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FORECASTING FOR DYNAMIC LINE RATING

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ABSTRACT

This paper presents an overview of the state of the art on the research on Dynamic Line Rating forecasting. It is directed at researchers and decision-makers in the renewable energy and smart grids domain, and in particular at members of both the power system and meteorological community. Its aim is to explain the details of one aspect of the complex interconnection between the environment and power systems.

The ampacity of a conductor is defined as the maximum constant current which will meet the design, security and safety criteria of a particular line on which the conductor is used. Dynamic Line Rating (DLR) is a technology used to dynamically increase the ampacity of electric overhead transmission lines. It is based on the observation that the ampacity of an overhead line is determined by its ability to dissipate into the environment the heat produced by Joule effect. This in turn is dependent on environmental conditions such as the value of ambient temperature, solar radiation, and wind speed and direction.

Currently, conservative static seasonal estimations of meteorological values are used to determine ampacity. In a DLR framework, the ampacity is estimated in real time or quasi-real time using sensors on the line that measure conductor temperature, tension, sag or environmental parameters such as wind speed and air temperature. Because of the conservative assumptions used to calculate static seasonal ampacity limits and the variability of weather parameters, DLRs are considerably higher than static seasonal ratings.

The latent transmission capacity made available by DLRs means the operation time of equipment can be extended, especially in the current power system scenario, where power injections from Intermittent Renewable Sources (IRS) put stress on the existing infrastructure. DLR can represent a solution for accommodating higher renewable production whilst minimizing or postponing network reinforcements.

On the other hand, the variability of DLR with respect to static seasonal ratings makes it particularly difficult to exploit, which explains the slow take-up rate of this technology. In order to facilitate the integration of DLR into power system operations, research has been launched into DLR forecasting, following a similar avenue to IRS production forecasting, i.e. based on a mix of statistical methods and meteorological forecasts. The development of reliable DLR forecasts will no doubt be seen as a necessary step for integrating DLR into power system management and reaping the expected benefits.

KEYWORDS

Rating, Overhead Lines, Forecast, Smart Grid

ABBREVIATIONS

Above Ground Level (AGL)
Active Network management (ANM)
Canadian Meteorological Centre (CMC)
Computational Fluid Dynamic (CFD)
Consortium for Small-scale Modelling (COSMO)
Direct Model Output (DMO)
Distribution System Operators (DSO)
Dynamic Line Ratings (DLRs)
Electric Power Research Institute (EPRI)
European Network of Transmission System Operators for Electricity (ENTSO-E)
Ensemble Prediction System (EPS)
Eulerian Autocorrelation Functions (EAFs)
Flexible Alternated Current Transmission Systems (FACTS)
Grand Limited Area Ensemble Prediction System (GLAMEPS)
High Resolution Limited Area Modelling (HIRLAM)
Information and Communication Technology (ICT)
Institute of Electrical and Electronics Engineers (IEEE)
Intermittent Renewable Sources (IRS)
International Council for Large Electric Systems (CIGRE)
Limited Area Model (LAM)
Low Wind Speed (LWS)
Micro Electro Mechanical Systems (MEMS)
National Centre for Environmental Prediction (NCEP)
National Oceanic and Atmospheric Administration (NOAA)
Net Transfer Capacity (NTC)
Numerical Weather Prediction (NWP)
Probability Density Function (PDF)
Real Time Thermal Rating (RTTR)
Red Electrica de España (REE)
Return on Investment (ROI)
Root Mean Square Error (RMSE)
Transmission System Operator (TSO)
Weather Intelligence for Renewable Energies (WIRE)
Wind Atlas Analysis and Application Program (WAsP)

1 INTRODUCTION

Dynamic Line rating (DLR, also referred to as dynamic thermal rating or real time thermal rating) is a technology that can dynamically increase the current carrying capacity of electric transmission lines. It is based on the observation that the ampacity of an overhead line is determined by its ability to dissipate into the environment the heat produced by Joule effect. The ampacity of a conductor is defined as the maximum constant current which will meet the design, security and safety criteria of a particular line on which the conductor is used [1]. This in turn is dependent on environmental conditions such as the value of ambient temperature, solar radiation, and wind speed and direction. Currently, only conservative seasonal estimations of meteorological values are used to determine ampacity. In a DLR framework, ampacity is considered as a dynamic variable giving a conservative estimate of the critical value at which the line may be operated at each time unit of operation. This phenomenon is particularly obvious on overhead transmission lines, where DLR can provide considerable uprating. In the current power system scenario, where the rise of power from Intermittent Renewable Sources (IRS) puts stress on the existing infrastructure, making network reinforcements necessary, DLR can represent a solution for accommodating higher renewable production whilst minimizing or postponing network reinforcements. Furthermore, similarly to IRS production forecasts, the development of reliable DLR forecasts is seen as a necessary step for integrating DLR into power system management and reaping the expected benefits.

Practices in power system operations are expected to evolve dramatically in the coming years under the pressure of an increasing share of renewable and intermittent energy generation in the energy mix and a changing environment due to the liberalization of electricity markets. The consumption patterns of end-consumers are also evolving, and more interactions are expected in the future, e.g. in the case of demand-side management. An overview of the challenges of wind power generation is given in [2] while some of the key issues and potential benefits of more proactive participation of electric demand in power system operations (potentially through electricity markets) can be found in [3]. It is worth mentioning that the share of solar energy in the electricity mix is sharply increasing and will represent a substantial proportion of the electricity mix in the future.

Transmission and distribution networks are conservatively dimensioned, resulting in a typical usage rate lower than their maximum transmission capacity for security reasons. This is because the system is planned and operated in order to guarantee the highest possible security and quality of supply, which involves using conservative worst-case assumptions at the planning stage. Furthermore, recent work [4] illustrates how wind power generation, or similarly, electricity prices, could highly influence power flows over the whole European power system governed by the European Network of Transmission System Operators for Electricity (ENTSO-E) and operated by its member TSOs. Such a situation calls for reinforcing and further developing the network from a strategic point of view, and accounting for the characteristics of such power flows as influenced by renewables, with their generation patterns of strong spatial correlations [5]. The evolving context of electricity markets also needs to be considered as part of the transmission expansion problem [6].

Transmission expansion planning is associated with longer time scales, since new lines typically take 5 to 10 years from the initial planning stage to construction and operation, and require massive investment (up to hundreds of thousands of euro per km) and social acceptance. Meanwhile, innovative solutions are being sought in a smart grid context, with increased capabilities for monitoring and communicating relevant information, combined with solid modelling and control approaches. Among the approaches studied over recent years, DLR has the potential to unlock latent network transmission capacity, delay network reinforcements, and facilitate the connection of renewables to the grid. Arguably, integrating DLR into power system operations may result in higher penetration of renewable energy, reduced greenhouse gas emissions [7] and increased social welfare in coupled electricity markets by lowering overall generation costs.

In order to incorporate DLR in TSOs' operational practices, reliable ampacity forecasts need to be available for specific lines or the full network. This challenge has already been highlighted in the relevant literature, such as the pioneering works by Hall and Deb [8], Douglass [9] and Foss [10]. In today's context, the time scales involved are in line with electricity markets where most operational decisions are made the day before operation: DLR forecasts should employ lead times roughly between 12 and 36 or 54 hours. Forecasts should also be available with a resolution specified by the users' needs (from minutes to hours).

This document is structured as follows: a historical perspective on the DLR challenge and the renewed interest in this concept are first presented in Section 2. Section 3 provides a review of some of the key characteristics of the DLR forecasting problem, covering the known relationship between meteorological variables and corresponding line rating, and the issue of predicting these meteorological variables is reported in Section 4. Finally Section 5 introduces the mathematical framework for forecasting and verification, applications and foreseen benefits are presented and discussed in Section 6, before the concluding remarks in Section 7.

2 HISTORICAL AND PRACTICAL PERSPECTIVES

Research related to DLR is based on investigations on overhead conductor ratings, which started before World War 2. In 1958, House and Tuttle at Alcoa Research Laboratories (USA) suggested the steady state ampacity model [11]) which is basically the one currently used. About ten years later, Morgan [12] at the National Standards Laboratory of Sydney (AU) proposed a similar steady-state rating model, while [13] and [14] at Jersey Central Power (USA) proposed dynamic models for describing the thermal behaviour of conductors. These models are the basis of the International Council for Large Electric Systems CIGRE [1] and Institute of Electrical and Electronics Engineers (IEEE) [15] models still broadly used today. These standards will be referred to simply as the CIGRE standard or IEEE standard throughout the document.

The possibility of using variable line ratings to increase line utilization was studied for the first time by Davis at the Detroit Edison Company (USA) who, between 1977 and 1980 published a series of texts [16][17][18][19][20] on different aspects of the problem, calculating daily and hourly ratings and comparing the actual rating distribution with the rating-risk curve applied.

Research continued with the group of Foss, Lin and Maraio at General Electric (USA) [21][22][23][10] who in the years 1983 – 1992 further developed the models and studied their dependence on each variable. [23] also reports the results of one of the first monitoring campaigns of the temperature of different points on an overhead line, and proposes the first method for DLR forecasting based on weather forecasts. During the same period, the first patent [24] for an overhead line temperature monitoring system was granted to Fernandes and Smith-Vaniz of the Niagara Mohawk Power Corporation.

Another research group was active around Douglass and Edris at Power Technologies and the Electric Power Research Institute EPRI in the USA [25][9][26][27][28]. From 1988 – 2000 they integrated a software for calculating dynamic thermal ratings for several power system components (not only overhead lines) in substation controls and tested it at four utilities in the USA. The system they developed employed thermal measurements and interpolated ratings using semi-empirical parameters. Another system, described by Seppa [29][30] at The Valley Group (USA), was based on measuring conductor tension and used cellular telecommunication to retrieve data from several locations. In 2000, according to [31] more than 50 utilities used a transmission line monitoring system on one of their lines to evaluate its thermal limitations, and most of these were based on a tension measurement method. The system described is also partially covered by a patent [32], and in 1999 a patent [33] was awarded to a weather-based ampacity calculation software.

Among the different methods proposed for estimating DLRs, it is also worth mentioning the use of differential GPS [34][35] at Arizona University, the use of phasor measurement [36][37] also covered by a patent [38], and the measurement of conductor vibrations [39] at the University of Liege in 2010, also covered by a patent [40]. Comprehensive DLR systems reviews and good operational practice recommendations are mentioned in technical brochures by international engineering organizations [1].

From an early stage, DLR technology was tested by several utilities and records of several pilot projects exist. In Europe, an early example is the DLR system developed by Red Electrica de España (REE) and Iberdrola in 1998 [41], where a minimal number of meteorological stations were used to gather real-time data. The data was then processed using a meteorological model based on the Wind Atlas Analysis and Application Program (WAsP), taking into account the effect of obstacles and ground roughness, and finally the rating was calculated. Another test was carried out by Nuon in 2004 [42] and consisted of a fiber-optic-based temperature monitoring system for electric cables, power transformers and overhead lines. In recent years, the application of DLRs has been studied and tested, particularly in the UK, for accommodating new wind power generation by Central Networks (Yip, 2009), Scottish and Southern Energy [43], Iberdrola Scottish Power [44][45][46] and Northern Ireland Electricity [47], and also the Belgian ELIA [48]. The situation is different for solar radiation, as few dedicated applications exist. Note that the characteristics of solar radiation (frequency distribution) are different from wind power.

The study of DLRs has proceeded almost continuously for more than thirty years, mainly in the USA, and by different groups. The predominance of American research may be explained by the fact that the USA experienced summer peaks before European countries, leading to more research and development on the physical limits of conductors. Several techniques have been developed around the world for real-time DLR, such as measuring conductor temperature, tension and vibration, but for long-term forecasts the greatest potential is clearly the estimation of DLRs from weather parameters combined with in-situ measurements. Recently, focus on this technology has increased because of the development of Micro-Electro-Mechanical Systems (MEMS), IT, and wireless communications, and its potential consequences on the integration of IRS, and the subsequent appearance of network congestions, particularly in Europe but also in the USA and Asia.

