Different Approaches of Dynamic Line Rating Calculations

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***Abstract* — Nowadays in the electricity system several challenges have been appeared that system operators have to cope with. One of the major challenges is to increase the transmission capacity of the overhead lines (OHL), while maintaining the safety and security level of the network. Dynamic Line Rating (DLR) by monitoring the real-time environmental parameters next to the conductor is a promising and cost-effective way to use the existing infrastructure with higher efficiency. There are several different deterministic DLR models in the international literature, but there are also other approaches based on soft computing or Monte Carlo simulations for the calculation of transmission capacity. The aim of this paper is to demonstrate the operation of the different models by presenting a real case study.**

Keywords — dynamic line rating, DLR, renewable energy sources, resource management, system resilience, transmission line, soft computing, neural network, Monte Carlo simulation

I. THE BASIS OF THE AMPACITY CALCULATION

The main consideration for the designers and transmission system operators (TSOs) in the construction of power lines were always the operational safety and continuity of supply. Accordingly, since the middle of the last century transmission capacity of transmission lines has been targeted for safe operation rather than the economic optimum [1][2].

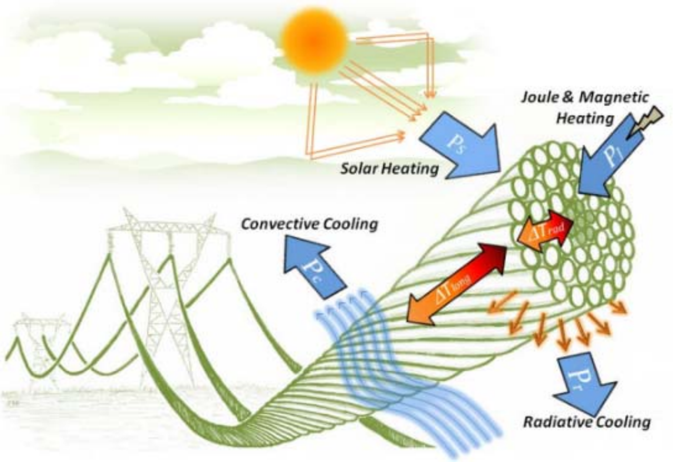

Figure 1 Factors influencing the conductor temperature [1]

The basis of the calculation was adjusted to the thermal equilibrium of the conductors, due to the result of excessive temperature increase could cause undesirable degradation processes and increment in sag. This latter should be avoided not only because of legal regulation but also for reasons of life protection. The classical way of transfer capacity calculation of power lines is called static line rating (SLR), the essence of which is to adapt the transmission capacity to the worst-case scenario of the environmental parameters. This worked well until the periodic, intermittent renewable energy generating units spread widely, as well as the concept of implementation of the Integrated Electricity Market (IEM). In this way, so-called bottleneck effect occurs on some transmission lines, so that there is a need to increase transmission capacity of these critical lines [3]-[5].

II. THE ESSENCE OF DYNAMIC LINE RATING

There are different options to increase the ampacity level of the transmission lines. Building new transmission lines or uprate the existing infrastructure (increase the diameter of the conductor etc.) seems to be an effective way, but the huge costs of the implementation, the strict legal issues and social resistance cause too much complications for the implementation. On the other hand, the better use of the existing grid also could be a promising way to reach higher transfer capacity barriers for an OHL [1][5][6].

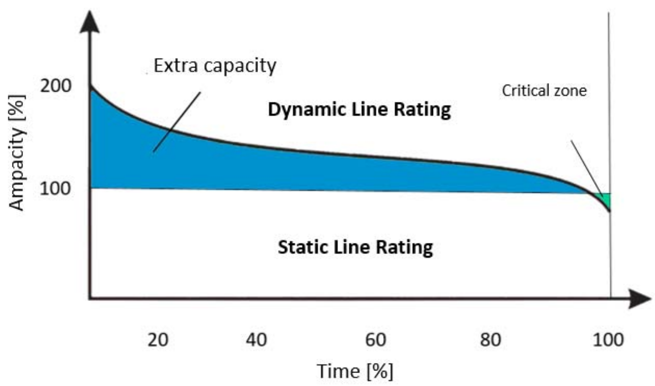

Figure 2 Duration curve of the OHL rating [7]

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This can be reached if the environment and load parameters in the vicinity of the line are monitored in real time with sensors and weather stations. In this way SLR could be substituted by a calculation method with which the ampacity is calculated from time to time e.g. for every 15 minutes [7][8].

According to simulations and case studies the ampacity calculated in this way is significantly higher in almost 95% of the time, and the cost of the implementation is less than in case of any modification of the OHLs. This method is the so-called Dynamic Line Rating and it seems to be a promising way to increase the ampacity of an OHL by adjusting the transfer capacity to the actual environmental parameters [5]-[10].

