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Understanding the Benefits of Dynamic Line Rating under Multiple Sources of Uncertainty

Fei Teng, *Member, IEEE*, Romain Dupin, Andrea Michiorri, George Kariniotakis, *Senior Member, IEEE*, Yanfei Chen and Goran Strbac, *Member, IEEE*

Abstract-- This paper analyses the benefits of dynamic line rating (DLR) in the system with high penetration of wind generation. A probabilistic forecasting model for the line ratings is incorporated into a two-stage stochastic optimization model. The scheduling model, for the first time, considers the uncertainty associated with wind generation, line ratings and line outages to co-optimize the energy production and reserve holding levels in the scheduling stage as well as the re-dispatch actions in the real-time operation stage. Therefore, the benefits of higher utilization of line capacity can be explicitly balanced against the costs of increased holding and utilization of reserve services due to the forecasting error. The computational burden driven by the modelling of multiple sources of uncertainty is tackled by applying an efficient filtering approach. The case studies demonstrate the benefits of DLR in supporting cost-effective integration of high penetration of wind generation into the existing network. We also highlight the importance of simultaneously considering the multiple sources of uncertainty in understanding the benefits of DLR. Furthermore, this paper analyses the impact of different operational strategies, the coordination among multiple flexible technologies and installed capacity of wind generation on the benefits of DLR.

Index Terms—Dynamic line rating, probabilistic forecasting, stochastic programming, wind generation.

NOMENCLATURE

A. Constants (Written in Normal Font)

D_n	Demand in node n (MW)
$\underline{F}_l / \bar{F}_l$	Minimum / Maximum capacity of AC transmission line l (MW)
$\bar{H}_g^{up} / \bar{H}_g^{do}$	Maximum reserve up / down holding amount of conventional generator g (MW)
$\underline{P}_g / \bar{P}_g$	Minimum / Maximum capacity of conventional generator g (MW)
$\bar{WP}_{s,w}$	Maximum available output of wind generator w in scenario s (MW)
X_l	Reactance of AC line l (p.u.)
$Voll_n$	Value of lost load at node n [£/MWh].

πfix_g	Fixed/Commitment cost of conventional generator g (£/MW/h)
$\pi fuel_g$	Fuel cost of conventional generator g (£/MWh)
πrdo_g	Utilization cost of reserve down service from conventional generator g (£/MWh)
πrup_g	Utilization cost of reserve up service from conventional generator g (£/MWh)
<i>B. Variables (Written in Italic Font)</i>	
$f_{s,l}$	Power flow of AC line l at scenario s (MW)
I_g	Binary variable. 1 means conventional generator g is committed
$ll_{s,n}$	Loss of load in node k at operating state s [MW]
P_g	Output of conventional generator g (MW)
$R_{s,g}^{up} / R_{s,g}^{do}$	Utilized reserve up /down service from conventional generator g at scenario s (MW)
$WP_{s,w}$	Output of wind generator w at scenario s (MW)
$\Delta_{s,l}$	Ratio of DLR to SLR for line l at scenario s (p.u.)
$\theta_{s,n}$	Voltage angle of node n at scenario s (rad)

C. Set Related Constants (Written in Italic Font)

G_n	Set of conventional generators in node n
I_n	Set of lines with positive power flow to node n
$n_1(l)$	First end node of line l
$n_2(l)$	Second end node of line l
Ng	Total number of conventional generators
Nl	Total number of transmission lines
Nn	Total number of nodes
Ns	Total number of scenarios
Nw	Total number of wind generators
O_n	Set of lines with positive power flow from node n
W_n	Set of wind generators in node n .

I. INTRODUCTION

High penetration of renewable energy resources (RES) are expected to be integrated into the future power systems. However, there are two main challenges associated with such massive integration. Firstly, most of RES are intermittent, leading to an increased need on the ancillary services [1]. Novel stochastic operation frameworks, along with flexible technologies (such as energy storage), have been proposed to accommodate the intermittence of RES. Secondly, RES is usually located in the remote areas, and hence large-scale

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network expansion is required to transfer the low-carbon electricity to the load centre [2]. This not only requires large amount of investment, but also takes long time to develop, potentially limiting the penetration of RES in the short term.

Dynamic line rating (DLR) [3] is an alternative technology to enhance the transfer capability of the existing network. Traditionally, static line ratings (SLR) are utilized, while the actual line capacity depends on various factors that change in time, such as solar radiation and wind condition [4]. SLR causes significant under-utilization of the actual network transfer capability. The application of DLR can effectively alleviate network congestion, lower the operating costs and RES curtailment in the short term and thus postpone and reduce the need of network reinforcement and support the high penetration of RES in the long term. Therefore, it is important to understand how DLR can be optimally integrated into the system operation and to what extent it can facilitate the cost-effective integration of RES [5].

The authors in [6] propose a general DLR calculation model and carry out cost-benefit analysis for the application of DLR. An “N-1” security constrained dispatch model is presented in [7] with the consideration of DLR and the results suggest that DLR reduces RES curtailment and dispatch cost with the expense of higher computational time for the scheduling problem. The study in [8] shows that the implementation of DLR to a 132kV line between Skegness and Boston can enable 20% to 50% more wind generation to be connected. The authors in [9] propose a distribution network investment model with DLR option to demonstrate the role of DLR in supporting distributed energy resources. Combined analysis of DLR and demand response in [10] identifies the synergy between these technologies. The authors in [11] apply a security constrained AC dispatch model to investigate the benefit of DLR in enhancing the system security.