3 THE IMPACT OF WEATHER PARAMETERS ON LINE RATINGS

Overhead line ratings are constrained by the necessity to maintain statutory clearances between the conductor and other objects or the ground. DLR is based on the concept that overhead line rating is limited by a maximum conductor temperature in order to respect these clearances and preserve mechanical integrity. Although the conductor's temperature is dependent on the electrical load, it is also strongly influenced by environmental conditions, such as wind speed, air temperature, and incident radiation.. But variable conductor temperatures on the line can modify the span sag by up to several metres, depending on the mechanical tension and the length of the span. In fact, a rise in temperature causes the conductor to elongate which, in turn, increases the sagging. A schematic vision of an overhead line and its sag and clearance is provided in Figure 1.

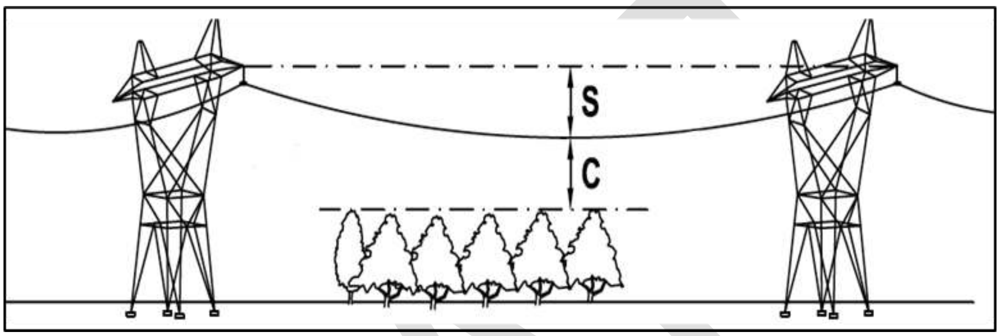

Figure 1: Sketch of Sag (S) and Clearance (C) of an overhead conductor in a level span. ***(courtesy: Ampacimon)***

The sag *S [m]* can be modelled as a catenary equation or as its parabolic approximation, given by:

$$S \approx mgL^2/8H, \tag{1}$$

depending on conductor properties (mass per unit length m [$kg \cdot m^{-1}$], span length L [m]) and the horizontal component of the conductor tensile force (H [$kg.m.s^{-2}$]), which depends in turn on the thermal-tensional equilibrium of the conductor [49].

$$A(Tc_2 - Tc_1) + B/H_1^2 - H_1 = B/H_2^2 - H_2 \,. \tag{2}$$

In the above formula,

- A [$kg.m.s^{-2}K^{-1}$] and B [$kg^3.m^3.s^{-6}$] are parameters depending on conductor properties such as the thermal elongation coefficient, Young's modulus, and the cross sectional area, conductor mass, and span length,
- T_c [K] is the conductor temperature,
- H is the horizontal component of the tension and the subscripts 1 and 2 refer to two different states.

A reference state 1 can be relative to standard design conditions, whilst state 2 changes according to temperature. Therefore a one-to-one relationship can be modelled between the span sag (and hence the clearance) and the conductor's mean temperature over that span, and more generally over the line section [50] [51].

However, it should be pointed out that standard design conditions are seldom respected in practice (e.g. plastic elongation due to initial tensioning and severe ice/wind loads, metallurgical creeping, installation conditions, etc.). Furthermore, it is difficult to measure the mean conductor temperature on which the sag (and thus the clearance) depends.

3.1 DYNAMIC THERMAL MODEL FOR OVERHEAD LINES

IEEE and CIGRE models have been regularly updated since they were first proposed and are frequently used by engineers as calculation standards to assess the thermal behaviour of overhead lines. Despite some differences in their detailed formulation, the approach followed is similar and the conductor steady-state temperature results from a heat balance:

$$R(T_c)\, I^2 + Q_s = Q_r + Q_c \tag{3}$$

where:

- Q_s [W/m] is the solar heating depending on solar radiation and albedo,
- Q_r [W/m] is the radiative cooling depending on conductor and ambient temperature (as a first approximation),
- Q_c [W/m] is the convective cooling, mainly influenced by wind speed and direction,
- I [A] is the conductor electrical load
- $R(T_c)$ [Ω/m] is the conductor's electrical resistance per unit length at the specified conductor temperature.

The main difference between the IEEE and CIGRE models lies in the expression of the convective term Q_c, which is also the prevailing term for conductor cooling. This term is essentially driven by wind speed, with a dramatic impact at low wind speeds (<5m/s). These different formulations result in significantly different line ratings for low wind speed values. However, the two models yield similar results for the design wind speed (usually in the region of 0.5 m/s). Both the IEEE and CIGRE models now include a fairly comprehensive solar irradiance model that takes account of the geographic position, altitude and time of year.

The non-steady-state heat balance is the same 1st order differential equation for both models:

$$\frac{dT_c}{dt} = \frac{1}{m\, C_p}\, [R(T_c) I + Q_s - Q_r - Q_c] \tag{4}$$

where:

- m [kg/m] is the mass per unit length of conductor material
- Cp[J/(kg·K)] is the specific heat capacity of the conductor's material.

This results in a time constant of about 10-20 minutes for the design wind speed for most of the conductors. The time constant can decrease to only 5-10 minutes for higher wind speeds (> 3m/s). An illustration of the transient temperature response is given in Figure 2.

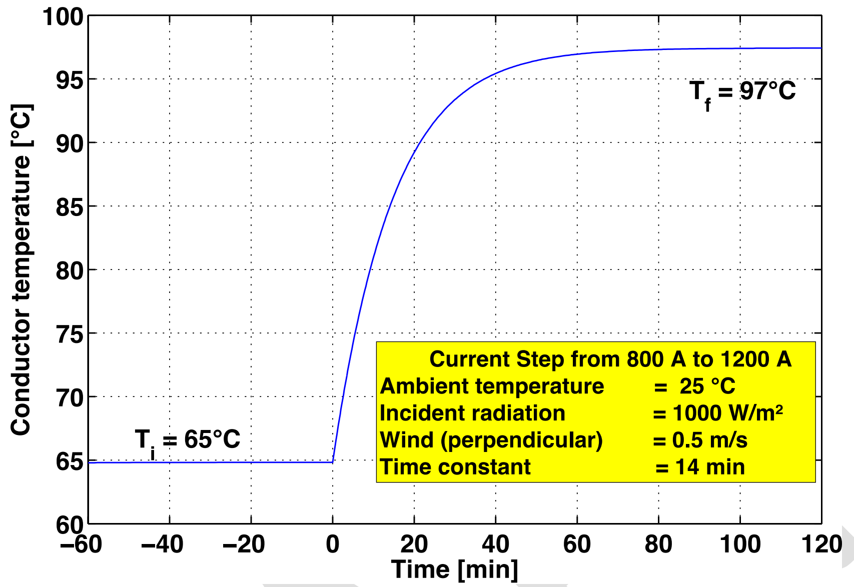

Figure 2: Transient temperature response to a "step" change in current. Three to four time constants are needed to reach the steady state; this dynamic aspect can be used by the TSO, as in a N-1 situation[1], it takes about 1 hour for the conductor to reach the steady-state temperature at the design wind speed (about 0.5 m/s) [AMS570 conductor].

3.2 RELATIVE IMPORTANCE OF ENVIRONMENTAL PARAMETERS

The influence of the four environmental parameters on the conductor rating is variable because of the non-linearity of the heat exchange mechanisms. This makes it impossible to reduce the study to a particular parameter and force a DLR system to take the value of all of the environmental parameters involved into account.

As reported in [45], wind speed is the most important variable for mid-range wind speed values, although the sensitivity of ampacity vs. wind speed is higher for low wind speed values. In parallel, the worst operating conditions for overhead lines occur in cases of low wind speed, when air temperature and solar radiation become critical factors. In an operational context, where all of these variables evolve rapidly and dynamically, the influence of all of these variables should be monitored and predicted. These variables include wind speed (Ws), wind direction (Wd), ambient temperature (Ta), and solar radiation (Sr).

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[1] The *N-1 principle* guarantees that the loss of any set of network elements is compatible with the system's operational criteria, taking into account the available remedial actions. For power lines, in practice this means keeping some line capacity reserve for each line in operation. It ensures that if one line trips, the additional electrical load shifted onto other lines will not lead to cascade tripping.

The relative impacts of weather variables are further described and discussed in the following paragraphs and in [52]. They are analyzed based on observations of the variables involved, and on IEEE and CIGRE standard models for overhead line rating. The nature and strength of such relationships between meteorological variables and overhead line rating should be appraised in a different manner when considering a forecasting setup perspective.

The case of solar radiation is particularly interesting: its effect is in general negligible since other parameters, notably wind speed, have a far larger impact on the cooling of the conductor. However, in low wind speed conditions, it can considerably increase the temperature of the conductor, also with low current values, and thus become a significant limiting factor.

Line icing and its impact on ratings forms a specific topic that includes studying effects such as over-sagging due to ice load, non-uniform icing, modification of the state-change equation, galloping and other vibration issues, etc. Thus, icing will not be discussed in this document.

Another aspect to be considered is the sensitivity of measurement equipment, which can vary according to the parameter measured and its impact. For example, air temperature can be measured accurately with respect to determining ampacity during the calculation process, whilst effective wind speed along the whole line section cannot (in particular for low wind speeds).

It should also be considered that environmental parameters, and in particular wind speed and direction, may change considerably along the path of a transmission overhead line. Indeed, the exploitable ampacity actually unlocked by DLR corresponds at any time to the *minimum* of all ampacities calculated for each critical span in the line. Therefore, a DLR system and a DLR forecast must take into account this phenomenon and provide estimates of the actual current carrying capacity for the whole line.

3.2.1 WIND SPEED

Wind speed has a prevailing impact on power line ampacity as it is the main variable responsible for cooling down the conductor, and hence for the sag value. Its influence is illustrated in Figure 3, based on the CIGRE and IEEE standards and for a given set of standard conditions with respect to wind angle relative to the conductor, temperature and incident radiation.

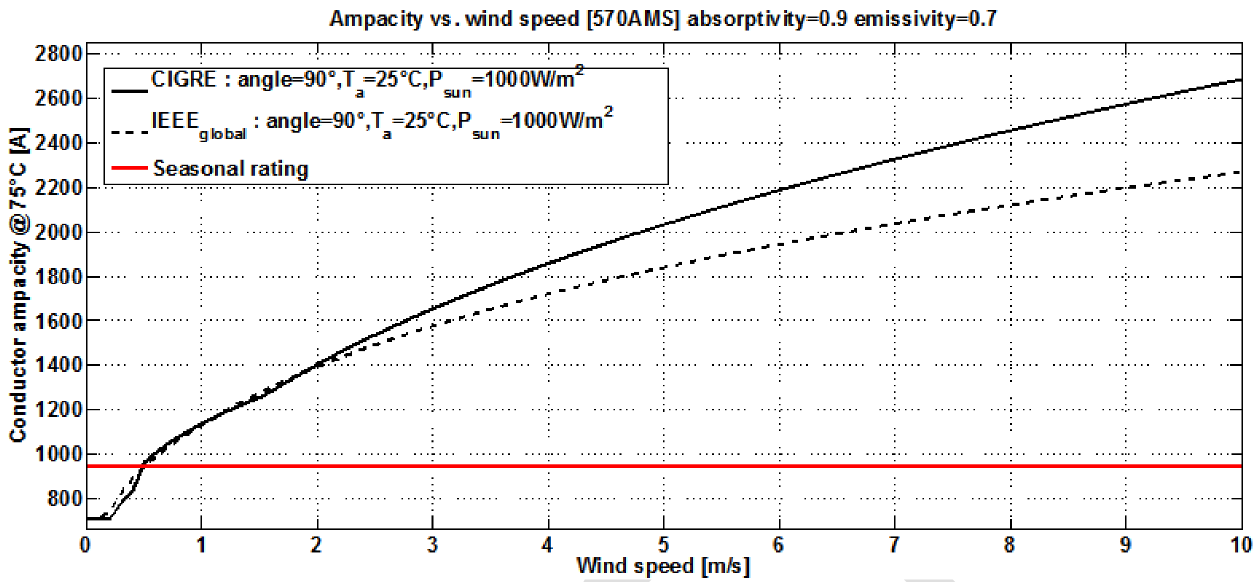

Figure 3: Relationship between wind speed and conductor ampacity, following the CIGRE/IEEE standards, for a set of other environmental variables for an AMS570 conductor rated at 75°C. The differences between the two standard models decrease near the seasonal rating due to the fact that the empirical equations used to calculate convective heat exchange are centred on the conservative conditions of very low wind speeds.

