} f_{jk} s_{jk} + c_{Rj} \sum_{k=1}^{M} f_{jk} t_{jk} \right] \tag{5}$$

Where the power output of wind generator j is P_{Wj} and the unit feed in cost is e_j. The cost of wind in (5) is subject to the constraints in (6).

$$\begin{aligned} t_{jk} &\geq P_{Wj} - w_{jk} \\ s_{jk} &\geq w_{jk} - P_{Wj} \\ t_{jk} &\geq 0, s_{jk} \geq 0 \end{aligned} \tag{6}$$

where (f_{jk}, w_{jk}) is the k^{th} ordered pair (out of a total of M) representing the discretized probability distribution of wind generator j. N_W is the number of wind generators in the system and c_{Wj} and c_{Rj} are the unit cost of wasted wind and reserve generation respectively at wind generator j. The cost of wasted wind represents the opportunity cost of not being able to sell the energy generated.

The problem was solved by transforming it to an extended conic quadratic (ECQ) form using the transformations in (7) [12, 16].

$$\begin{aligned} R_{in} &= V_i V_n \cos(\delta_i - \delta_n) \\ T_{in} &= V_i V_n \sin(\delta_i - \delta_n) \\ u_i &= \frac{V_i^2}{\sqrt{2}} \end{aligned} \tag{7}$$

Adding the rotated conic quadratic and arctangent equality constraints in (8) captured the nonlinearity of the classical OPF problem [12, 16].

$$\begin{aligned} 2u_i u_n &= R_{in}^{\ 2} + T_{in}^{\ 2} \\ \delta_i - \delta_n &= \tan^{-1}\left(\frac{T_{in}}{R_{in}}\right) \end{aligned} \tag{8}$$

All other constraints are transformed into linear expressions making the ECQ-OPF problem easily tractable by primal-dual interior point methods.

2.3 Metrics for indicating the level of congestion

The severity of congestion is quantified by the volatility in LMP and the amount of wind curtailment. Volatility in LMP is most commonly used as an indicator of network congestion as congestion cost is a significant component of LMP in transmission systems [2, 3, 19]. Pricing signals have been proposed as a control mechanism for renewable energy integration [20]. The proposed method first establishes a base case for LMP without incorporating network constraints. For each outage scenario, the LMP at each bus is compared to the base case LMP, weighted by the load at that bus and the overall weighted variation in LMP is found. To compare the LMP profile of a specific case to the base case, the term LMP_V is defined by (9).

$$LMP_V = \sqrt{\frac{1}{\sum_{i=1} P_{D,i}}\left(\sum_{i=1}\left[P_{D,i}\left(\frac{LMP_i - LMP_{i,base}}{LMP_{i,base}}\right)^2\right]\right)} \tag{9}$$

LMP_V is the LMP normalized by base LMP. A large value of LMP_V generally indicates that the given LMP profile is very different to the uncongested LMP profile which most likely suggests that the network is congested.

The other important indicator of network congestion in the context of the problem of wind curtailment is the level of curtailment compared to the uncongested base case. Wind curtailment is normalized with respect to the wind generation in the uncongested base case and determined by (10).

$$\text{wind curtailed} = \frac{P_{w,base} - P_w}{P_{w,base}} \tag{10}$$

The wind curtailed percentage is defined as difference between the wind scheduled in the base case and the case under consideration, normalized with respect to wind scheduled in the base case. The level of wind curtailment independently cannot indicate the level of congestion as wind may be curtailed due to multiple reasons such as low demand. Similarly, if the wind curtailment is low then the network congestion may not necessarily be low. Thus, if both the variation in LMP and wind curtailment indicates that there is network congestion then there is a high probability that congestion induced wind curtailment occurs. If LMP_V is high but wind curtailment is low, then it indicates that there is network congestion but it may not necessarily be leading to curtailment of wind power. Alternatively, congestion may have affected individual wind farms but the total wind curtailed may not have changed.