III. Different types of DLR models

Although DLR is a novel method in practice, there are several existing models in the international literature. These models could be categorized according to different principles. Some models are deterministic while others are stochastic ones, some of them are based on empirical, physical properties while also black box models exist. There are implementations where different machine learning algorithms are applied while others put emphasis on some external factors [1][2][12][14].

All these types of models have advantages and disadvantages, but neither of them could claimed to be the most accurate without application under real circumstances. At this point, it is important to mention that thanks to international projects funded by the European Union, there are several pilot projects are in progress to clarify the existing models [7][10].

Figure 3 Installed sensor on the conductor and weather station on the high voltage tower [7]

IV. Deterministic models

Initially, mostly deterministic DLR models were developed. A common feature of these models is that the outcome is generated via known relationships from the group of inputs without any random factor. In these models the output is always the same for a given input [7].

A. *Physical models*

In DLR literature, IEEE and CIGRE models belongs to this group by calculating ampacity and conductor temperature based on the thermal behavior of the conductor. Both models determine the heat losses and gains thus forming a heat balance equation for the thermal behavior of the conductor. One big advantage of these models is that they can make calculations for the real-time case and predictions depends on the input parameters. However, while these models have same approach for ampacity calculation, it is important to notice that in some cases (e.g. above 5 m/s in the wind speed) the ampacity determined by the IEEE and CIGRE model is significantly different. The main cause of this phenomenon can be that these models neglects some parameters (e.g. the cooling effect of precipitation) that has effect on the result. This recognition implicated clarification in these models and also new approaches for ampacity calculation [1][2][8].

One way to refine the physical models is to supplement them by considering the neglected factors. Of the IEEE and CIGRE models, the latter is less negligible, thus a so-called extended CIGRE model was developed taking into account the cooling effect of the precipitation [9][11].

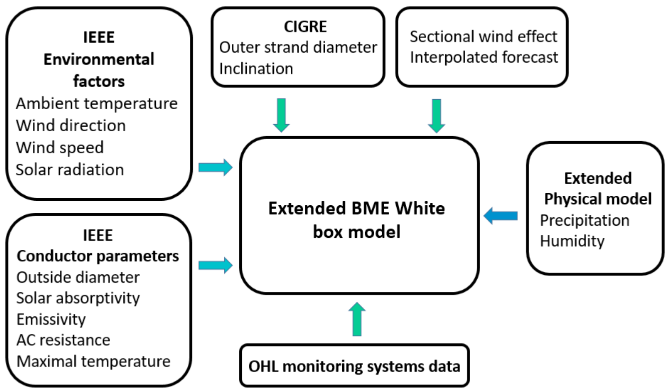

Figure 4 BME extended white box model [7][11]

B. *Black Box DLR model*

New approaches based on black box models could also be applied to avoid the mentioned neglected factors of the physical models. The common point of the black box models is that the internal work of the observed system is unknown, only the input and the output are realized. Black box modelling can be applied also in DLR models, in which different soft computing agents forms the basis of the calculations. A possible solution for such a model is the BME Black Box DLR model, which calculates the real-time thermal rating of the conductor in 2 steps.

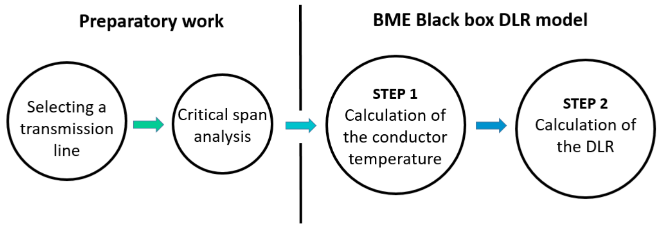

Figure 5 Structure of the DLR calculation method via BME Black box model [7]

In the first step, a neural network is used to determine the real-time conductor temperature, which represent the starting point for the second step. The model has three weather input parameters (ambient temperature, solar radiation and wind speed) and a load parameter, which is the real-time current value. However, this process requires a set of training data provided by different sensors and weather stations. The sensor installed on the conductor measures the temperature in real time, which includes the combined effect of all the environmental factors. This is the main strength of the black box model due to there are no neglecting of any individual weather parameter. In the second step, the real-time transfer capacity can be determined from the conductor temperature with the use of a thermal-differential equation. This is since each conductor has a maximum temperature that cannot be exceeded due to material factors and critical sag. It can be calculated how many surplus currents can be passed through the transmission lines to achieve this maximum temperature. The addition of the current and the surplus load represent the dynamic line rating [7]-[9]

V. PROBABILTY BASED MODELS

In the recent period, other probability based DLR models have appeared alongside deterministic ones. These models are based on probability-functions and according to this provide more accurate information about the environmental and load conditions. One of the main strengths of these models is that the output, such as the inputs, is not a specific value but also a distribution. Based on this distribution a risk factor can be introduced that could provide a surplus information about each circumstance. This also gives an opportunity to system operator to have an easier decision-making process [7][10][13][14].