Although the relationship between wind speed and ampacity is clearly defined in the IEEE and CIGRE standard models, in practice such dependence may be more complicated to establish and observe, since wind speed varies in time along the length of each span and vertically.

First, wind speed exhibits significant temporal variability in magnitude and even in the nature of its dynamics, evolving significantly within minutes [53] and hence challenging the steady-state representation of the various standard models. Second, the spatial variability in wind is such that wind speed also varies along the span (spatial coherence), wind vortices having a typical average size of several tens of metres [54]. Therefore, a typical span length of several hundred metres is subject to a variable wind speed along its length. Third, wind speed also varies greatly vertically, as the conductor is located within the boundary layer. Wind speed may also vary due to local effects, such as screening from trees or buildings. Note that the elevation of the conductor may change by more than 15 metres in a single span. Consequently, the sag may also be subject to differences in level between the end points of a span. Such elevation differences near the ground may have huge effects on the wind characteristics, which are highly sensitive to changes in elevation so close to the ground.

On a line section made up of multiple spans linked to each other via suspension insulators, the horizontal component of the tension – and thus sag - is balanced to a certain extent [55]: therefore, the behaviour of a single span (typically 400 m length) within a line section depends on all the other spans in the same section. This means that environmental parameters, such as wind speed or wind direction varying over several tens of metres, should normally be considered for the whole section. The integrated effect of high frequency wind variations can also be used to calculate the mean effect of wind on ampacity since the dynamic behaviour of the conductor (time constant) acts as a filter.

3.2.2 WIND DIRECTION (AND ITS ANGLE WITH LINES)

Wind angle is defined as the angle between the wind vector and the conductor axis of the span of interest. Figure 4 shows the relationship between wind angle and ampacity, based on IEEE and CIGRE standards, and for various sets of wind speed, incident radiation and ambient temperature. In addition to wind speed, wind angle may have a non-negligible impact on ampacity, especially for almost-parallel wind flows. In practice, due to turbulence, the variation in conductor temperature and line ratings caused by wind direction is substantially lower than assumed based on theoretical DLR calculations. Therefore conservative assumptions are usually made. For example, on hot summer days with low wind speeds, the standard deviation of the wind angle is typically about 45 degrees or more [56]. In such situations, the effective yaw angle of the wind is set between 35 and 45 degrees (depending on user practices) irrespective of the average wind direction [57].

For this reason, the concept of "effective" wind speed has been introduced: effective wind speed is defined as the equivalent perpendicular wind speed that produces the same cooling effect as the actual wind. The wind angle is considered only under laminar conditions, e.g. with a standard maximum deviation of 20 degrees, which can occur at night.

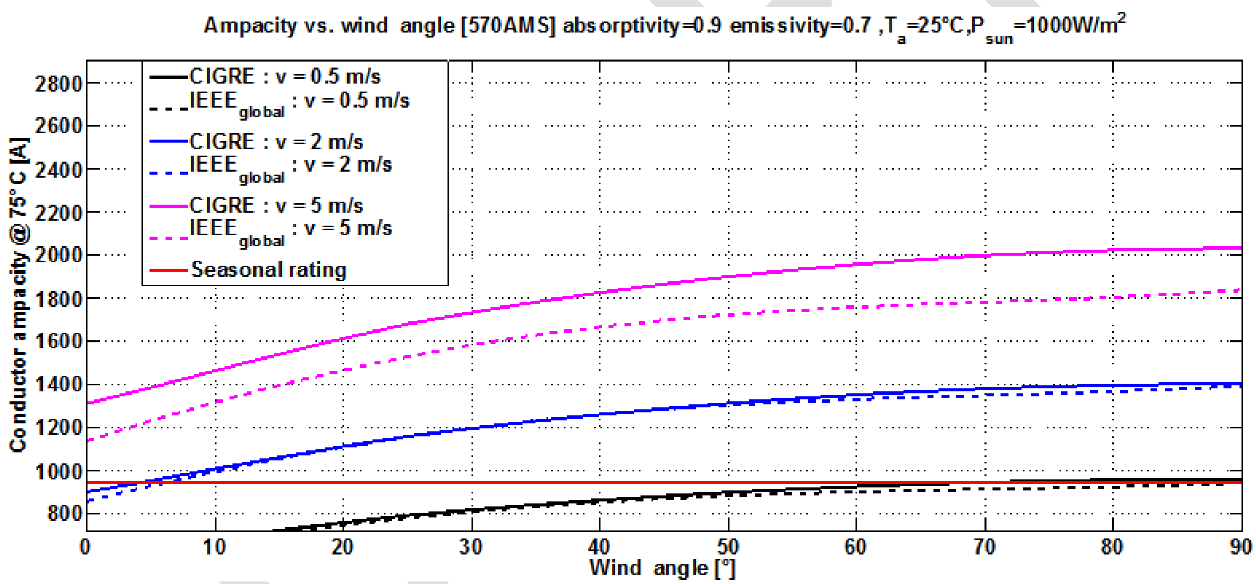

***Figure 4:** Relationship between wind angle (i.e., angle between wind vector and the span direction) and conductor ampacity, based on IEEE/CIGRE standards, and for various sets of other environmental variables for an AMS570 conductor rated at 75°C, T_a=25°C, P_{sun}=1000W/m^2).*

3.2.3 AMBIENT TEMPERATURE

Ambient air temperature has a significant impact on ampacity, as illustrated in Figure 5. This effect is quasi linear considering a limited range of temperatures and substantial for all temperature levels in a temperate climate range. A Root Mean Square Error (RMSE) < 2°C in the modelling or forecasting of ambient temperature may be considered satisfactory. This is easily achievable using weather stations and state-of-the-art meteorological forecasting approaches. Another advantage is that the temperature varies little over the time and spatial scales of interest here, except perhaps in highly complex areas, for instance from one valley to the next in mountainous terrains.

It should be also considered that ambient temperature influences both convective and radiative heat exchange, with an almost linear effect on ampacity behaviour shown in Figure 5.

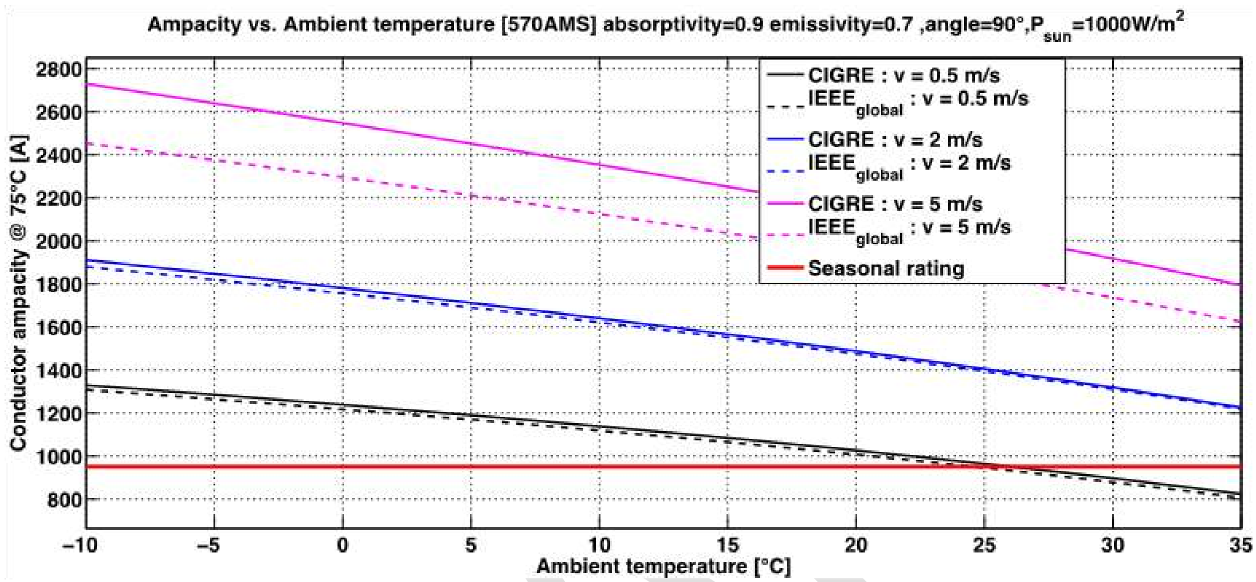

Figure 5: Relationship between ambient temperature and conductor ampacity, based on IEEE/CIGRE standards, and for various sets of other environmental variables for an AMS570 conductor rated at 75°C, angle=90°, P_{sun}=1000W/m^2).

3.2.4 PRECIPITATION

Rain has a significant impact on conductor cooling but, as heat loss rate modelling requires several parameters, such as the water's physical state, relative humidity, precipitation rate, wind speed, and air pressure, it is often neglected in line design standards. However, for DLR, as the ampacity is computed dynamically, rain cannot be put aside completely. Precipitation information gathered from observations or forecasts can be valuable for computing a conservative ampacity using a somewhat simplified model. An example of an overhead conductor rating model incorporating the role of precipitation can be found in [58][59].

3.2.5 SOLAR RADIATION

Similarly to wind speed, a single-point measurement of effective incident radiation is not sufficient to compute the global combined effect of solar irradiance and albedo over a whole span. Its influence can be considered linear for this application. This is represented in Figure 6 based on the IEEE and CIGRE standards, for various sets of other environmental variables. For very low wind speed conditions (Ws<0.5 m/s), solar radiation can become a limiting factor for overhead line ampacity, since it can raise the temperature of the conductor far above the air temperature.

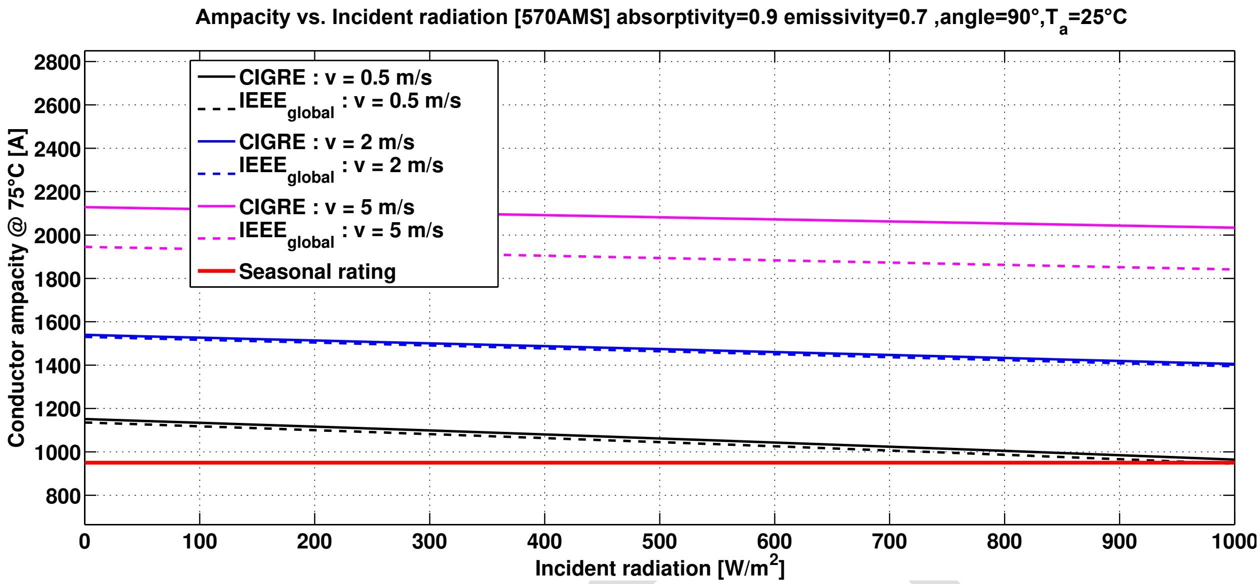

Figure 6: Relationship between incident radiation and conductor ampacity, based on IEEE/CIGRE standards, and for various sets of other environmental variables for an AMS570 conductor rated at 75°C, angle=90°, T_a=25°C).