However, like other weather-dependent elements, the line ratings cannot be perfectly forecasted in advance, which is not explicitly considered in the above literatures. The authors in [12] highlight the need to develop DLR forecast models to facilitate its application and present a state-of-art review on the forecasting techniques. Machine learning techniques [13] and ensemble weather forecast [14] are among the most widely used method in the forecasting of DLR. A novel probabilistic DLR forecasting method is developed in [15] to derive the expected value and important percentiles of ratings.

The forecasting error of DLR imposes significant challenges on its optimal implementation in the system operation. A cost-benefit based optimal quantile selection approach is developed in [23] and the selected quantile can be used as the input into the system scheduling model. The authors in [16] propose a novel robust congestion management model to optimally use DLR on critical lines, while keeping the risk of overloading below certain level. However, this model relies on a simple binary line rating forecast and requires pre-selected risk level. The work in [17] incorporates DLR with forecasting error distribution into a robust system dispatch framework, but only considers the uncertainty related to DLR forecast. Two-stage stochastic

programming is the most widely used method to coordinate day-ahead dispatch and real-time re-dispatch actions under uncertainty [18]. However, none of existing stochastic model directly incorporates DLR into the optimal system operation when simultaneously considering forecasting errors of DLR and wind generation as well as line outages. Furthermore, in addition to DLR, there are multiple flexible network technologies (e.g. FACTs). In the literature and industrial applications, there is lack of understanding on how DLR can be optimally utilized to support high penetration of RES when considering the interaction among multiple sources of uncertainty and the coordination among multiple flexible technologies.

In this context, this paper extends a two-stage stochastic optimization model to include the probabilistic forecasts of DLR so that the model can co-optimize the energy and reserve holding levels in the scheduling stage as well as the re-dispatch actions in the real-time operation stage. Therefore, the benefit of higher utilization of line capacity can be explicitly balanced against the cost of increased holding and utilization of reserve services and/or demand shedding. The key contributions can be summarised as:

- 1) this paper presents a stochastic assessment framework with the probabilistic forecasts of DLR, which, for the first time, enables the understanding of optimal utilization of DLR with consideration of the interaction among multiple sources of uncertainty (DLR, wind outputs and line outages) and the coordination among multiple flexible network technologies (DLR and FACTs).
- 2) to tackle the computational burden driven by the large number of integer variables associated with FACTs devices and the large number of scenarios driven by the multiple sources of uncertainty, we investigate the minimal value of “big-M” used in the disjunctive approach and apply an iterative filtering model to select a subset of the scenarios to represent the multiple sources of uncertainty.
- 3) comprehensive analysis is carried out to understand the benefits of DLR in the system with high penetration of wind generation under different operational strategies and to investigate how the correlations among multiple sources of uncertainty as well as the coordination with FACTs devices may affect the benefits of DLR.

The paper is organized as follows. Section II presents the modelling framework for DLR and its forecasting. Section III introduces the two-stage stochastic scheduling model that is used to optimize the system operation with probabilistic forecasts of DLR. The benefits of DLR are firstly demonstrated through a simple 2-busbar system in Section IV and a study on IEEE 24 bus RTS system is then presented in Section V. Final conclusions are discussed in section VI.

II. DYNAMIC LINE RATING

A. Modelling of Dynamic Line Rating

The current carrying capacity of overhead line conductors is determined by the maximum sag, which guarantees the minimum allowed clearance. Conductors lose tensile strength and hence increase their sag with the increased temperature,

as summarised in (1) with the link between tensile strength F_t and vertical sag L_{sag} and (2) with the relation between conductor temperature T_c and axial tensile strength F_t .

$$L_{sag} \approx \frac{F_p L_{span}^2}{8 F_t} \quad (1)$$

$$E_c A_c \beta_c T_{c,i} + \frac{E_c A_c}{24} \left(\frac{F_{p,i} L_{span}}{F_{t,i}} \right)^2 - F_{t,i} = K \quad (2)$$

where L_{sag} [m] is sag, F_p [N] is linear weight of the conductor, F_t [N] is tensile strength of the conductor, L_{span} [m] is length of the span, E_c [Pa] is Young's modulus, A_c [m²] is conductor cross sectional area, β_c [K⁻¹] is conductor's expansion factor, T_c [K] is conductor's temperature and K [N] is a constant value.

This shows that the sag can be limited by constraining the conductor's temperature T_c . In the steady state, this parameter in turn is dependent on the thermal equilibrium between the heat dissipated by joule effect in the conductor and the heat exchange on its surface, as shown in Equation (3), usually represented in the form (4).

$$q_c + q_r = q_s + q_l \quad (3)$$

$$I = \sqrt{\frac{q_c + q_r - q_s}{R}} \quad (4)$$

where I [A] is maximum allowable current, q_c [W/m] is convective cooling, q_r [W/m] is radiative cooling, q_s [W/m] is solar heating and R [Ω /m] is conductor resistance.