A. Types of the probability based models

There are two types of the probability based DLR models. One big type is hybrid models while the other one is the absolute probabilistic models. In the former model, discrete inputs and distribution functions are mixed, and they combine the positive properties of physical and probability models. However, the risk factor calculated for such hybrid models always represents only a relative risk, since it does not cover the variation of various external factors. Absolute probabilistic models, on the other hand, also take into account the impact of factors such as increased risk of lightning strikes or distances in this way represent an absolute risk calculation [7].

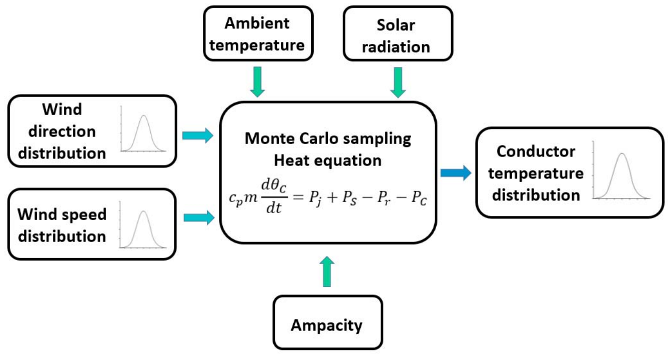

Figure 6 Structure of the temperature calculation by Monte Carlo sampling in the hybrid DLR model [7][9]

B. Application of Monte Carlo simulations in DLR

In case of real-time DLR calculations it is possible to link hybrid models and different Monte Carlo simulations. Monte Carlo simulation is a general term for procedures, sampling forms and technics based on random number generation. In hybrid DLR models these methods could be applied for the forecast of the weather parameters and also for calculation of risk factor [7][9][13][14].

1) Forecast weather conditions

The real challenge in DLR calculation is to provide precise ampacity prediction for the near future. For these calculations it is necessary to make predictions for the environmental parameters which represent one group of the model inputs. Usually data of meteorology stations are used for these weather forecast. However, in most of the cases the spatial or time resolution of these forecasted data are unsatisfactory. On the other hand, it is not economical to install meteorological stations next to OHL, so the use of other different options is required for more precise prediction [7][9].

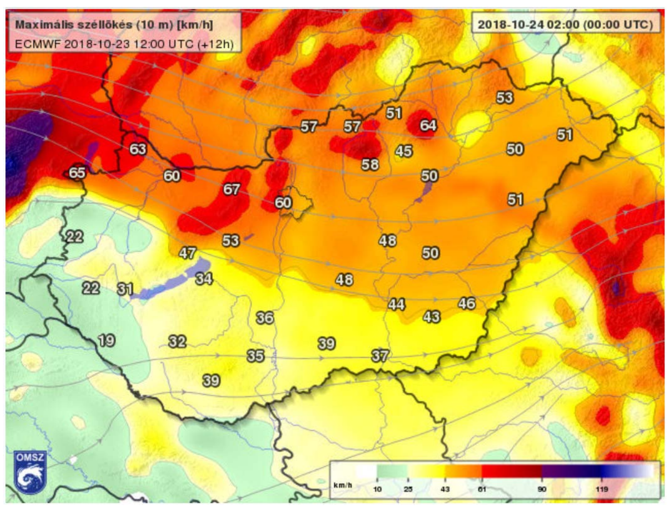

Figure 7 ECMWF meteorological forecast for wind speed [7]

At this point, a type of Monte Carlo simulation, the so-called Markov Chain Monte Carlo method could lead to result. The essence of this simulation is to apply different time series models for each environmental factor. Each of these models contain different parameters and the aim is to determine the posterior distribution of these parameters to represent the possible values of the actual environmental factor. According to the Bayesian approach, if the prior distribution is known and there are also measured data, the posterior could be determined. However, in this case this distribution cannot be calculated or estimated. This is where MCMC could help, by structuring an ergodic Markov chain from the past values of the parameters. This chain has a stationary distribution that could represent the required posterior distribution. If the posterior distributions of the parameters are known, a full prediction could be provided for each of them [7][9][13][14].