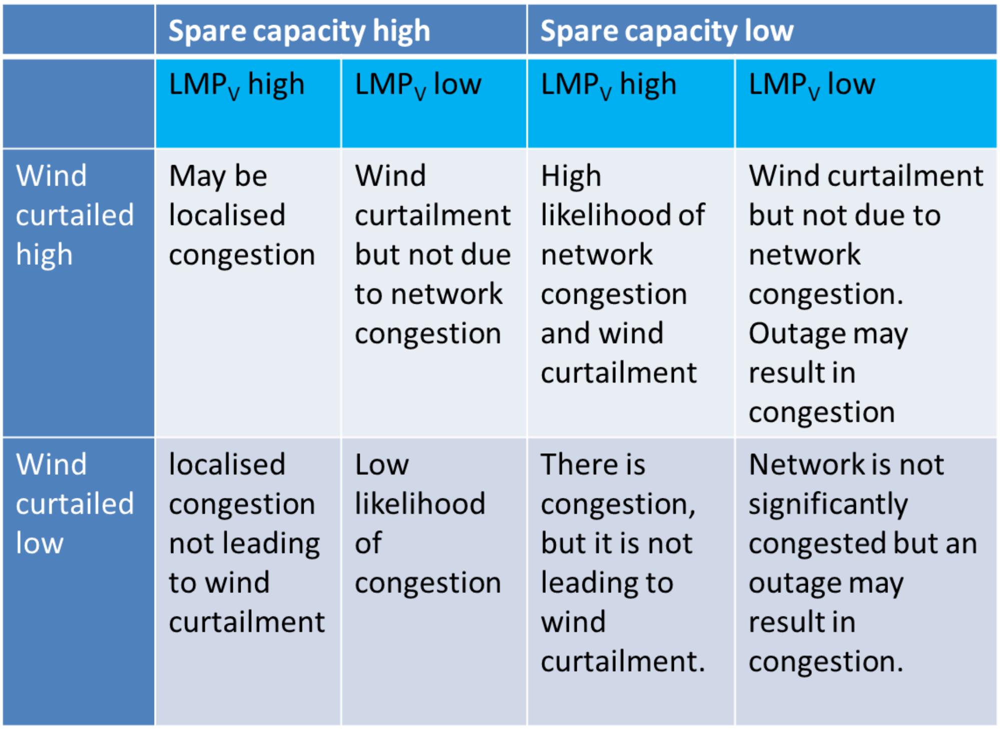
A third indicator of network congestion, in addition to the LMP volatility and wind curtailed, is the spare capacity in the network. It is measured as the total available capacity expressed relative to the total rated capacity of all lines and is determined by equation (11).

$$\text{spare capacity} = \frac{\sum_{all\ lines} (I_{\max} - I_{flow})}{\sum_{all\ lines} I_{\max}} \tag{11}$$

Where I_{max} is the magnitude of maximum current in a line and I_{flow} is the magnitude of current actually flowing in the line. I_{max} is the deterministic thermal limit of the line and when DLR is implemented the spare capacity may be negative. This is because I_{flow} will exceed the deterministic I_{max}. In the case studies, additional spare capacity required to relieve network congestion with deterministic ratings is used to determine the capacity released by DLR.

The metrics presented in this section are not exhaustive. Considering all three metrics would indicate the likelihood that congestion is occurring and that a detailed investigation of nodal pricing distribution and wind generation profile should be undertaken. Table 1 shows how to interpret the metrics for cases when no DLR has been implemented.

Table 1 Matrix for network congestion and wind curtailment



	Spare capacity high		**Spare capacity low**	
	LMP$_V$ high	LMP$_V$ low	LMP$_V$ high	LMP$_V$ low
Wind curtailed high	May be localised congestion	Wind curtailment but not due to network congestion	High likelihood of network congestion and wind curtailment	Wind curtailment but not due to network congestion. Outage may result in congestion
Wind curtailed low	localised congestion not leading to wind curtailment	Low likelihood of congestion	There is congestion, but it is not leading to wind curtailment.	Network is not significantly congested but an outage may result in congestion.

If DLR is implemented, the spare capacity will be negative in lines with DLR as the flow will exceed the deterministic thermal limit. The overall spare capacity may not be negative if the congestion is localised and DLR is only implemented in a few lines in the network. The other indicators can be used in the same way as shown in Table 1.

3. Results and discussion

3.1 Effect of wind penetration level

Figure 1 shows the effect of varying the total available wind capacity on the scheduled wind and the LMP_V for DLR and non DLR cases in the IEEE 14 bus test system.