As seen above, these terms depend on conductor's temperature and environmental parameters such as air temperature, wind speed and solar radiation. Details on the calculation on each one of these terms can be found in [6]. Due to the non-linear relations between conductor rating and wind speed and the variability of environmental parameters, it is common practice to use static ratings based on conservative assumptions. This has two main drawbacks: the use of a small part of the circuits' current carrying capacity and the presence of high risk situations where real ratings are below the SLR.

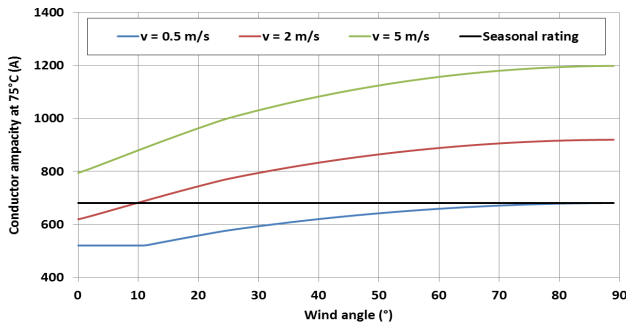


Fig.1 Relation among wind speed, wind direction and conductor ampacity

For an example of a Lynx cable with a maximum temperature of 75°C and according to the CIGRE standard, Fig.1 shows an illustration of the relationship between conductor rating, wind speed and wind direction, the ambient temperature being set to 20°C and the global solar radiation being null. These are compared with the summer static seasonal rating. The static seasonal rating is the current standard adopted by network operators for setting line maximum ampacity and is calculated considering static

values for weather parameters. In this case the values used are: 0.5 [m/s] for wind speed, wind direction perpendicular to the axis of the conductor, 20 [°C] for air temperature and 0 [W/m²] for solar radiation.

B. Forecast for Dynamic Line Rating

Like other weather-dependent elements, the actual line ratings cannot be perfectly forecasted in advance, which explains the slow take-up rate of this technology. Due to the strong dependence of DLR on the weather conditions, the procedure proposed for DLR forecasts is similar to the approach commonly used for renewable energy production forecast, i.e. based on a mix of statistical methods and meteorological forecasts. The problem of forecasting is treated as a regression problem, where it is to be found a function f_h able to provide an ampacity forecast $\hat{Y}_{t+h|t}$ at time $t+h$ knowing a set of information X_t at time t .

The line rating forecast $\hat{Y}_{t+h|t}$ at a time t for a horizon t , considering a series of explanatory variables X_t is given by:

$$\hat{Y}_{t+h|t} = f_h(X_t) \quad (5)$$

where f_h returns the random variable Y_{t+h} with an explicit distribution. Given that the conductor ampacity is not observable, we consider it as a nonlinear function $g(\cdot)$ of exogenous variable X_t . This function does not depend on the time step and can be calculated as detailed in [4,6].

System operators consider security constraints in a conservative way, and so the probability of having a forecast higher than the observation must be set as equal to a value τ defined by the operator as specified in (6). Such forecasts can be provided through various methods, directly providing a quantile forecast $\hat{Y}_{t+h|t}^\tau$ or a probability density function \hat{f}_h used for its calculation.

$$P(\hat{Y}_{t+h|t} > Y_{t+h}) = \tau \quad (6)$$

In this work, DLR forecasts are calculated with a Quantile Regression Forest algorithm [19], a machine learning method successfully used for probabilistic ampacity forecasts [13]. In this method, k different decision trees are generated and trained on a randomly generated dataset through bootstrap aggregation. After this at each split of the tree, features are selected through a random features' subset. The model calculates the k different ampacity values describing a distribution of results from what is possible to calculate an average or the values of different quantiles.

An example of the forecasts is presented in Fig.2. Historical records for wind and other weather parameters relevant for the calculation of DLR relative to southern Sweden for the year 2010 have been used. The records contain hourly measurements of wind speed, wind direction, solar radiation and air temperature. They are coupled with hourly Numerical Weather Prediction for horizon up to 48h for the same variables and updated once a day. These forecasts are obtained from the European Centre for Medium-Range Weather Forecasts.

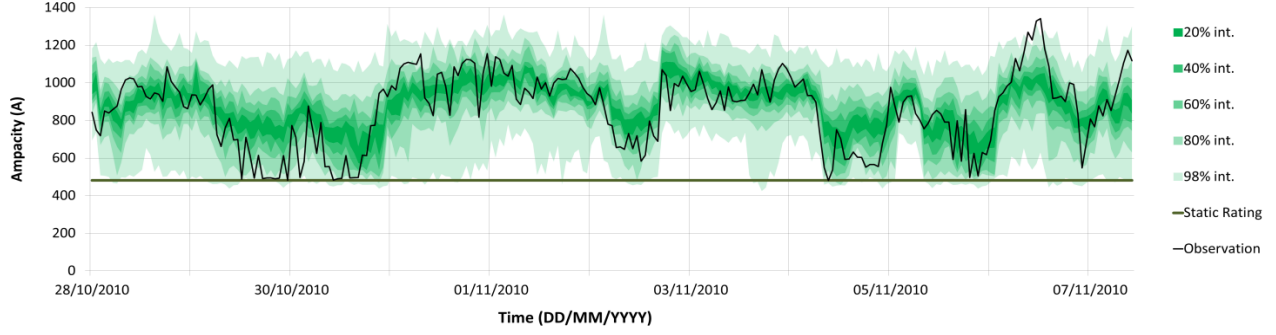


Fig. 2: Example of Dynamic Line Rating observations and day-ahead probabilistic forecasts

III. ASSESSMENT APPROACH: TWO-STAGE STOCHASTIC OPTIMIZATION MODEL

A two-stage stochastic optimization model is proposed based on the scenarios that combine the possible realizations of line ratings, wind levels and line outages. The corrective cost-benefit based framework incorporates control actions from all sources (generators, demand and network) during pre and post-fault conditions. The aim of this framework is to efficiently balance costs of generation dispatch (including energy supply and reserve holding) and costs of corrective control actions (including reserve utilization and post-fault demand shedding).