4 METEOROLOGICAL MODELLING AND FORECASTING CONSIDERATIONS

4.1 METEOROLOGICAL AND FORECASTING MODELS RELEVANT TO DLR

The basis for meteorological modelling and modern weather forecasting was laid down in the early 20th century, when it was established that if the state of the atmosphere is known at any point in time, its future state can be determined using the fundamental laws of standard physics. The standard principles in fluid mechanics of mass conservation, and momentum change due to mechanical forces, were combined with the standard fundamental laws of thermodynamics to produce a closed set of non-linear, partial differential equations (thermo-hydrodynamic equations). These equations give time tendencies of the standard meteorological variables, wind, pressure, temperature, and humidity, in any part of the atmosphere, provided their values are given in the entire atmosphere at a given time (the initial state, also called the analysis) and at any time at the top and bottom of the atmosphere (the boundary conditions). Fundamental mathematical theory predicts that a single solution to the equations with the given initial and boundary conditions exists. As such, the problem of weather prediction is formally deterministic. However, practical solution methods for general cases are not known. Thus, systematic simplifications and discretization of the equations in time and space are necessary to find an approximate solution. The outcomes of this process are numerical models of the atmosphere, which for the purpose of weather forecasting, are referred to as Numerical Weather Prediction (NWP) models. The numerical discretizations and other approximations necessitate so-called parameterizations, which are empirical formulae that represent the effects of the simplifications. NWP models are computationally very demanding and some of the most powerful supercomputers are today employed for this purpose [60].

The horizontal domain of a NWP model is either global, covering the entire earth, or regional, limited to a smaller area. Due to atmospheric motions, a global domain is required for forecast horizons beyond three or four days. For shorter horizons, computational resources often focus on a smaller domain implying the possibility of higher spatial resolutions and more accurate modelling of the physical processes. The latter so-called Limited Area Models (LAMs) are, however, dependent on forecasts from global models at the boundaries of their domains. Most of the systems being developed are NWP systems, run on an operational basis by national meteorological services and universities. To date, there are roughly ten operational NWP models for the global domain, running with horizontal resolutions between 15 and 40 km. For smaller domains, typically a few thousand kilometres in each direction, LAMs run with a horizontal resolution of a few kilometres. For special applications, NWP models with even finer horizontal resolutions are also applied.

Weather forecasts are calculated using LAMs that simulate atmospheric flows from synoptic scale to a few kilometres. These solve the averaged Navier-Stockes equation and parameterize turbulence using different schemes, which entail diffusion coefficients and turbulent kinetic energy. The equations are solved on different nested grids. The resolution of the inner grid is usually two kilometres, while the ratio between the resolutions of the different grids is about four. Topography is usually introduced using terrain-following vertical coordinates. Schemes are determined for the lateral boundary conditions and the radiation parameters for evaluating both shortwave radiative transfer and long wave radiation.

The process of making weather forecasts starts by collecting measurement data from satellites, radars, aircrafts, ships, buoys, radiosondes and conventional instruments at the Earth’s surface for a relatively large geographical area. To achieve this, all countries share a huge amount of observational data using fast telecommunication networks. Information from the measurements is then extracted in a dynamic and consistent way to estimate the state of the atmosphere on a three-dimensional spatial grid at a given point in time. The irregularly spaced observations are insufficient on their own. The best estimates are obtained by combining these observations with a previous forecast in a process known as data assimilation. Data assimilation provides initial conditions for forecast models, which then are integrated forward in time, step by step with time resolutions in the order of seconds/minutes until the required length of forecast has been reached. Forecast models are very complex due to a large number of mathematical and physical challenges that must be considered - ranging from numerical aspects in the dynamical part of the model to parameterizations of physical processes that are too small in scale or too complex to be modelled explicitly.

National Meteorological Services (NMS) are required to provide short- and medium-range weather forecasts, warnings and alerts for their territory. Medium-range forecasts require global models such as those provided by the European Centre for Middle Range Weather Forecast (ECMWF) or the National Oceanic and Atmospheric Administration (NOAA). For short-range applications, it is more cost effective, and even necessary for very high resolution, to run the Numerical Weather Prediction (NWP) systems for only a limited part of the globe using an LAM. These LAMs require boundary conditions from global models, like the ECMWF model.

4.2 INCREASING ROLE OF METEOROLOGICAL FORECASTING IN POWER SYSTEMS OPERATIONS

With the further deployment of renewable energy generation capacities in Europe, but also in the US, China, etc., it is clear that power generation is increasingly reliant on the weather and climate. Power generation from most renewable energy sources is a direct function of the onsite meteorological conditions. This is the case for wind farms and solar panels, which are at the origin of the increasing role of meteorological forecasting in power system operations, especially over the last few decades. Hydro power is also directly dependent on weather conditions, but its different time dynamic makes it much less variable than the previously mentioned renewable sources. A comprehensive, recent overview of the importance of weather and climate for energy-related problems is given in [61].

Prior to the recent large deployment of renewable energy capacity, a number of researchers and practitioners had already observed that the electrification of heating and cooling in a number of areas of the world was making electricity consumption increasingly sensitive to ambient temperature. Consequently, temperature forecasts became the first and most relevant type of meteorological information to take part in power system operations, following the pioneering work of Papalexopoulos and Hesterberg [62] among others. Note that in addition, the relatively high accuracy of temperature forecasts make them an ideal input for load forecast algorithms. Meteorological information for renewable energy forecasting, and dynamic line rating forecasting prediction in particular, is more complex. The methods used for electric load forecasting have thus been gradually extended to a probabilistic framework, for instance based on overall temperature forecasts, discussed below. As an example, the reader is referred to [63].

In comparison, since the beginning of the new millennium, renewable energy generation (first wind power, then solar power) has been the main driver for using basic and advanced meteorological forecasting products in power system operations. The focus has also shifted to variables that were formerly considered less important. For instance, the accuracy of wind predictions had been considered sufficient for most applications, but with the sensitivity of wind turbines' power output to changes in wind speed/direction, even small errors in wind forecasts can lead to significant errors in power predictions. Similarly, the need for additional variables has become apparent, for instance related to solar radiation or to a better description of wind profiles. Recent overviews and discussions of load and renewable energy forecasting can be found in [64] and [65]. The renewed interest in the impact of the weather on electric lines will also potentially strengthen the focus on various types of meteorological predictions.

4.3 DOWNSCALING

Wind speed depends both on atmospheric conditions and topographical features. Different stability conditions develop during the daily cycle, and particularly during the night, when the stable boundary layer creates conditions for low wind speeds. Wind velocity is influenced by surface roughness, topography features such as the presence of flat or complex terrains, and the presence of a coastline. Mountains act as shield for the wind, which descends low into valleys, and breeze circulation may develop.

Wind speed and direction have a high temporal and spatial variability. Significant changes in wind speed and direction in the space of a few metres are caused by obstacles, terrain and roughness changes in the vicinity of the span. In order to consider these effects in a weather forecast model, meter-sized grid sizes would be required. However, the grid sizes on today's high-resolution weather forecast models are in the range of about 1 km. Thus, important impact factors are not resolved in the models. Regarding ampacity, though, the effect of weather parameters is integrated over the span's length, and more generally over each line section, leading to less constraining requirements on the grid size.

Different methodologies exist to refine the results of weather forecast models. These methods basically fall into two groups: statistical and dynamical downscaling procedures.

Statistical downscaling describes the relationship between the results of weather forecast models and measurements using statistics, e.g. multiple linear regressions or Kalman filtering. These methods are well tested for wind forecasting for wind power predictions and result in significant improvements compared to Direct Model Output (DMO) from weather forecast models. Statistical methods require on-site measurements/estimations of wind speed and direction. However, measurements are not available at every point of interest and additional methods are needed for e.g. spatial interpolation. An example is a method that interpolates in space the coefficients of a multiple linear regression in order to obtain forecasts for positions between the measurement sites [66]. This and other similar methods need to be tested in the framework of DLR, especially in complex terrains.

An alternative approach is dynamical downscaling. Dynamical downscaling increases the spatial resolution of weather forecast models by applying higher resolution dynamical models. This kind of grid size requires switching to LES or Computational Fluid Dynamic (CFD) models.

A common method for simulating a wind field is the mass-consistent model. This is a diagnostic model based on mass conservation for incompressible fluids ($\nabla \cdot u=0$). Measurements are interpolated on a high-resolution (up to 100 m) grid. Stationary conditions are assumed and the turbulence is not simulated.

More sophisticated models account for turbulence. Three main approaches can be considered.

- Reynolds-Average models (RANS)
- Direct Numerical Simulation (DNS)
- Large Eddy Simulation (LES)

In a RANS model, mesoscale models resolve the equation for the mean values of each parameter but parameterize the turbulence in an approximated way. In a DNS approach, the equations for the second order moments (Reynolds stress) are solved and a closure problem arises. To prescribe these quantities, on which the mean values depend, dynamical equations must be resolved. These equations entail the third-order moments, which in turn depend on the fourth-order moments and vice versa. Therefore a closure hypothesis is needed. Generally the fourth-order moments are expressed as a function of the second ones, assuming a Gaussian probability density function of at least this order, [67][68][69]. Unfortunately this approximation does not apply in low-wind conditions [70]. In this model, Navier-Stokes equations are resolved at all scales. This implies a very high computational power and as a consequence Reynolds numbers, as those of the atmosphere cannot be reproduced. However, DNSs are useful for theoretical studies.

In an LES approach, turbulence is divided into so-called "large eddies" containing most of the energy, which are directly resolved, and so-called "sub-filter scale eddies" with low energy content, which are not resolved but parameterized. LES is generally used to simulate the stationary atmospheric boundary layer in different stability conditions but it can be also nested in the mesoscale models. The sub-filter-scale model makes the hypothesis that LES is not sensitive to the sub-scale filter itself, but the model is not totally reliable close to the surface, where smaller scale eddies develop.

Several studies have tested LES for wind energy applications. In simple terrains, the effect was found to be small [71], while other studies showed good results in complex terrains and for flow around obstacles [72]. LES involves large amounts of computing time, which explains why it is currently not possible to run online-forecasts. It could, however be used in a statistical-dynamical approach.

CFD models are often used for wind resource assessment to simulate the flow field in complex terrains. CFD models are run with grid sizes as small as a few metres and thus allow a fine resolution of obstacles and terrain features. Unfortunately, CFD models' ability to correctly simulate situations with low wind speeds is not yet proven. Additionally, CFD models do not cover important atmospheric processes that might be relevant for local circulation systems, like radiation or clouds. This shortcoming is tackled by coupling CFD models with weather forecast models, whereby local flow regimes are simulated by the weather forecast model and the flow field is refined by the CFD model. First studies show promising results [73].

Dynamical-statistical downscaling is used to keep the forecasting computation time short: it describes an approach where relevant weather situations are defined, refined to very high resolution by dynamical downscaling, and correction factors are derived. The daily weather forecasts are classified according to the relevant weather situations and the correction factors are applied. These methods have been successfully applied in the framework of regional climate modelling and also in wind power forecasting [74][73].

4.4 FOCUS ON LOW WIND SPEEDS

Low Wind Speed (LWS) conditions, roughly defined as periods when the mean wind speed at 10 m a.g.l is less than 2 $m \cdot s^{-1}$, are particularly important for the science of air pollution dispersion because it is under such conditions that the severity of pollution is often high due to weak dispersion [75]. Despite their considerable practical interest, LWS are difficult to predict, especially in conditions of strong atmospheric stability when the state of the lower atmosphere is not well defined.

Due to the non-linearity of a conductor's thermal behaviour, wind speed and in particular LWS is considered as a critical parameter. Furthermore, low wind speeds are expected to be the limiting parameter in a DLR forecast application and an accurate forecast of this parameter is considered crucial for R&D. However, in operational practice, the important information is the probability of LWS occurrence, which is the information that TSOs require. As forecasting LWS will remain difficult in the near future, standard rating may continue to be used in such cases.

LWS is a very common condition in many European areas, for example, in the Po valley in Italy, which is characterized by frequent low wind speed conditions. More than 80% of mean wind measured there is $u < 1.5 ms^{-1}$ at 5m a.g.l, probably due to the shielding effect of the surrounding mountains and hill chains. The rare cases of strong wind are caused by the dry down-slope wind from the Alps, also known as "Foehn", which occur in the cold season typically about 15 times per year.

4.4.1 LOW WIND CHARACTERISTICS

Most papers proposed in literature on low wind focus on the dispersion issue. The turbulence, e.g. the standard deviation of the wind velocity fluctuation, needs to be determined in order to provide input for a dispersion model.