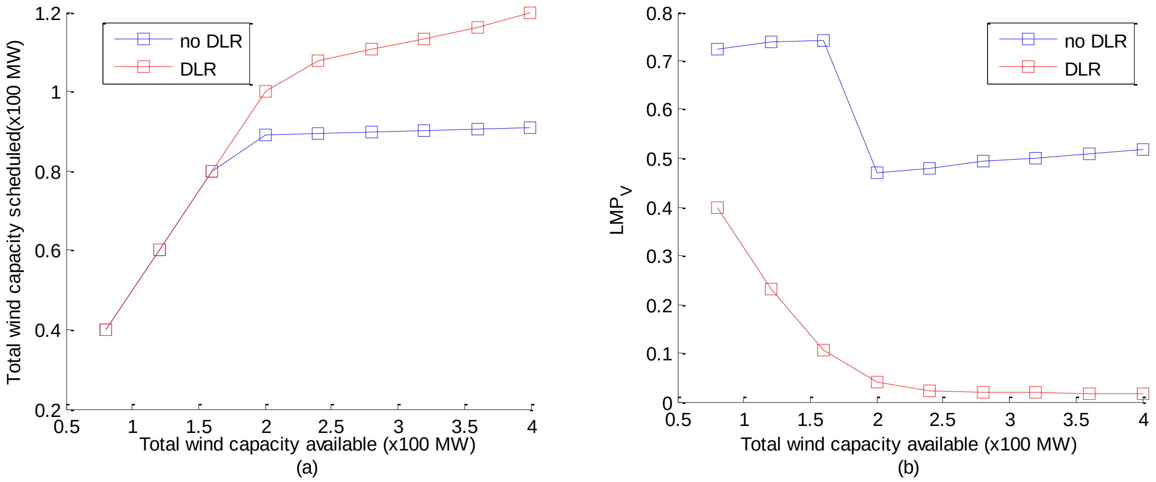


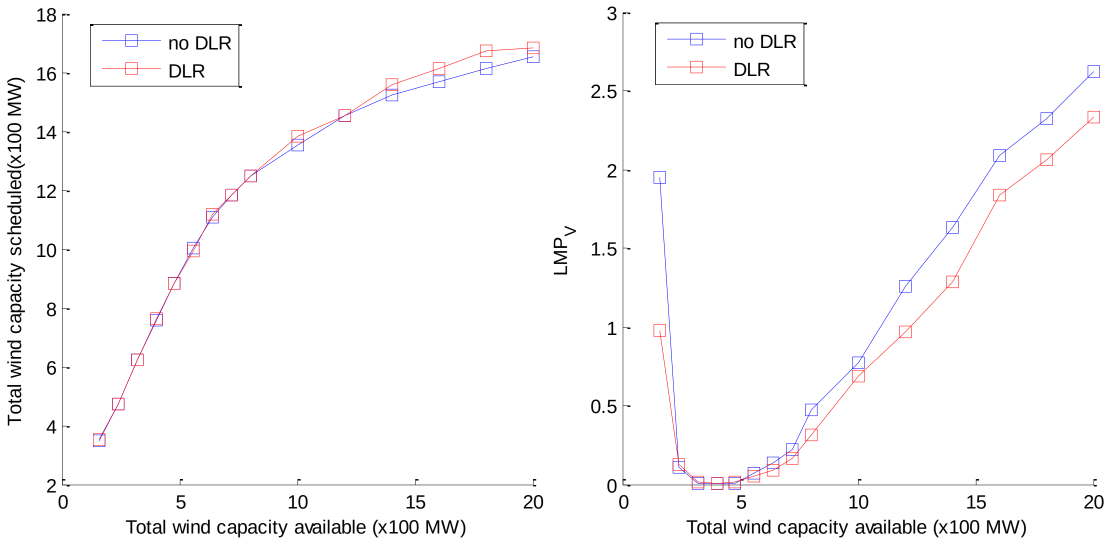
Figure 1 Effect of varying wind penetration level on (a) wind scheduled and (b) LMP_V for IEEE 14 bus test system

In Figure 1 the wind scheduled with and without DLR appears to increase linearly until approximately 150 MW of wind is available. The wind scheduled is identical between DLR and non DLR cases. If the total wind available is increased above 150 MW, the DLR case shows a higher amount of wind scheduled than the non DLR case. Furthermore, above 200 MW of available wind, no additional wind is scheduled as available wind is increased for the non DLR case. However, if DLR is implemented, the amount of wind scheduled continues to increase as the available wind capacity is increased. Thus, without DLR the amount of wind in the system reaches saturation much earlier than with DLR.