The objective function of the probabilistic optimization is introduced in (7), where “ t ” is the time duration of each selected operating condition and “ ρ_s ” represents the probability of the selected scenario “ s ”. The model is formulated as a mixed integer linear programming problem. The first components represent the dispatch costs (variable and fixed/commitment cost of conventional generators) in the scheduling stage, and the second and third cost components represent the costs of corrective control actions from generation side (reserve up/down services activation) and demand side (post-fault demand shedding) in each of the potential realizations.

$$\text{Min} \left\{ \begin{aligned} & t \cdot \sum_{g=1..Ng} \{ \text{pfuel}_g \cdot P_g + \text{pfix}_g \cdot I_g \} + \\ & t \cdot \sum_{\substack{g=1..Ng \\ s=2..Ns}} \rho_s \cdot \{ \text{prup}_g \cdot R_{s,g}^{\text{up}} - \text{prdo}_g \cdot R_{s,g}^{\text{do}} \} + \\ & t \cdot \sum_{\substack{n=1..Nn \\ s=2..Ns}} \rho_s \cdot \{ \text{Voll}_n \cdot ll_{s,n} \} \end{aligned} \right\} \quad (7)$$

The optimization problem is subject to the following constraints. Wind generator output (8) is a decision variable through each node of the scenario tree. Generation capacity boundary constraint is formulated in (9). The availability of reserve provision is constrained by the commitment decisions and physical limits of conventional generation, as in (10)-(16). Power flows in the network are calculated in (17)-(18), while power balance constraint containing wind generator for each node is given in (19).

$$0 \leq WP_{s,g} \leq \overline{WP}_{s,g} \quad \forall s = 2..Ns \quad \forall g = 1..Nw \quad (8)$$

$$\underline{P}_g \cdot I_g \leq P_g \leq \overline{P}_g \cdot I_g \quad \forall g = 1..Ng \quad (9)$$

$$H_g^{\text{up}} \leq \overline{H}_g^{\text{up}} \cdot I_g \quad \forall g = 1..Ng \quad (10)$$

$$H_g^{\text{do}} \leq \overline{H}_g^{\text{do}} \cdot I_g \quad \forall g = 1..Ng \quad (11)$$

$$H_g^{\text{up}} \leq \overline{P}_g - P_g \quad \forall g = 1..Ng \quad (12)$$

$$H_g^{\text{do}} \leq P_g - \underline{P}_g \quad \forall g = 1..Ng \quad (13)$$

$$0 \leq R_{s,g}^{\text{up}} \leq H_g^{\text{up}} \quad \forall s = 2..Ns, g = 1..Ng \quad (14)$$

$$0 \leq R_{s,g}^{\text{do}} \leq H_g^{\text{do}} \quad \forall s = 2..Ns, g = 1..Ng \quad (15)$$

$$R_{s=1,g}^{\text{up}} = R_{s=1,g}^{\text{do}} = 0 \quad s = 1, \forall g = 1..Ng \quad (16)$$

$$f_{s,l} = \frac{\theta_{s,n_1(l)} - \theta_{s,n_2(l)}}{X_l} \quad \forall s, l = 1..Nl \quad (17)$$

$$\theta_{s,n=\text{ref}} = 0 \quad \forall s \quad (18)$$

$$\begin{aligned} & \sum_{g \in Gn} (P_g + R_{s,g}^{\text{up}} - R_{s,g}^{\text{do}}) + \sum_{w \in Wn} WP_{s,g} + \sum_{l \in ln} (f_{s,l} + P_{s,l}^{\text{SC}}) \\ & - \sum_{l \in On} (f_{s,l} + P_{s,l}^{\text{SC}}) \\ & = D_n - ll_{s,n} \quad \forall s, n = 1..Nn \quad (19) \end{aligned}$$

Lines without and with DLR are contained in set A and B, respectively. The traditional line rating constraint is introduced in (20), while the constraint (21) is utilized to represent the lines equipped with DLR. In the case of line outage, constraint (22) is imposed.

$$\underline{F}_l \leq f_{s,l} + P_{s,l}^{\text{SC}} \leq \overline{F}_l \quad \forall s, l \text{ available}, l \in A \quad (20)$$

$$\underline{F}_l \cdot \Delta_{s,l} \leq f_{s,l} + P_{s,l}^{\text{SC}} \leq \overline{F}_l \cdot \Delta_{s,l} \quad \forall s, l \text{ available}, l \in B \quad (21)$$

$$f_{s,l} + P_{s,l}^{\text{SC}} = 0 \quad \forall s, l \text{ outage} \quad (22)$$

With the disjunctive approach, power flow modified by series compensation (SC) can be determined by:

If $\Delta\theta_{s,l}$ is positive, then

$$\varphi_l \cdot \Delta\theta_{s,l} \leq P_{s,l}^{\text{SC}} \leq \eta_l \cdot \Delta\theta_{s,l} \quad \forall s, l \in L \quad (23)$$

If $\Delta\theta_{s,l}$ is negative, then

$$\eta_l \cdot \Delta\theta_{s,l} \leq P_{s,l}^{\text{SC}} \leq \varphi_l \cdot \Delta\theta_{s,l} \quad \forall s, l \in L \quad (24)$$

To linearize this, “big-M” approach is applied to transfer (23)-(24) into 4 mixed integer linear constraints (25)-(28):

$$P_{s,l}^{\text{SC}} \leq \eta_l \cdot \Delta\theta_{s,l} + Y_{s,l} \cdot M_{s,l} \quad \forall s, l \in L \quad (25)$$

$$P_{s,l}^{\text{SC}} \geq \varphi_l \cdot \Delta\theta_{s,l} - Y_{s,l} \cdot M_{s,l} \quad \forall s, l \in L \quad (26)$$

$$P_{s,l}^{\text{SC}} \geq \eta_l \cdot \Delta\theta_{s,l} - (1 - Y_{s,l}) \cdot M_{s,l} \quad \forall s, l \in L \quad (27)$$

$$P_{s,l}^{\text{SC}} \leq \varphi_l \cdot \Delta\theta_{s,l} + (1 - Y_{s,l}) \cdot M_{s,l} \quad \forall s, l \in L \quad (28)$$

where $\eta_l = \frac{\overline{X}_l^{\text{SC}}}{X_l^*(X_l - \overline{X}_l^{\text{SC}})}$, $\varphi_l = \frac{\underline{X}_l^{\text{SC}}}{X_l^*(X_l - \underline{X}_l^{\text{SC}})}$, $\Delta\theta_{s,l} = (\theta_{s,k_1(l)} - \theta_{s,k_2(l)})$ and $Y_{s,l}$ is a binary variable.

The parameter " $M_{s,l}$ " is a sufficient large number. However, inappropriate selection of $M_{s,l}$ may lead to long calculation time and limit the application of the model. Hence a minimum value of $M_{s,l}$ is investigated to accelerate the optimization. When $\Delta\theta_{s,l}$ is positive and $Y_{s,l}$ is 0, in order to guarantee only (25) and (26) are activated, the right-hand side (RHS) of (28) must be bigger than the RHS of (25), and the RHS of (27) must be smaller than the RHS of (26). Consequently, (29) can be deduced as

$$(\eta_l - \psi_l) \cdot \Delta\theta_{s,l} \leq M_{s,l} \quad (\Delta\theta_{s,l} > 0) \quad \forall s, l \in L \quad (29)$$

Similarly, when $\Delta\theta_{s,l}$ is negative and $Y_{s,l}$ is 1, in order to only activate (27) and (28), the following constraint needs to be met:

$$(\psi_l - \eta_l) \cdot \Delta\theta_{s,l} \leq M_{s,l} \quad (\Delta\theta_{s,l} < 0) \quad \forall s, l \in L \quad (30)$$

Combine (29) and (30), the range of $M_{s,l}$ can be obtained:

$$(\eta_l - \psi_l) \cdot |\Delta\theta_{s,l}| \leq M_{s,l} \quad \forall s, l \in L \quad (31)$$

Assume $\Delta\theta_{s,l} = f_{s,l} \cdot (X_l - X_{s,l}^{SC})$ is used to calculate the power flow over the line installed with SC. If $X_{s,l}^{SC} = \underline{X}_l^{SC} = -\delta \cdot X_l$, where δ is the maximum SC degree of compensation, then the positive maximum value of $\Delta\theta_{s,l}$ is $\bar{f}_{s,l} \cdot (1 - (-\delta)) \cdot X_l$. Since $(\eta_l - \psi_l) > 0$, the minimum $M_{s,l}$ is hence $\frac{2\delta}{1-\delta} \cdot \bar{f}_{s,l} \cdot X_l$.

In the system with large amount of DLR devices, significantly increased number of scenarios are required to represent the multiple sources of uncertainty. This leads to high computational burden and may potentially prevent the implementation of DLR in the large scale system. Consequently, an extended filtering model based on [21] is applied in this paper to select a subset of scenarios so that the balance between computational time and optimality can be achieved. The fundamental idea is to select the scenarios that have high impact on the objective function for a given dispatch and hence may lead to a change of dispatch decision.

The proposed modelling framework can be executed iteratively by the following steps:

- 1). Input the weather forecasts into the proposed DLR forecasting model and obtain the associated DLR forecasts;
- 2). Define the full set of scenarios through combining DLR forecasts, wind forecasts as well as line outages; the initial subset is also selected;
- 3). Run the two-stage stochastic optimization framework based on the selected subset;
- 4). Calculate the probability weighted costs for all the scenarios with respect to scheduling decisions from step (3); this step is carried out by multi-threading parallel processing;
- 5). Rank the scenarios that are not in the selected subset with a descending order based on the calculated costs.
- 6). If the total cost of the scenarios, that are not in the selected subset, is higher than the pre-set tolerance, select and add the first 'm' scenarios with highest costs into the subset, and go to step (3); or, the algorithm terminates;

FICO Xpress v7.8 [22] is used on a server with two Intel Xeon E5-2687W processors and 512 GB of RAM to implement this algorithm.