LWS can have different origins, but in general it is associated with stable atmospheric conditions, such as high atmospheric pressure. LWS can also originate at night when the ground surface cools down and creates a stable temperature gradient in the surface layer.

Important aspects for the study of LWS are:

- Meandering
- Turbulence statistics

Meandering is defined as the slow oscillating motion of airflow. Oettl and Goulart [76][77] suggested that meandering is an inherent property of atmospheric flows in low-wind speed conditions and generally does not result from any particular trigger mechanism. According to those works, meandering can exist in all meteorological conditions, regardless of the atmospheric stability, specific topographical features, or season, provided the average wind speed is less than about 1.5 ms^{-1}.

The causes of meandering vary. One possible cause is the vertical directional shear induced by a terrain. Gravity waves, vortices with either a horizontal or vertical axis, and so-called vortical modes, are potential mechanisms for generating a meandering flow. A stable stratification of the boundary layer is seen as a necessary pre-requisite for obtaining a meandering flow regardless of the possible processes initiating it.

The meandering scale lies in between the turbulence scale and the mesoscale. A parameter sometimes used to detect meandering is the standard deviation of the crosswind component σ_v scaled by the friction velocity u_* [78][79]:

$$\frac{\sigma_v}{u_*} = 2.0 + 4.0\frac{z}{L} \qquad (5)$$

where is the friction velocity, z the height above the ground and L the Monin-Obhukov length which indicates the stability. This quantity indicates the extent of the wind lateral fluctuations, which are determined by the turbulence and, in the LWS case, by the horizontal meandering as well.

Regarding turbulence statistics, LWS presents specific features in its auto-correlation function and Eularian auto-correlation function. The horizontal wind velocity autocorrelation functions do not fit in with an exponential decay but display oscillating behaviour [78] probably determined by horizontal coherent structures. Another characteristic is that the horizontal Eulerian Autocorrelation Functions (EAFs) are not exponential (as in a windy case) but rather reveal a negative lobe and an oscillating behaviour. Also, in low wind conditions, the higher order of the probability density function reveals specific behaviour. In normal conditions, the wind EAF is positive, but during meandering its values are in general lower and present negative values for some spatial and time lags. This is a consequence of the mass conservation law applied to slow oscillating incompressible flows.

Observed spectra for the crosswind component for different meteorological conditions [78] show that in low wind, the spectra are lower and the peak is not present, regardless of the stability conditions. Other turbulence analysis results in low wind [70] show that the fourth-order moments of the velocity probability density function are not Gaussian, as generally assumed, and that skewness is generally different from zero, while kurtosis attains higher values than Gaussian.

Another relevant aspect in forecasting low wind speed conditions using mesoscale modelling is that wind meandering is determined by motions whose scales lie between those resolved by the model and the parameterized turbulence. Thus the meandering motion itself needs to be parameterized. This necessarily involves understanding the motions resolved by the NWP model. Some interesting considerations on this topic have been discussed in [80]. In this paper, NWP model data with different time and space resolutions are compared with measured data that evaluate the missing wind speed variance. It is important to stress that unresolved computed variance can reach values slightly greater than 1 m/s. Considering a different instantaneous wind *U* representation from that usually considered by the Reynolds average hypothesis, the meander term must be added as follows:

$$U = \bar{u} + u' + u_t' \qquad (6)$$

where:

$-\bar{u}$ is the NWP-resolved mean wind velocity,

$-u'$ is the turbulent velocity component from the turbulence parameterization

$-u_t'$ is the low frequency meander velocity component from the meander parameterization.

The relevant conclusion is that if $\bar{u}$ is lower than 3 m/s, thenu_t' considering a variance of up to 1 m/s will determine stochastic oscillations of U of the same order of magnitude as $\bar{u}$ itself (the data usually supplied as output by the NWP model). This confirms the low predictability that occurs when wind speed drops to a threshold of 3 m/s.

In summary, low-wind speed simulation is a very difficult task and turbulence is very different from usual strong-wind conditions. Description of turbulent processes needs to be improved in mesoscale models. This can be accomplished by including higher order moments in the RANS models, by nesting LES in mesoscale models, or by directly parameterizing the low-frequency meander.

4.5 EXTENSION TO ENSEMBLE FORECASTING

The traditional method for producing a deterministic weather forecast has been to take the best-available model and run it until it loses its skill due to an increase in small errors in the initial conditions. Typically, a meteorological model's skill is quite low after 6-7 days, depending on the season and on the specific initial state of the atmosphere. However, a deterministic NWP model forecast can provide useful information for decision-making for such a forecast lead-time. Its capacity is however fundamentally limited as it represents only a single possible future state of the atmosphere from a continuum of possible states which results from imperfect initial conditions and model deficiencies that lead to non-linear error growth during model integration [81].

In the last 30 years, some methods have been developed that produce forecasts with skill up to 15 days after the initial forecast and attempt to represent that continuum: these are called "ensemble forecasting" models. Instead of using just one model run, multiple runs are performed with slightly perturbed different initial conditions. An average, or "ensemble mean", of the different forecasts is produced. This ensemble mean is likely to have more skill because it averages out over the many possible initial states and essentially smoothens the chaotic nature of the atmosphere. This approach makes it possible to forecast the probabilities of different future conditions because of the broad ensemble of forecasts available. The two main benefits of the ensemble model forecast are: the estimate of the forecast error (uncertainty) and the increased predictability.

Forecast errors occur during each process of a numerical weather prediction system, due to observation uncertainty, data assimilation, forecast model (dynamical process, discretization, physical parameterization, etc.) and grid resolution (vertical and horizontal). Early studies [82][83] suggested that initial errors could grow very fast into the different scales independently from how small the initial error is. In fact, forecast errors increase continually with the model's integration until it is saturated. The optimum solution to capture and reduce this forecast error (uncertainty) is to use an ensemble forecast instead of a single deterministic forecast, because an ensemble forecast produces a set of randomly-equally-likely independent solutions for the future. In an optimal ensemble model, the diversity of these solutions, which is called the forecast spread, accurately represents the forecast uncertainty. The relationship between ensemble spread and ensemble mean error (uncertainty) is one of the main performance tests for an ensemble model. In fact, if evaluated over a long period, the perfect ensemble prediction system is expected to produce a very similar spread to the ensemble's mean error (or a high correlation between the ensemble spread and ensemble's mean error).

In the past 15 years, different methodologies have been applied at the National Center for Environmental Prediction (NCEP) in the USA, the ECMWF and the Canadian Meteorological Centre (CMC), to simulate the effect of initial and model uncertainties on forecast errors. The different performances of these three main models have been examined and compared in many studies as in [84][85] and summarized in [86]. There are two main ways of producing ensemble meteorological models. One of these (as used by NCEP and ECMWF) is to consider that a deterministic model is perfect and then introduce uncertainty into the initial conditions, based on the fact that the state of the atmosphere is measured with a sparse network allowing room for different states of the model all of which are compatible with the measurements. As a consequence, the initial analysis field is appropriately perturbed, introducing random equally probable deviations from the best guess. In particular, the ECMWF Ensemble Prediction System (EPS) applies initial condition perturbations using a mathematical method based on singular vector decomposition and stochastic parameterization to represent model uncertainty. The approach searches for perturbations that maximize the impact on a two-day ahead forecast, as measured by the total energy above the reference hemisphere (at 30° latitude). ECMWF EPS consists of 50 different evolutions of the desired atmospheric variable, plus a non-perturbed member (the control run, which only differs from the deterministic run for its lower resolution). The horizontal resolution of EPS was increased in January 2010 from approximately 60 km to 32 km [87].

Another way to produce ensemble forecasts is to use different numerical models and different physical parameterization in the same models. An example is the COSMO-LEPS system. The Limited-Area Ensemble Prediction System (LEPS) is created with 16 different integrations of the non-hydrostatic mesoscale model COSMO, which in turn is nested on selected members of the ECMWF EPS. The so-called "ensemble-size reduction" process is required to maintain affordable computational time. The selected global ensemble members provide initial and boundary conditions to the integrations, and the COSMO model is then run for each selected member with a different physical parameterization. The basic principle of COSMO-LEPS is to combine the advantages of a probabilistic approach based on the use of a global ensemble system with the details obtainable from high-resolution mesoscale integration. COSMO-LEPS runs daily with a horizontal resolution of ~10 km and 40 vertical layers, starting at 12 UTC with a forecast range of 132 hours [87].

The COSMO-LEPS application on DLR forecasting is particularly interesting. This is because its higher resolution compared to other "global" EPS models could be an advantage in complex topography applications, where low wind speeds are more difficult to predict using a low spatial resolution.

In recent years, EPS systems have been applied to energy related applications, like wind power forecasting. In general, they present a bias of the ensemble mean compared to wind observations. Furthermore it has been shown in different studies [88] that these kinds of models are under-dispersive in the first 72 hours of prediction lead times. This means that the ensemble spread, computed as the standard deviation between the ensemble members and the ensemble mean, is lower than the error calculated as the RMSE between the mean of the ensemble and the wind measurement. To overcome this issue, different calibration techniques have been proposed to appropriately increase the spread and at the same time remove the bias of the ensemble mean. Incidentally, all of these methods require local wind measurements. Furthermore, it is not a straightforward process to take one calibration post processing assessed at one point and then use it in another position where local measurements are not available. This means that applying EPS models to forecast DLR with a probabilistic approach cannot be done without a calibration of meteorological variables. Wind, which is one of the main influences on ampacity, requires particular attention: the model output calibration cannot avoid the use of time series of observations performed very close to the line section of interest.

4.5.1 EXISTING MODELS FOR DAY-AHEAD EPS

In Europe, different consortia collaborate on LAM, such as the High Resolution Limited Area Modelling (HIRLAM), the Limited Air Adaptation dynamic International Development (ALADIN) and the Consortium for Small-scale Modelling (COSMO). HIRLAM was the first group to be established and has expanded from the Nordic countries to include others in western and southern Europe. The system is mainly used to produce operational weather forecasts for its member institutes, with particular emphasis on detecting and forecasting severe weather, supporting aviation meteorology and services related to public safety. The modelling system forms the basis of a very wide range of national operational applications, such as oceanographic, wave and storm surge forecasting, road condition predictions, aviation, hydrological forecasting, etc. Further applications involve regional climate modelling, air quality prediction, dispersion modelling and use of the model as a tool for other atmospheric research.

The models that are being developed within the context of HIRLAM are:

- An operationally suitable mesoscale model at a target horizontal resolution of 2.5 km (HARMONIE)
- The synoptic scale (5 - 15 km horizontal resolution) HIRLAM model
- An operationally suitable short-range multi-model limited area ensemble prediction system, specifically suitable for severe weather, the Grand Limited Area Ensemble Prediction System (GLAMEPS).

Several HIRLAM and ALADIN institutes have either developed or are in the process of developing a variety of techniques for short-range ensemble forecasting in limited domains. The HIRLAM and ALADIN consortia aim to integrate the knowledge, experience, and results from these activities, and incorporate them into an operationally feasible distributed ensemble forecasting system. The major challenge for this system is to provide reliable probabilistic forecast information, for the short term (up to 60h), at a spatial resolution of 10-20 km, and particularly suited to the probabilistic forecasting of severe, high-impact, weather. Individual countries from HIRLAM and ALADIN each produce a subset of ensemble members in a variety of ways. Results from each member are exchanged in real-time between GLAMEPS participants and combined into a common statistic for probabilistic forecasting.

Examples of GLAMEPS forecasts are shown in Figure 6 which represents a meteogram collecting a series of runs of this model.

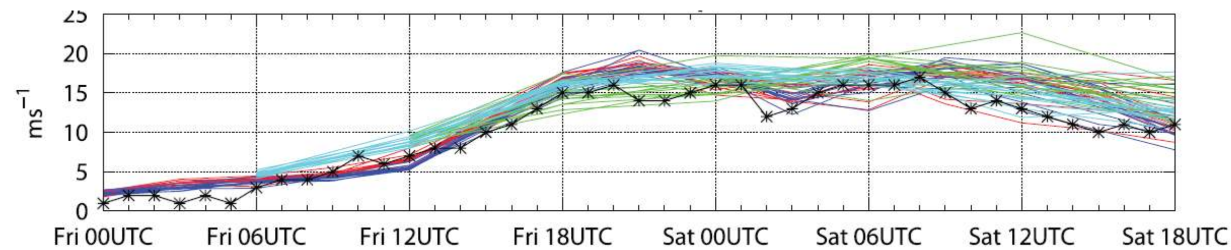

Figure 7: EPS-meteograms for the site 06235 De Kooy on the northwest coast of the Netherlands for an extreme weather case. The dates on the x-axes start on 29 February 2008 00UTC and end 42 h later, with 6 h between tick marks. Multicoloured curves on the bottom two diagrams are from the different model components of GLAMEPS EXP_0.2. Black curves with markers are observations. The curves show wind speed at a height of 10 m.