Figure 1 shows the variation in LMP_V with varying wind penetration. When no DLR is implemented the level of congestion appears quite insensitive to the total available wind capacity until it is increased to 150 MW. Beyond this value there is a drop in the level of LMP_V indicating a reduction in congestion between a total available wind capacity of 150 MW to 200 MW. Above 200 MW the variation in LMP_V appears to be minimal with a slightly increasing trend. Since additional wind in the system is not scheduled as per Figure 1, the associated cost of wind curtailment may cause slight increase in the LMP_V. However, this increase is small since the cost of wind curtailment is typically considered to be negligible considered to cost of unsupplied load and cost of scheduling emergency generation.

When DLR is implemented the LMP_V decreases with increasing levels of wind availability and reaches a minimum value at 250 MW of wind availability. This is possibly due to the extra latent capacity released by DLR which can accommodate the increased wind availability. Since the cost of wind and ancillary services is lower than the cost of supplying demand during congestion, this leads to a reduction in the *LMP_V*. As evident from 0, not all the available wind is scheduled when DLR is used, however, a fixed percentage of available wind is scheduled.

Figure 2 shows the effect of varying wind penetration level for the IEEE 118 bus system. In contrast to the 14 bus system, the trend for the wind scheduled versus wind available is nearly identical for DLR and non DLR cases. This indicates that DLR does not lead to any increase in the wind scheduled.



(a)

(b)

Figure 2 Effect of varying wind penetration level on (a) wind scheduled and (b) LMP_V for IEEE 118 bus test system

An examination of the variation in LMP_V shows that DLR causes a reduction in the level of LMP_V for almost all levels of available wind. In a large system with multiple generators it may not necessarily be economical to allocate latent capacity released by DLR to wind generation. The overall effect on the system due to DLR is not as high as for the 14 bus system. However, DLR may still be effective to relieve localised congestion if a smaller part of the network was considered as seen in the 14 bus system.

According to Figure 2(b) the LMP_V reaches a minimum value at an available wind capacity of 500 MW with and without DLR. This indicates there is an optimum penetration level of wind at which network congestion will be minimised. This point nearly coincides with the point in Figure 2(a) where the sensitivity of wind scheduled to available wind decreases significantly.

Initially wind penetration is limited by network capacity but as penetration of wind increases, cost of reserves starts to limit the amount of wind that can be scheduled. This eventually leads to a maximum level of wind penetration and any wind added above this level is unutilised. This maximum penetration was 150 MW in the 14 bus system and 500 MW in 118 bus system. If cost of reserves did not limit the wind scheduled, the curve in Figure 2(a) may have shown a linear increase. Due to the high cost of reserves relative to conventional generation, the cost of reserves is the limiting factor for the maximum penetration of wind rather than available network capacity. Thus the reserve cost is expected to have an impact on how much latent capacity is released and how this is allocated to various generation sources.

3.2 Effect of varying reserve cost on wind scheduling

Reserves are necessary to manage the intermittency of wind. These reserves may be storage or additional generation maintained on site at the wind farm to enable the wind power producer to regulate their output to the grid. In this case the cost of the reserves is borne by the wind power producer and they can make decisions on how much wind to commit to the system. Alternatively, the system operator may choose to maintain reserves in the grid if there is a large penetration of renewables. These may be in the form of thermal generators' inherent capability to adjust output over a range, grid connected storage, or smaller high speed generators. Impact of cost of reserves on the effect of DLR for the IEEE 14 bus system is shown in Figure 3. Reserve cost is expressed in $1000 per 100 MW of reserves.