IV. SMALL-SCALE SYSTEM STUDY

To demonstrate the impact of DLR on the system operation, the two-stage stochastic scheduling model is firstly applied in a simple 2-busbar system, where the line outage is also neglected. There are four conventional generators (G1-G4) located in node 1, two conventional generators (G5-G6) located in node 2 and a wind farm with capacity of 70 MW located in node 2. The physical limits and cost information for the generators are summarised in TABLE I. In addition, 70 MW demand is located in the node 1, while a transmission line with DLR of 26 MW links these two nodes. The value of lost load is set to be 30 k£/MWh.

TABLE I TWO-NODE SYSTEM'S GENERATION AND NETWORK DATA

Generator	Capacity	Minimum Generation	Ramp up/down	Fuel	Reserve Utilization	Fixed
	MW			£/MWh		£/MW/h
G1	20	7	13	70	70	600
G2	15	5	10	50	50	300
G3	15	5	10	50	50	300
G4	15	5	10	50	50	300
G5	5	1	3	30	30	400
G6	12	3	10	15	15	50
W1	70	0	0	0	0	0

This case study considers two sources of uncertainty, forecasting errors of DLR and wind generation. The expected wind production is assumed to 50% of the installed capacity and the forecasting error is assumed to follow a normal distribution with 0.2 standard deviation. 9 scenarios are generated to describe the distribution of wind forecasting. Table II presents a sample of the probabilistic forecasts of DLR. In the base case analysis, the two forecasting errors are assumed to be independent and hence there are in total 81 scenarios to be considered.

TABLE II DYNAMIC LINE RATING SCENARIOS

Rating over SLR	1	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8
Probability (%)	0.5	4	12	15	40	20	5	3	0.5

A. Benefits of DLR

To understand the benefits of DLR, three different cases are compared:

- 1) SLR: No DLR monitoring stations are deployed. Hence, SLR strategy is used in both scheduling and operation phases. This approach represents the counterfactual case, against which the benefits of DLR can be assessed.
- 2) Real-time only DLR: DLR monitoring stations are assumed to be installed, but the forecast of DLR is not available. Therefore, SLR is applied in the scheduling phase, while DLR is allowed by using the data from monitoring stations in the real-time operation.
- 3) Fully-optimized DLR: DLR monitoring stations are assumed to be installed and the forecast of DLR is also available. DLR is therefore adopted in both the scheduling and the real-time operation phases.

The results in TABLE III show that the implementation of DLR in real-time only reduces the operation cost by 166 K£ and wind curtailment by 6 MW, while under the fully-optimized case, the operation cost saving of 315 K£ and wind curtailment reduction of 6 MW can be achieved.

The real-time only DLR case has the same dispatch decision as SLR case, but the extra available capacity from DLR in the real-time operation allows accommodating more wind energy to replace high cost generators in Node 1. The expected wind curtailment is reduced by three times. Negative re-dispatch cost in Real-time only DLR is achieved through utilizing reserve down services in real time. In this case, the expected utilization of transmission line is increased from 26 MW to 32.4 MW. However, the dispatch decision with SLR leaves the low-cost generators G6 off-line, which limits the further utilization of DLR in the real time even when extra capacity becomes available.

For the fully optimised case, the optimal flow over the transmission line in the dispatch stage is increased to 36.4 MW through balancing the cost and benefit associated with higher transfer capacity. The additional transfer capacity allows the low-cost generator G6 in Node 2 to stay online. In addition, the wind generation can be fully absorbed in the scheduling stage, leading to a significant cost reduction. However, it is worth to point out that the fully optimized DLR case increases the amount of the reserve holding and the expected demand shedding in order to better utilize the low-cost resources in Node 2. Compared with SLR where the wind penetration is limited to 38%, DLR allows the wind penetration to reach above 46%.

TABLE III COSTS AND OPERATION PARAMETERS FOR DIFFERENT CASES

Approach		SLR	Real-time only DLR	Fully-optimized DLR
Dispatch Decision	Dispatch Cost [£/30mins]	2018	2018	1661
	Line power flow [MW]	26	26	36.4
	Reserve holding [MW]	26	26	32.4
	Wind curtailment [MW]	9	9	0.6
Real-time operation	Expected re-dispatch cost [£/30mins]	9	-158	41
	Expected demand shedding cost [£/30mins]	4	4	10
	Expected line power flow [MW]	25.7	32.4	36
	Expected wind curtailment [MW]	9	3	3
Total Cost [£/30mins]		2031	1865	1716

B. Reserve Sharing among Multiple Sources of Uncertainty

Previous work [17] investigates the optimal utilization of DLR under uncertainty, but only considers the forecasting error associated with DLR. The paper concludes that significant amount of reserve services are required to accommodate the forecasting error of DLR. However, there are multiple sources of uncertainty existing in the power system. They can in fact share some of reserve services and hence reduce the need of extra reserve services driven by each individual source of uncertainty.

By comparing the reserve levels under SLR and DLR in Table IV, it is clear that 26 MW of extra reserve needs to be held if DLR is the only source of uncertainty, while if both

forecasting errors of DLR and wind are considered, only 6.4 MW of extra reserve is needed. Similar conclusion can be drawn that with the optimal application of DLR, the reserve services driven by wind forecasting error itself reduces.