5 MATHEMATICAL FRAMEWORK FOR DYNAMIC LINE RATING FORECASTING

An introduction to the mathematical framework of DLR forecast is presented here. As a reminder, DLR forecasts must be calculated for an entire line section or with a resolution up to the single span. Also, DLR forecast leadtime can be split into intraday forecasts (a few hours) and day-ahead forecasts, similar to other energy-related problems, which may involve different approaches.

Observations of raw ampacity may be available at temporal resolutions in the order of minutes, for instance from sag measurements post-processed with the meteorological conditions in the vicinity of the span. Let us denote by r_t the raw ampacity reported at time t. In practice, for operational management decisions, the temporal resolution for the line rating forecast does not need to be too high. Time steps of 1-3 hours may be considered sufficient for operational purposes, but the dynamic thermal behaviour of the conductor must be taken into account at least for very short-term predictions (< 1h) as the typical time constant of a conductor is 10-20 min. In parallel, overhead line thermal rating is defined as a conservative estimate of the raw ampacity that may be observed within a time interval. Therefore typically for a time interval covering time steps from $t\text{-}\Delta t$ to t, the minimum ampacity y_t over that time interval is given as:

$$y_t = \min_{t=t_i,\dots,t_f} r_t \tag{7}$$

Other versions of this sampling procedure may be employed, i.e., more robust ones, in cases where it is suspected that outliers or poor-quality measurements may be present in the raw data reported. By applying this sampling procedure over the whole set of data available, the result is a time series of minimum ampacity for a span or line section of interest.

Since DLR forecasts give a conservative estimate of the ampacity of a span or line section, they may be naturally defined in a quantile forecasting framework. Indeed, when issuing a forecast at time t for lead time $t+k$, a quantile forecast with nominal proportion α is such that:

$$P\left[y_{t+k} < \hat{y}_{t+k|t}\right] = \alpha \tag{8}$$

This means that there is only a probability α that the actual observed ampacity for the span or line is less than that forecast $\hat{y}_{t+k|t}$. By setting this nominal proportion at a sufficiently low level, say, 0.02, one may then consider that the forecast gives a fairly safe minimum ampacity for the time interval index by $t+k$. Working with a quantile forecasting framework has the advantage that a number of time series and regression models exist that may be applied, inspired for instance by literature on probabilistic forecasting of wind power generation [89], or more generally literature on probabilistic forecasting in meteorology or economics.

5.1 LINE CAPACITY FORECAST, EXAMPLE

DLR forecasts were calculated for the EU project TWENTIES, and in particular in the demonstration NETFLEX, for which the overhead line of the Belgian TSO ELIA was instrumented, with sag measurement units providing real-time ratings. During the project, line ampacity values were forecast for different time horizons up to 48 hours. Being able to forecast line capacity up to 2 days ahead is crucial to efficiently operate a flexible network and brings added value to DLR. Indeed, firmly forecast extra capacity can be directly used in today's electricity market. In reality, essential core security calculations providing the grid's operational limits for the market, e.g. the capacity allocations (Net Transfer Capacity, NTC) for cross-border energy markets, are carried out two days in advance.

After the electricity market trade is settled, thorough network security calculations are performed one day ahead. Therefore, a utility that uses dynamic rating forecasting instead of the traditional seasonal rating needs a very reliable ampacity forecast (e.g. 98% confidence, which means that 98% of real-time ratings are higher than the forecast value), backed up by real-time monitoring and some form of real power flow control, such as Active Network management (ANM), Phase-Shifting Transformers (PST), or Flexible Alternated Current Transmission Systems (FACTS) to cope with unexpected ratings variations occurring in real time.

Considering the costs, constraints and advantages of a real-world application, the goal is to use the DLR forecast to be able to move closer to the physical limits, while maintaining the current levels of safety and security obtained in real-time with DLR technologies. Results of the NETFLEX Demo showed that the DLR day-ahead forecast depicted in Figure 8 yielded an average gain of over 10% more than static rating with 98% confidence on two 150kV overhead lines located close to the North Sea.

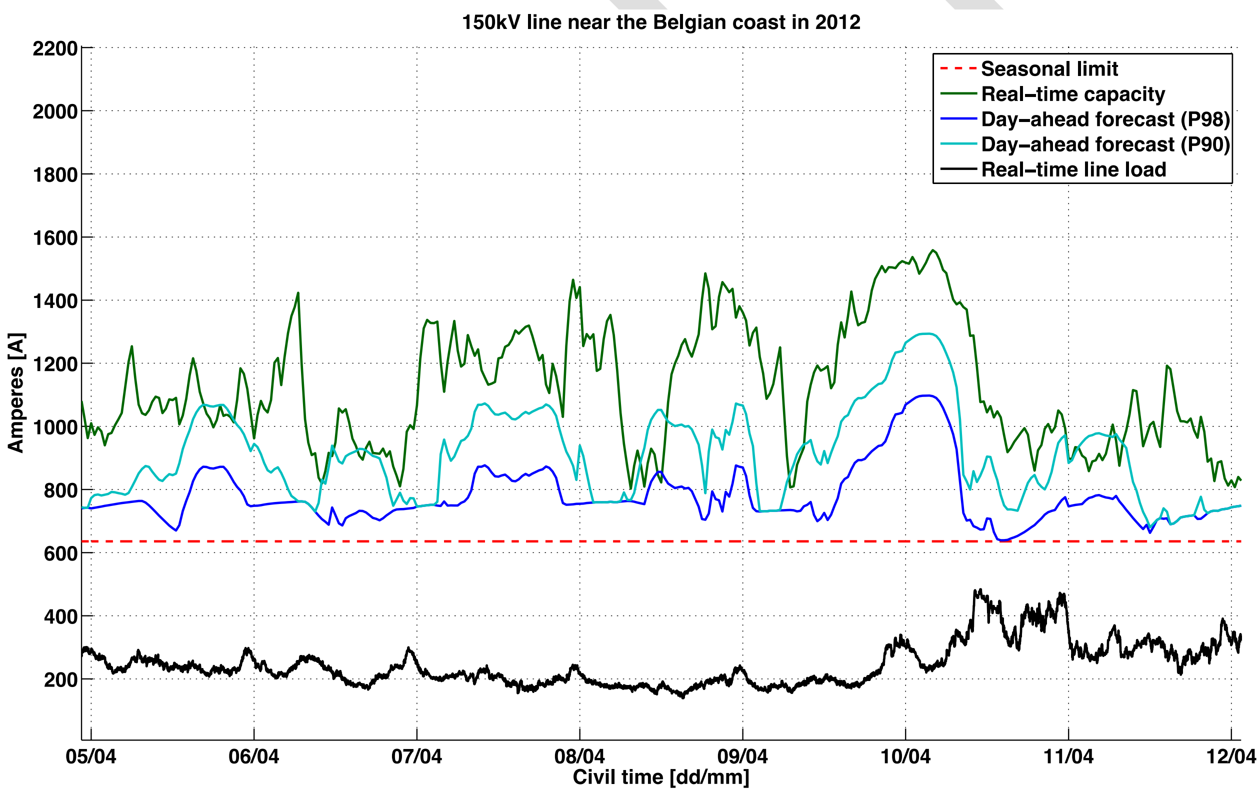

Figure 8: Results of EU TWENTIES Project: Comparison of real-time and day-ahead forecasts (prediction interval P90 and P98) for one week in 2012. Lower prediction intervals than P90 may be used to increase ampacity gains if power flow control tools are available in real time to compensate for erroneous DLR predictions.

Since DLR forecasts are strongly dependent on weather variables, weather forecasts can be used as an input to calculate ampacity forecasts up to 48 hours. However, the impact of the weather variables forecast is different with respect to the real-time impact, because some variables are robustly forecast while others are not. For example it is known that the ampacity variation is strongly influenced by low wind speeds values (<5m/s), however, as the wind speed variable is poorly predicted at these ranges (notably because of the dependency on local effects), its relative importance decreases in practice under such conditions. The forecast variables are thus, in decreasing order of importance: ambient temperature, wind speed, wind angle and solar radiation. This can be seen from an analysis of Figure 9 - Figure 12, where the ampacity measurements for the monitored line are compared to each main weather variable. In each figure, individual combinations of values are reported as a scattered plot, and for each chart the mean (solid black) and standard deviation (dotted black) are reported. Figure 9 shows the dependency between measured ampacity and forecast air temperature, whilst in Figure 10 gives the relation between ampacity and perpendicular wind speed, with a significant dependence for wind speeds > 5m/s. Figure 11 shows the relationship between ampacity and wind angle for low and high wind speeds: in the case of low wind speeds, it is not possible to identify a clear correlation between the two variables, but for high wind speed values, above 10 m/s, the ampacity clearly increases as the wind direction becomes more perpendicular to the conductor. In Figure 12 the relationship between forecast solar radiation and ampacity is shown for the winter and summer seasons: in both cases no clear trend emerges for the bottom 2% of the ampacity values, although in the winter the median ampacity clearly decreases as solar radiation increases [90]. It should be noted though that real-time ratings considered in *Figure 9* to *Figure 12* are conservative estimates of the actual ampacity, i.e. the minimum of estimates of ampacities which are compatible with sag observation (or another physical measurement of the state of the line). Hence, real-time rating values provided by real-time monitoring typically underestimate the actual ampacity, which in turn affect the study of forecast variables. More accurate measurement techniques in real-time, in particular the ones dealing with effective wind speed measurement, will improve forecast study.

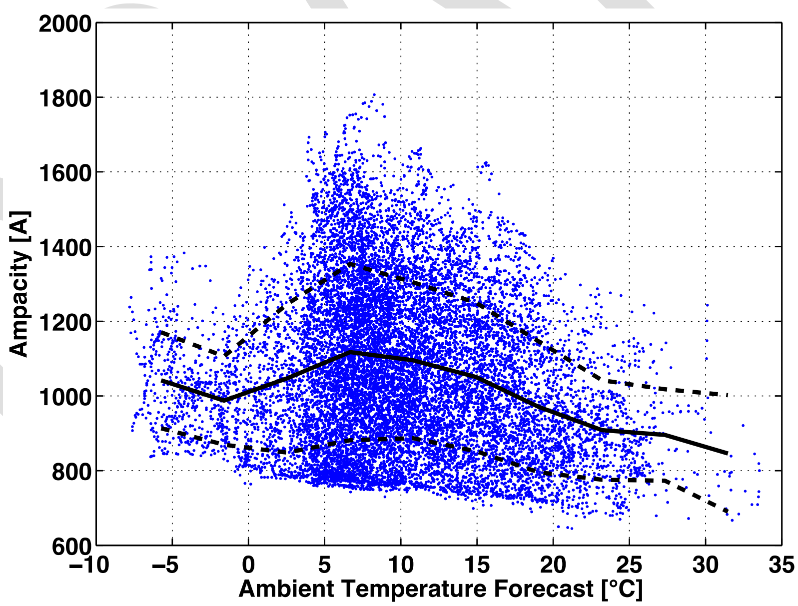

Figure 9: Two-day ahead ambient temperature forecast has a significant influence on ampacity; data from a 150kV line in Belgium, near the North Sea [mean ± 1 std] (EU funded TWENTIES project, NETFLEX Demo)