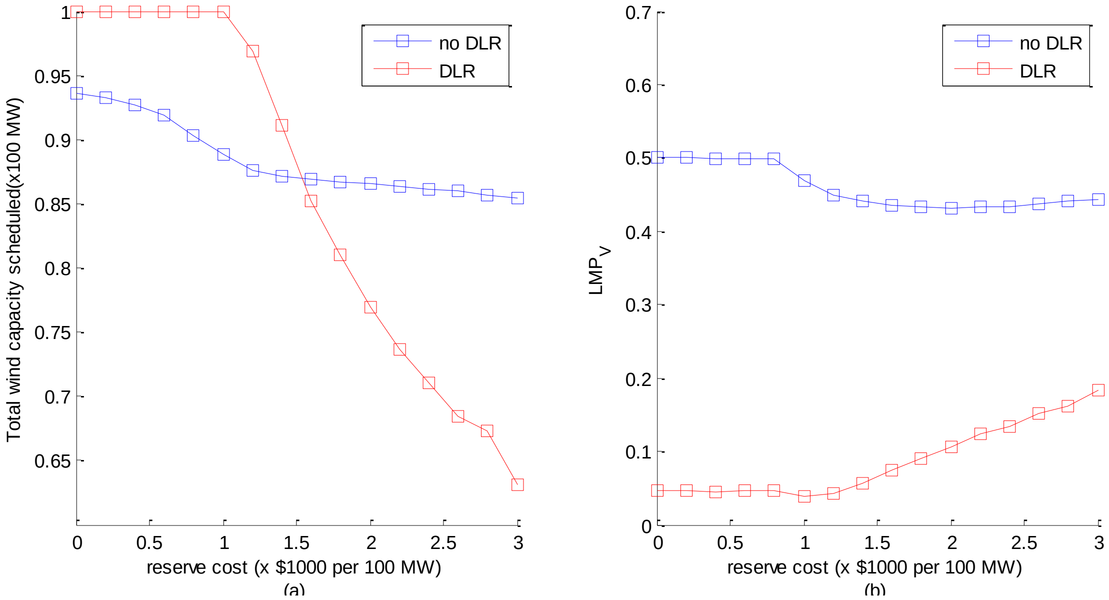


Figure 3 Effect of varying reserve cost on (a) wind scheduled (b) LMP_V for IEEE 14 bus test system.

According to Figure 3(a) there are three distinct regions in the curve. For reserve cost less than 1, wind scheduled due to DLR is constant. Between reserve cost 1 to 1.5, the wind scheduled with DLR decreases sharply and becomes less than the wind scheduled without DLR. Above reserve cost of 1.5, the wind scheduled without DLR decreases at a much slower rate than wind scheduled with DLR.

In region 1, the LMP_V in Figure 3(b) does not vary with reserve cost for reserve cost up to 1. However, the LMP_V is lower with DLR than without since any latent capacity is allocated to low cost wind generation. As the wind scheduled does not change significantly with reserve cost in this region, there is no change in LMP_V.

In region 2, the DLR cost is higher, and it starts to become uneconomical to allocate latent capacity to wind. As a result, the wind scheduled with DLR decreases sharply. Since cost of wind has increased, this leads to an overall increase in generation cost which results in the increase in LMP_V in Figure 3(b). In the case without DLR, wind scheduled does not decrease as sharply as the DLR case, since the lack of transmission capacity may not allow this. The reduced wind may allow more economical forms of generation which leads to a slight decrease in LMP_V. However, this LMPV is still higher than the LMP_V with DLR.

In region 3, less wind is scheduled with DLR than without indicating it is uneconomical to allocate latent capacity released by DLR to wind. The overall cost of generation continues to increase leading to the increase in LMP_V in Figure 3(b). In the no DLR case, the trend from region 2 continues for the wind scheduled. The LMP_V appears to reach a constant value due to any decrease in wind scheduled being compensated by conventional generation which has a similar cost.

Generally, increasing reserve costs adds to the overall cost of wind generation since reserves are required to manage intermittency, thus leading to less utilization of wind. When the reserve cost is comparable to cost of conventional generation, more wind is scheduled since it is more economical than conventional generation. Lack of transmission capacity does not limit the wind generation in this case since conventional generation is reduced accordingly.

The variation of wind scheduled and LMP_V with reserve cost for the IEEE 118 bus test system is shown in Figure 4