TABLE IV RESERVE HOLDING LEVELS

	SLR	DLR
With Wind Forecasting Error (MW)	26	32.4
Without Wind Forecasting Error (MW)	0	26

However, the reserve sharing effect between wind farm and DLR also depends on the locations of the sources of uncertainty. If the wind farm is located in the “importing” area, as opposed to the above case where the wind farm is located in the “exporting” area, the reserve sharing effect between DLR and wind farm is negligible.

C. Correlation between Forecasting Errors

In the previous analysis, the forecasting errors of wind generation and DLR are assumed to be independent. However, the positive correlation between DLR and near-by wind farm production has already been observed [20]. To demonstrate the impact, the correlation between forecasting errors of wind generation and DLR is assumed to be “1”. According to the results in TABLE V, positive correlation increases the benefit of DLR by 16%. This is due to the fact that the realization of higher wind availability in exporting area can be accommodated by the realization of higher line capacity from DLR when the correlation is positive.

TABLE V IMPACT OF CORRELATION ON THE BENEFITS OF DLR

	Positively correlated	Independent
Benefits [£/30mins]	367	315

V. IEEE 24-BUS RTS SYSTEM

To further understand the benefits of DLR, the proposed optimization framework is applied on a modified 24-bus IEEE RTS system, as shown in Fig.3. The specifications of generators, branches and demand can be found in [21]. Fuel costs of generation technologies are 7, 50, 125 and 8 £/MWh for nuclear, coal, oil and hydro, respectively. The reserve utilization costs are assumed to be same as fuel costs. The value of lost load is 30 k£/MWh. To increase the need for extra transmission capability of the North-South boundary, the demand levels in node 1-3 are doubled and 200/500 MW of nuclear plants are added in node 22/23. Generators in node 18 and node 21 are replaced by 2600MW wind farm. Additional 1000MW wind farm is placed in node 16. Two lines, marked with red colour in Fig.3, are equipped with DLR devices. The SLR of the lines are 350MW. The forecasting errors of wind generation and DLR remain the same as in the 2-busbar system. In this case, by combining 9 scenarios for each of two lines with DLR, 9 scenarios for wind generation and 38 potential line outages, there are 27702 scenarios in total. The proposed filter is hence applied to accelerate the calculation.

A. Impact of Operation Strategies on the Benefit of DLR

Alternative operation strategies have been proposed for DLR. This section compares the benefits of DLR under three different strategies, the results of which can be used as a guideline for the optimal implementation of DLR. In the base case that SLR is applied, the operation cost is 42.3 k£ and 525 MWh of wind generation is curtailed.

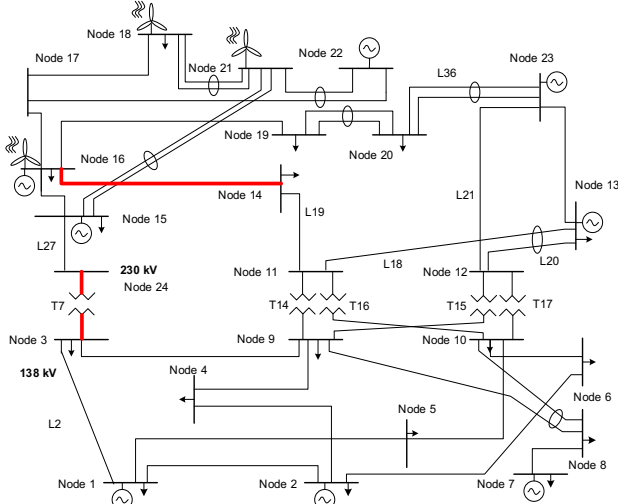


Fig. 3. Modified IEEE 24-Node RTS Topology

For the application of DLR, the simplest way is to implement it only during the real-time operation stage when the actual ratings of the lines become available. In this case, SLR is used in the dispatch stage and re-dispatch actions are activated in the real-time stage to make use of the extra transfer capability. In this case, the cost reduces to 35.1 k£ and only 387 MWh of wind generation are curtailed.

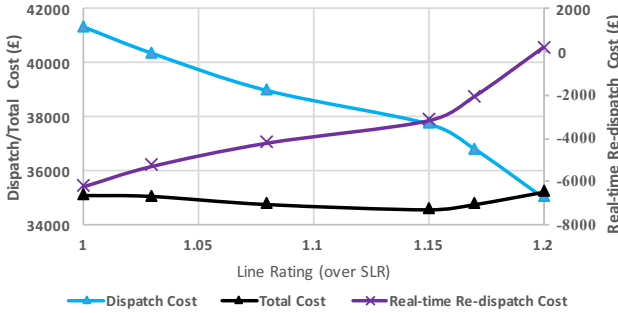


Fig. 4. Operation cost under different quantiles of DLR

Furthermore, previous study in [24] has been carried out to select the single “optimal” quantile of DLR forecast to be used in the dispatch stage under a deterministic fashion. As shown in Fig.4, when higher line rating is used in the dispatch stage, the system dispatch cost reduces due to the increased transfer capability, while the real-time re-dispatch cost would increase in order to deal with the forecasting error in the real-time operation. Therefore, the optimal balance between these two costs leads to the maximum benefit of DLR. In the given case, 1.15 over SLR is the optimal selection with the total operation cost at 34.5 k£ and wind curtailment at 428 MWh.