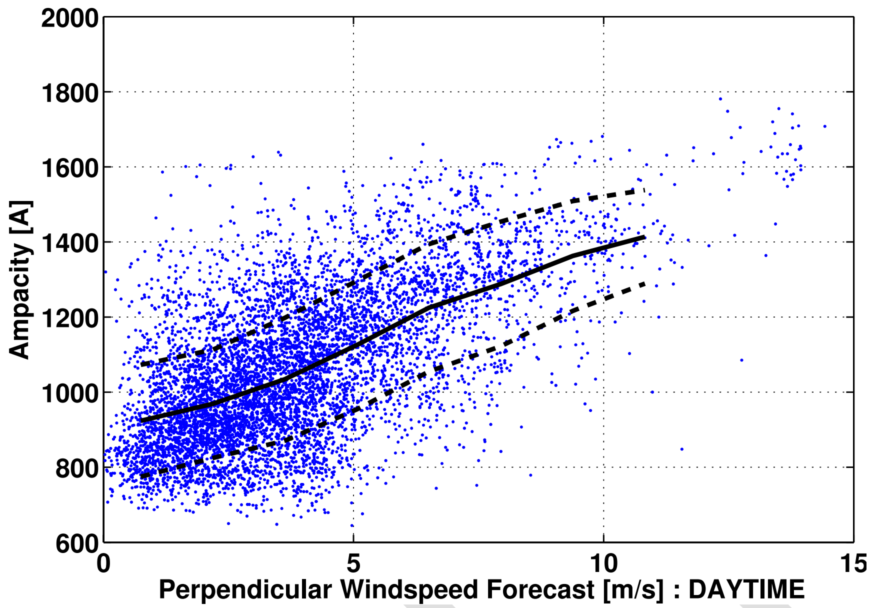

Figure 10: Projected perpendicular windspeed forecast has a significant impact on ampacity during daytime, for values >5m/s [mean ±1 std] (EU funded TWENTIES project, NETFLEX Demo)

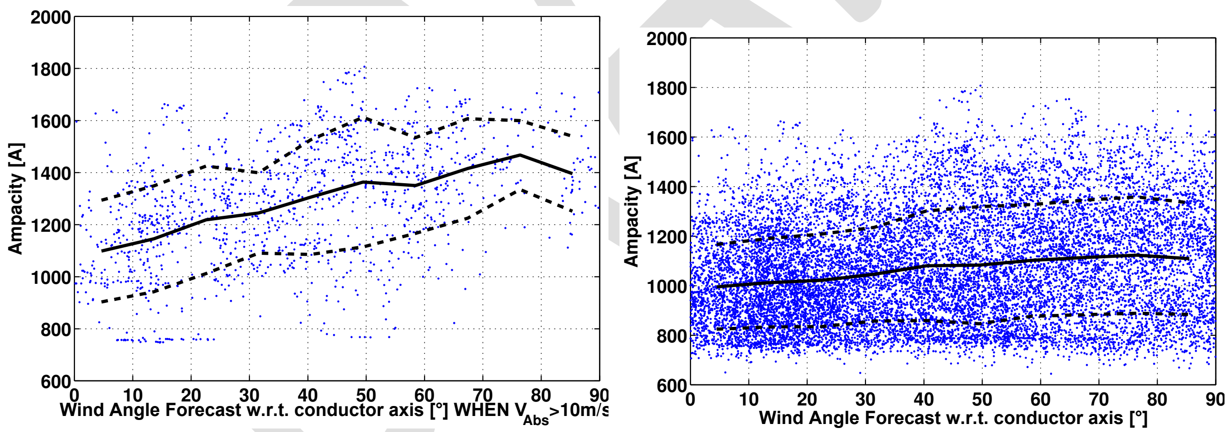

Figure 11: left: wind angle has a significant impact on ampacity for values >10m/s; right: this is not the case in general [mean ±1 std] (EU funded TWENTIES project, NETFLEX Demo)

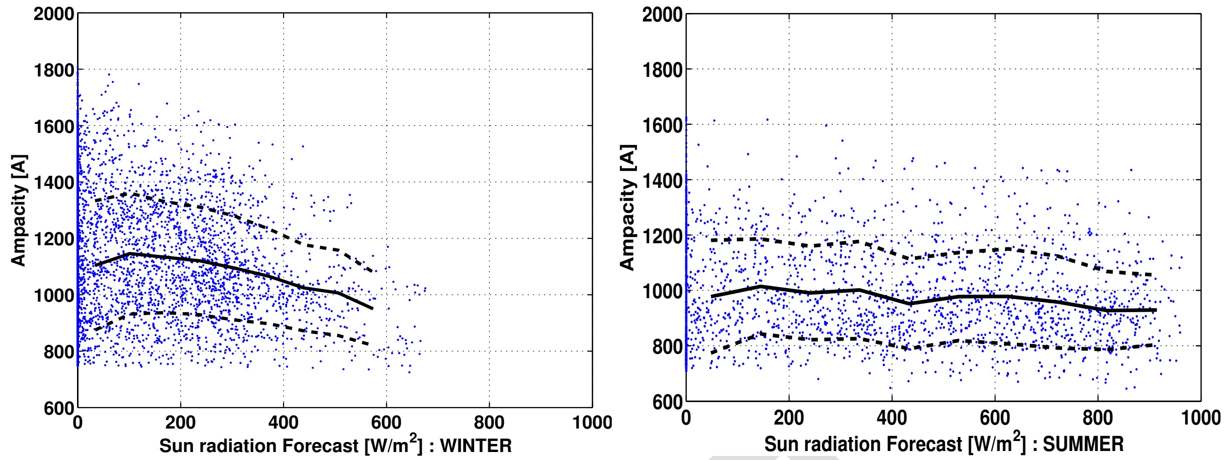

Figure 12: Sun radiation has a moderate impact on ampacity during winter for the mean trend, but this is not the case for summer [mean ± 1 std] (EU funded TWENTIES project, NETFLEX Demo)

6 ECONOMIC ASPECTS, APPLICATIONS AND LIMITATIONS OF DLR AND FORECASTING

6.1 DLR IN SMART GRIDS DEVELOPMENT

There are many smart grid definitions, but a common element to most definitions is the presence of digital processing together with information and communication technologies applied to the power grid in order to efficiently deliver sustainable, economic and secure electricity supplies. A smart grid employs innovative products and services together with intelligent monitoring, control, communication, and self-healing technologies and integrates them into utility processes and systems.

As the electricity network was originally designed to hold power flows from centralised generation units to distributed consumption areas, the increased penetration of decentralised and intermittent renewable sources significantly changes the power flows patterns, making them more dynamic, and thus modifying the way to manage them. This is one of the main issues from which smart grids technologies originated.

In order to efficiently deal with those new power flows patterns, different complementary methods can be implemented to improve network flexibility [51] and they can be summarised in four points: 1) controlling power flows with FACTS, 2) monitoring network and components' status, 3) introduce active components at the planning stage and finally 4) managing load and generation with active network management, demand side management, virtual power plants etc.

The consequence of the application of these technologies and the coordination between different actors coming with them result in a series of advantages reducing the necessity of new investments and facilitating the operation of the power system. In particular it is possible to 1) minimise power reserves and peak power plants, 2) enhance power system security with regard to failures of transmission or generation components and 3) reduce volatility of the electricity prices, by mitigating the consequences or removing the causes of high demand or excess power.

In the light of this, DLR can be considered a Smart Grid technology. Although it is based on traditional physical properties of power system components, its implementation and exploitation are made possible only by improvements in monitoring and communication technologies. Furthermore its application will be enhanced by the flexibility provided by all power system actors, network operators, market players, producers or consumers through automatic control, when information on eventual variable constraints is available. In this framework, combined implementation of smart grids technologies increases the overall efficiency. Therefore, even a few percent increases of dynamic ratings can significantly enhance network operation and flexibility when other smart grids tools are being used simultaneously. This can then benefit all stakeholders by increasing overall social welfare.

6.2 ECONOMIC AND MARKET IMPLICATIONS OF DYNAMIC LINE RATING

DLR has received constant attention from the power system and academic community as a promising strategy for maximizing the utilization of the network's infrastructure and bringing low-cost energy to heavily loaded sections of the grid. It is of crucial importance from the perspective of integrating regional networks into a fully interconnected European super-grid. Undoubtedly, the great majority of research studies focus on how flexible line-rating policies could be used to tackle operational and safety issues in grid management. However, when it comes to the economic or market implications, there is an obvious literature gap, with a few noticeable exceptions [91], [92] [93]. For instance, little has yet been written on the extent to which consumers might benefit from flexible rating mechanisms or how much capital could be released from the required network extension/upgrade projects or the extent to which consumers might benefit from flexible rating mechanisms. These questions are very important when it comes to convincing grid operators or regulators to adopt new, and perhaps radical, network management rules. Furthermore, whereas it may be easier to compare a conventional network reinforcement (i.e., building additional transmission lines, and adhering to static line ratings) investment and an investment on DLR implementation on specific congested power lines as an alternative, the assessment of overall economic implications may be very difficult.

Generally, the discussion on whether DLR presents an economically feasible and rational solution focuses on two dimensions that mainly represent the viewpoints of different network stakeholders (utilities and consumers).

Switching to a DLR operation mode requires installing new equipment for conductor monitoring and adopting new technologies for ambient conditions measurement/forecasting. In addition, it may require upgrade of some other transmission line components, but the conductors, in order to allow higher loading with DLR. For a utility company, this amounts to launching a new, possibly riskier project whose benefits must be weighed against the obvious choice of upgrading an otherwise seasonally rated grid. The relative merits of each alternative can be evaluated on the grounds of several investment performance metrics (capital intensity, project lifetime, payback period, etc.) provided, of course, that all inputs into the decision-making process (costs/benefits) can be adequately expressed in financial terms. This can be a tedious task when taking into account the complexity of modern networks and the great number of parameters involved, although flow-based approaches presently being developed in central Western Europe may be significantly helpful. Furthermore, cost estimates are typically uncertain and can significantly vary across countries or regions.

The potential of DLR to release capital for use on network reinforcements provides a strong incentive to utility companies to reduce their customer rates, with obvious advantages for consumers. Theoretically, utility customers could additionally benefit from DLR through higher utilization rate of the existing power transmission assets, lower electricity prices due to decreased transmission constraints and the distribution of cheap renewable power over a larger network area (especially in nodes of the grid with limited access to abundant RE resources). These benefits may be inevitable and significant, but being rather indirect the implications may be difficult to assess both beforehand (i.e. in the decision making phase), as well as retrospectively (i.e., evaluating the profitability of decision taken for different stakeholders).

In [92], was introduced a calculation method for the assessment of possible economic benefits for the consumers in a price area if the bottleneck between the price areas could be relieved by employing DLR. The method was demonstrated with a case study based on historical power system, electricity market, and weather data. Without committing to the actual applicability of DLR on the case study bottleneck connections, nor possible relieve potential in congestion, the results point out that the economic benefits of DLR employment on crucial connections, may have wide-spread and significant overall economic implications in total. The method in [Sanna] could be used for the motivation for further study and consider DLR applicability and benefits on constrained connections between electricity market price areas.

A series of studies [94][95] deal with the consequences of increasing RE generation shares on electricity prices. A typical study of this sort would investigate the impact on local area networks (or nodes adjacent to the production) as well as cross-country power exchanges. The general finding of this stream of literature is that the growing penetration of cheap renewable power can have a positive effect on electricity consumer rates, provided sufficient line capacity is available to transfer renewable energy to distant, heavily loaded nodes. In the specific case of the German grid, [95] conclude that without particular extensions in the existing network configuration, it will be difficult to reap the benefits of the offshore wind capacity envisaged by the 2020 German RE development programme. If these upgrades are not implemented quickly, high wind power injections are likely to cause congestions with subsequent price upshots both in the domestic grid and neighbouring countries (e.g. Belgium, the Netherlands). Decentralizing electricity markets and introducing flexible pricing schemes, such as zonal or nodal pricing, could mitigate the adverse effects of high wind generation but not fully eliminate them.

The literature presented points to a physical network expansion as the only way to accommodate growing RE production. However, this conclusion implies that electricity networks will continue to be operated in the same way as today. Could real-time monitoring of overhead lines and/or of ambient conditions help stabilize electricity prices without the need for major network reinforcements? This is an issue that deserves further investigation in the future.

Overall, DLR being dependent on the local dynamic weather conditions, and combined with individual constrained transmission line or multiple connections dynamic transmission capacity needs, the DLR applicability must always be studied and weighted case specifically. In each case the benefits, both technical and economic benefits, as well as the cost of DLR implementation and continuous monitoring ought to be assessed. The DLR monitoring, however, most likely brings along additional value in the form of increased awareness of power line operating states.