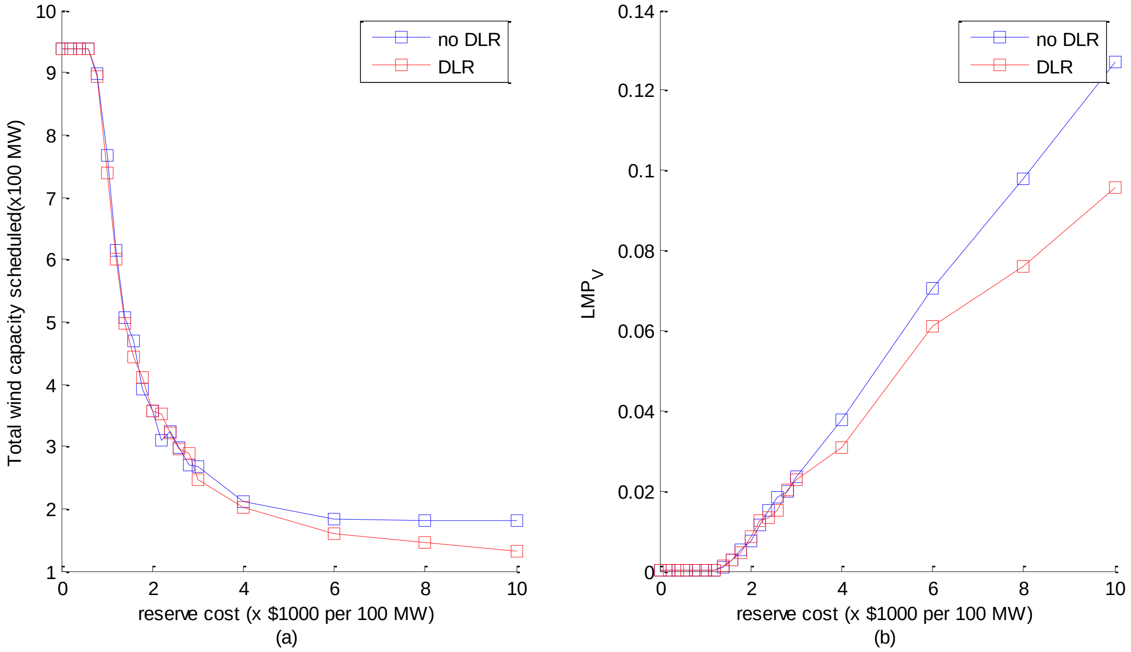


Figure 4 Effect of varying reserve cost on (a) wind scheduled (b) LMP_V for IEEE 118 bus test system

In Figure 4(a) the trends are less prominent. The wind scheduled is similar between DLR and no DLR cases for low reserve cost. As reserve cost increases, the total wind scheduled with DLR is lower than total wind schedule without DLR. Similar to the 14 bus system, the capacity released by DLR is not allocated to wind if the cost of reserves is too high. In Figure 4(b) the LMP_V with and without DLR are similar for reserve costs below 3.5. However, at higher reserve costs LMP_V is lower with DLR. The steady increase in LMP_V is due to the overall increasing cost of generation when reserve costs are increased. However, any latent capacity released is allocated to less expensive generation sources thus ensuring that LMP_V is lower when DLR is used.

The weather patterns will determine the amount of wind available and the available network capacity will determine the extent of wind utilisation. While the analysis in this section refers to congestion under normal operating conditions (without outages), there is always a risk of further congestion if a system contingency occurs. When DLR is not used, the risk of network congestion for a given penetration level of wind would be significantly higher and the risk is reduced by using dynamic line ratings.

For systems without contingencies, the effect of DLR may not be evident in large systems. However, localised congestion may be relieved when DLR is implemented. While DLR usually releases some amount of latent capacity, this is allocated to the most efficient forms of generation which may or may not be wind. Thus while DLR can reduce congestion, it may not necessarily increase wind integration.

Dynamic Line rating methodologies present a viable temporary alternative to network reinforcement and expansion to alleviate localised congestion. Smart grid infrastructure for monitoring ambient conditions as well as asset conditions need to be in place to implement dynamic line ratings. Protection devices will have to adapt to levels of current flow which would exceed conventional ratings. Distance relays monitor voltage in addition to current so it is likely to operate under DLR events compared to current relays. Alternatively, smart protection devices may be used which could operate on the basis of line temperature or line sag exceeding a specified limit rather than line current.

4. Conclusion

The paper proposed a new mathematical framework to assess the potential ability of DLR to reduce the level of network congestion and limit the curtailment levels of wind power in power systems. The model converts conventional thermal constraints to dynamic constraints by using a discretized stochastic penalty function with quadratic approximation of constraint relaxation risk. The novelty of this method is that it allows real time variation of dynamic line rating to be modelled stochastically and incorporated into planning and scheduling decisions while controlling the extent of DLR by varying the cost parameters. This method is ideal for application in a smart grid environment where real time data about the network status is readily available.

Case studies suggest that DLR can potentially release a considerable amount of capacity of network assets in systems under congestion, enabling increased wind power integration. DLR is especially effective in reducing localised congestion and may be considered as an alternative for deferring or completely avoiding network expansion in congested areas. While DLR releases latent network capacity it does not directly influence the allocation of the latent capacity released among generators. The effect of DLR on increasing wind integration depends on factors such as reserve cost and the level of available wind relative to conventional generation.

Power systems need periodic investment planning to meet growth in demand, uncertainties, and risks associated with active operation. In that context, the proposed approach can be used to monitor the net network reinforcement requirement in power systems by utilizing the benefits that can be offered by DLR of assets under normal operation and credible contingencies.

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