Instead of pre-selecting a single rating, it is possible to explicitly optimize the application of DLR by using the probabilistic forecasts of DLR in the proposed two-stage stochastic dispatch model. In this way, the benefits of higher utilization of line capacity can be explicitly balanced against the costs of increased holding and utilization of reserve services. The fully-optimized case leads to the lowest operation cost at 32.3 k£ and wind curtailment at 316 MWh.

The results clearly demonstrate that the optimal application of DLR can not only save the system operation cost but also reduce the wind curtailment to achieve higher penetration of

wind generation in the existing network. However, it is worth noting that considering the multiple sources of uncertainty significantly increases the computational burden. For the case that SLR is applied, the computational time is 65s. For the fully-optimized case without filter, it takes more than 3 hours to solve the full problem and hence is not applicable in the large-scale system. By applying the proposed filter with multi-threading parallel processing, the optimization is finished in 497s with 0.5% tolerance.

B. Coordination with FACTS Devices

In addition to DLR, there are multiple flexible network technologies. There is lack of understanding on how DLR can be optimally coordinated with other flexible technologies and whether they would compete or facilitate with each other. FACTS devices are one of the most efficient and reliable solution to increase the flexibility of the network. In this section, we demonstrate the potential synergy between DLR and FACTS devices.

Two series compensation devices with ± 0.4 degree of compensation capability are installed at line 2 and line 18. The results in Fig.5 show that the benefit of DLR (cost difference between DLR and SLR) can be potentially increased by 30% through the optimal coordination with FACTS devices. Moreover, the result suggests that the extra benefits from coordinating with FACTS devices is mainly from reducing the cost to deal with the DLR forecasting error.

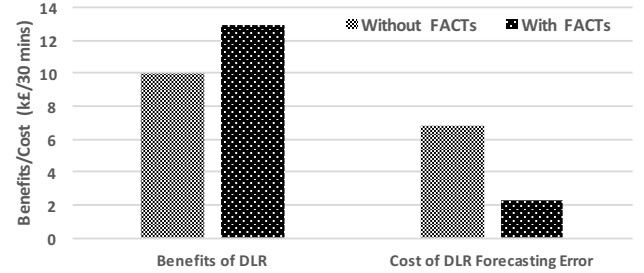


Fig. 5. Benefit of DLR with/without FACTS

C. Impact of Installed Capacity of Wind Generation

This section analyses the impact of different levels of installed wind generation on the benefit of DLR. The results in Fig. 6 clearly show that a higher installed capacity of wind generation leads to higher benefit of DLR. This is driven by the increased need to transfer the low cost wind generation through the North-South boundary. However, the results also demonstrate that after a certain level of installed capacity, the benefit of DLR tends to saturate, implying the need for extra transmission capability through alternative measures.

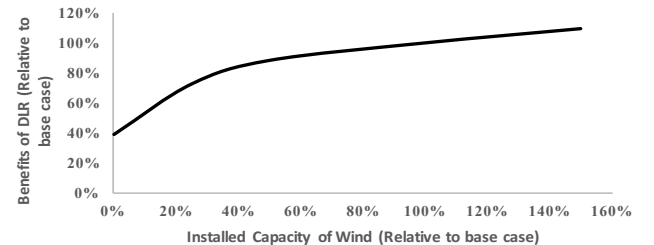


Fig. 6. Impact of installed wind capacity on the benefits of DLR

VI. CONCLUSIONS AND FUTURE WORK

This paper investigates the benefits of the optimal implementation of DLR in the system with high penetration of wind generation under multiple sources of uncertainty. To do so, probabilistic forecasts for DLR are considered, combining with a two-stage stochastic optimization model that co-optimizes the energy production and reserve holding levels in the scheduling stage as well as the re-dispatch actions in the real-time operation stage. Therefore, DLR can be optimally utilized by balancing the benefits of higher utilization of line capacity against the costs of increased holding and utilization of reserve services due to the forecasting error of DLR. Several case studies show that the proposed stochastic framework allows DLR to be optimally utilized, leading to significant operation cost savings and wind curtailment reduction to support the cost-effective integration of wind generation. We also demonstrate that the reserve services can be shared among multiple sources of uncertainty under stochastic dispatch framework, which needs to be recognized in order to avoid the over-estimation of the required reserve services driven by each single source of uncertainty. This paper also identifies the potential synergies between DLR and FACTS devices. The benefits of DLR are shown to increase along with the higher installed capacity of wind generation, but saturate after a certain level of installed capacity.

In the next step, we plan to enhance the modelling framework by explicitly modelling the high-dimensional dependencies among the multiple sources of uncertainty as discussed in [24]. For the long-distance transmission lines, other factors, such as stability constraints and angle limits, may prevent the higher utilization of transfer capability, limiting the benefit of thermal dynamic line rating. We plan to investigate under which conditions and to what extent these factors may potentially affect the utilization of DLR. Furthermore, annual analysis based on European power systems will be carried out with measured system and weather data to further assess the benefits of DLR in supporting high penetration of RES. In particular, the optimal balance between higher utilization of transmission lines and the reduced lifetime need to be investigated. In addition, as there is significant uncertainty associated with the development of renewables, the option value of DLR in supporting cost-effective transition toward low carbon system needs to be investigated.

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