6.3 APPLICATIONS AND LIMITATIONS

Dynamic line ratings and dynamic line ratings forecasts have the potential to unlock latent network capacity, with several advantages for the power system and its stakeholders, but also several limitations, both described in this section. The main areas of application identified are listed and described below. They are based on a vision of the power system enhanced by ICT where network operators can exploit better their assets through better monitoring and other actors are also able to exploit this information in order to add value to their business model.

1. Reduction of non-firm (interruptible service) wind power curtailment
2. Coupling of electricity markets
3. Reduction of re-dispatching (congestion management costs)
4. Delay of network reinforcements due to both increased generation and demand
5. Mitigation of reliability issues

The reduction of wind power curtailment is one of the most recent DLR applications, and has been especially studied and applied Europe in connection with new wind farm developments [96]. It is based on the idea that if a wind farm produces a considerable output that could involve curtailment to avoid infringing standard line thermal constraints, then power lines in nearby areas are also exposed to higher-than-average wind speeds (although in general less than the production sites) that are sufficient to cool them down and consequently temporarily increase their current carrying capacity. Initial evidence of this (expected) correlation has been gathered in the field [97]. It would allow wind farms subjected to curtailment to maximize their exports and also reduce the associated connection cost of installing new wind farms, thus increasing the share of low-carbon electricity injected into the network.

When two or more energy markets are coupled through overhead lines and present a thermal rating bottleneck, DLR can help alleviate the problem [98]. This is true both in the case of two separate markets managed by different entities and in the case of power systems managed with zone or nodal prices. The use of DLR can enhance the average connection capacity between the different areas of the power system, and also increase the share of low-carbon, low-marginal-cost electricity consumed. In this case, a reliable DLR forecast is necessary to integrate the variable capacities into the operation and day-ahead electricity market.

DLR can be used to reduce congestion management costs (generation re-dispatching) when caused by the thermal limits of a circuit. A typical example is during winter evening peak times: low temperatures cause higher loads on transmission lines, but could also lead to higher actual rating on these lines. An extra temporary transmission capacity would also reduce the amount of disconnected loads in case of planned or unplanned outages on the network. This effect may be considered by some TSOs to temporarily increase components ratings with appropriate security buffers: DLR forecasting and real-time monitoring of this available extra capacity would facilitate its systematic exploitation.

When a DLR system is applied to a component or a grid portion, it may increase the components' operating time and reduce the need for network reinforcements by accommodating the growing demand or production [44]. This is true even if it the exploitable ampacity increase is limited to a value around 10% of the static rating, as network infrastructures are sized on peak demand, occurring for few hours per year. This can be seen with the following example. If the peak current on a saturated line grows of 1% per year and the DLR provides an upgrade of about 10% on the static rating, it will add about 13 years of life to the current line. For an expected life of the circuit of 50 years, this corresponds to an increase of life of the 26%. DLR can also be used to cope with the rise in unexpected load flow changes caused by the fast growth of intermittent generation, and the very dynamic context of a deregulated market in large, interconnected meshed networks. In this context, DLR provides more flexibility and closes the gap between congestion appearances and the effective commissioning of new or upgraded lines that may last for five to ten years [97]. Another consideration is that DLR could increase the average operating temperature of power components and thus also increase the losses and aging speed of these components, although the cost of this side effect has been evaluated [91] as a small fraction of the benefits.

Finally DLR improves reliability by improving the system operator's awareness thanks to real-time monitoring of power line status. In fact, owing to various events and aging, lines do not respect the initial design in many cases, especially older lines as seen for example during the 2003 blackout in North America due to a clearance violation. New American standards have tightened rules since then, and have specifically allowed use of real-time ratings, as reported in [99].

In conclusion, DLR brings an opportunity to reduce electricity delivery costs and carbon footprints, by reducing both the necessary investment on the network and the constraints for transmitting green electricity at lower marginal costs. Although in point 1 above, the benefits of DLR can only be achieved if the thermal constraint is relative to an overhead line, in cases 2, 3 and 4 the advantages of DLR and DLR forecasting can also be achieved in the case of thermal limits relative to underground cables and power transformers. In such cases, the available headroom and its dependence on weather forecasts is reduced, and it would be more correct to use the generic term of Real Time Thermal Rating (RTTR).

Despite the advantages mentioned above, the limited application of DLR in today's power systems cannot be investigated without considering the challenges inherent to the adoption of such a new technology. In order to successfully exploit the potential of DLRs and DLR forecasting, these drawbacks need to be overcome or limited. The main challenges identified today for the extensive deployment of DLR technology are:

1. Non-firm capacity that is difficult to exploit
2. Other network constraints
3. Modification of protection settings
4. Integration into TSO/DSO ICT system
5. Definition and implementation of new processes
6. Lack of experience
7. Existing alternatives

The first limitation stems from the difficulty of making full use of the circuits' non-firm transmission capacity. This is because in a grid, different circuits may experience different upratings at the same time, limiting the effective transmission capacity of the whole grid. Flexible generation and loads would allow for more efficient use of the extra capacity made available by DLR. Furthermore, errors in ratings forecasts would require the additional use of balancing capacity, incurring potential extra costs.

The second limitation is the presence of other constraints, such as voltage limits or fault level limits that should be met by the network when the thermal constraints are lifted. In some cases, the presence of these limits would reduce the actual transfer capacity of the network and decrease the benefits of using DLR. System stability might also be affected in particular situations.

The third limitation relates to the impact that DLR would have on circuits' thermal protection settings. Currently, protection systems disconnect circuits when a current higher than the rated one is measured. The application of DLR may require replacing or upgrading current protection or other equipment (transformers). This would also involve paying special attention to circuit breakers, since they would have to be rated for higher values of current, and using Remote Terminal Units (RTUs) or other similar technologies to continuously update the settings of the protection switchgears. This may also have implications for the network's cyber security.

Note that when operating an electricity network with dynamic ratings, weather/DLR forecasts should always be coupled with DLR sensors that monitor lines in real time. This guarantees grid operation/public safety and security to respect statutory clearance and verify maximum allowable conductor temperatures at all times.

Furthermore, Transmission or Distribution System Operators (TSOs, DSOs) need to ensure the smooth and global integration of this technology into their IT systems, in particular by implementing DLR information in their Energy Management System (EMS), preferably through their SCADA, e.g. including the data for ‘N-1’ calculations and keeping the information up-to-date continuously. In this regard, the reliability of communication systems and network cybersecurity has become a major concern for smart grid technologies. Consequently, in the case of a communication failure, the ability of DLR technologies to work in safe fallback mode must be implemented, e.g. a safety value such as the seasonal rating.

New processes need defining to adapt system operations to DLR. Indeed, highly regulated entities like TSOs follow very strict operating rules and processes. These processes may vary from one TSO to another, depending on the availability of control tools (FACTS, ANM, etc.), the specific topology, and regulation guidelines. DLR installation procedures need improving to include criteria to determine what kind of line should be installed with DLR, and which critical spans should be monitored in order to speed up deployment. Other limitations in adopting DLR include lack of experience in operating a network with flexible constraints, and the need for staff training.

A final consideration is the existing or future alternatives to DLR that can be used to mitigate congestion and lead to generation re-dispatch. These may include conventional network reinforcements and uprating, which are sometimes impractical. On the other hand, other smart grid technologies may offer alternatives in some situations. The optimal solution will therefore probably be a mix of conventional solutions and new monitoring/control developments.

7 CONCLUSIONS

DLR is a technology that can increase the current carrying capacity of electric transmission lines. It is based on the observation that the ampacity of overhead lines is determined by its ability to dissipate the heat produced by joule effect into the environment. This in turn is dependent on environmental conditions such as the value of ambient temperature, solar radiation, and wind speed and direction. This phenomenon is particularly evident in overhead transmission lines, where DLR can provide considerable upratings. In the current power system scenario, where the rise of power injections from intermittent renewable sources puts stress on the existing electric infrastructure, DLR can represent a solution for accommodating higher renewable production whilst minimizing or postponing network reinforcements.

This technology has been developed since the 1970s by different research groups in the USA and used mainly for monitoring purposes. DLR has been demonstrated more recently in Europe, like in the EU TWENTIES project, for facilitating the integration of wind power: for example, when overhead lines' design thermal ratings are infringed because of high wind power production in nearby areas, the strong wind blowing on the region is actually able to cool the conductor, resulting in a simultaneous increase of thermal rating over design, which can be exploited by DLR.

Among the environmental parameters affecting DLRs, wind speed and direction have the largest impact, but are also the most variable and difficult to predict. Precipitation also has a considerable impact, but because of its intermittent behaviour and difficult modelling, to date it has not been used in DLR applications or static line rating definition. Historically, ambient temperature and solar radiation have been used to determine seasonal ratings thanks to their relatively predictable patterns and limited variability. DLR applications can take advantage of weather forecast characteristics, by coupling weather forecasts with real-time-rating in-situ measurements obtained from monitoring sensors that ensure grid operation/public safety and security.

Regarding meteorological forecasts, global models are run at the ECWMF, the NOAA and other international laboratories. National consortia of meteorological centres use these global models to produce smaller-scale weather forecasts that integrate local measurements by running mesoscale models, such as ALADIN or HIRLAM. Current research models are focused on developing models able to generate probabilistic or ensemble forecasts with models such as GLAMEPS. For DLR, low wind speed modelling has been considered as fundamental, since low wind speeds seem to represent a limiting factor for conductor ampacity. Today, for TSOs' operational practice, the important information for forecasting is the probable occurrence of low wind speeds, but future research will further improve the use of DLR by improving low wind speed modelling. In this document we have explained why the turbulent description of wind flow should be improved at the level of the mesoscale model in order to correctly predict low wind speed conditions.

The benefits of DLR are related to its capacity for delaying network reinforcements and reducing network congestion costs. In order to achieve these objectives, it is clear that DLR should move from a monitoring technology used to control individual lines to a more deeply integrated approach in the proactive management of the network. The main challenges identified lie in the development of suitable DLR forecast techniques and methodologies for integrating DLRs into the present and future decision-making process of power system actors. Furthermore, DLR forecasts should be enhanced by improving mesoscale meteorological forecasts for low wind speeds. Finally, DLR in situ measurements may also help improve low wind speed forecasts.

Regarding DLR forecasts, it is necessary to further develop the methodology for providing reliable and stable ratings for different time horizons. For efficient usage, forecasted ratings should not change continuously in time and their value should be sufficient for the conductor temperature to never exceed the design limit or infringe the statutory clearance. In order to do this, probabilistic forecasts represent a powerful solution, since they provide results that correspond to a pre-determined value of probability excedance. It is therefore possible to select a reasonably low probability of exceedance, e.g.: 2%, corresponding to a risk level accepted by the network operator, and thus help the decision-making process. It should be also noted that current seasonal static ratings are calculated using a similar risk-based probabilistic approach that takes into account historical weather data for each country or region.

Regarding DLR integration, both operational procedures and the legal framework necessary to exploit variable ratings need developing. This includes the introduction of variable ratings constraints into day-ahead and intraday power markets and a study of the resulting impact on generation, transmission and balancing costs. The risk approach used to rate the lines should also be reviewed in order to take into account the presence of monitoring equipment, control means, and flexible generators and loads. The impact of DLR and DLR forecasts on power system reinforcements and planning should also be investigated. It should also be mentioned that no research has been carried out on the effect of DLR for PV power integration. In the case of large solar plants connected at high voltage, it is expected that power flows would be higher in hours of maximal solar radiance, thus of lower DLRs. Anyway in this case, DLR and DLR forecast would help to increase network operation security from current level, as they would highlight potentially dangerous situations. On the other case for small scale solar plants connected at the distribution level, higher production should be absorbed at the local level, reducing the power flow on the lines, even in the case of reverse power flows.

Finally, work must be done in order to improve the quality of DLR forecasts, and specific research is required on forecasting low wind speeds along a line spanning several NWP grid points. This involves the use of downscaling techniques and the integration of a more sophisticated modelling of wind turbulence into mesoscale meteorological models. These models could in turn usefully take advantage of measurements from DLR sensors installed on the field, which would both improve the modelling and avoid the need for a detailed model of the topography. Other possible research areas on DLR and DLR forecasts are the effects of icing and DLR and the automated identification of the most sensitive spans using high-resolution geographic information systems (GIS).

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