2) Calculation of the risk factor via Monte Carlo sampling

The aim of the hybrid DLR model is to predict the conductor temperature for the near future. According to this, there are 5 input parameters in the model. The four weather parameter inputs are predicted values or distributions, while the load parameter is the DLR value calculated for the actual state by CIGRE DLR model. In the determination of conductor temperature, a differential-equation defined by CIGRE is applied. In this step a Monte Carlo method is used to sample the input values from the distribution of the environmental parameters. As a result of these simulation cycles there will be a distribution for the conductor temperature. As it was mentioned all the conductors has a maximal temperature that cannot be exceeded. From the temperature distribution it is possible to calculate how many times were this maximal temperature exceeded, and in this way a risk factor can be determined. However, in real life this situation is reversed: the system operator determines the risk factor and if this value is clarified with the iterative change of the load parameter it can be defined, which current limit could be allowed for the thermal limit. In this way it is possible to find the exact value of the line rating for the near future [7][9][13][14].

VI. Simulations with Different Models

The presented simulations were carried with the data of FLEXITRANSTORE which is a pilot DLR project funded by the European Union. In this project sensors and weather stations are installed on two observed lines to collect real-time data for simulations and further developments. The simulations are made for a 110 kV OHL on which an ACSR 240/40 mm2 conductor is installed that has a maximum temperature of 40 □ and SLR of 530 A [7].

A. Comparison of Physical and DLR Black Box model

In order to compare the physical and BME DLR Black box models a simulation was carried out. As an initial step the neural network was trained with almost half year sensor and weather station data. For this, a 4-layer cascade-forward neural networks was applied with Levenberg-Marquardt training method. In the first layer 4 neurons, in the second and third layer 32 neurons and in the last one only one process unit worked.

After the training method, a test was carried out with data that were not used in the training and validation process. Figure 8 represent the result of the conductor temperature test, and the average error is under 2 °C which is the measuring uncertainty of the applied sensor.

For the determined temperature it is also possible to calculate the ampacity limit. It is shown in Figure 9 and Figure 10 how CIGRE, IEEE and BME Black box DLR results vary as a function of the time. It can be seen, that the difference is more relevant in this case, but the curves are in the same range, and the transfer capacity is significantly higher than the SLR of the OHL. The main reason of the difference is due to the different operation of the models, since they have a completely different approach to the ampacity calculation.

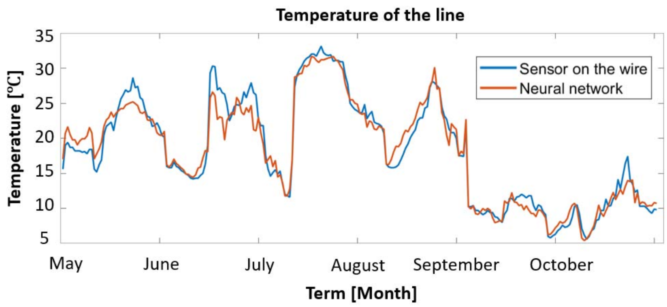

Figure 8 Comparison of conductor temperatures [7][8]

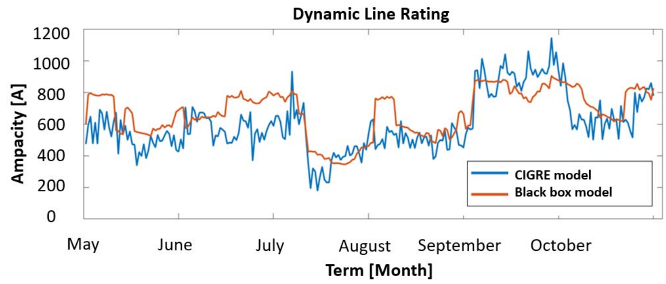

Figure 9 Transfer capacity calculation with CIGRE and Black box model [7][8]

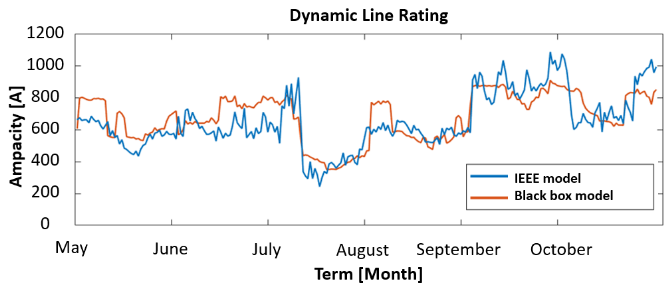

Figure 10 Transfer capacity calculation with IEEE and Black box model [7]

B. Weather Prediction with Monte Carlo Simulation

In this section a prediction of the environmental parameters is presented by an example, which refers to the direction of the wind.

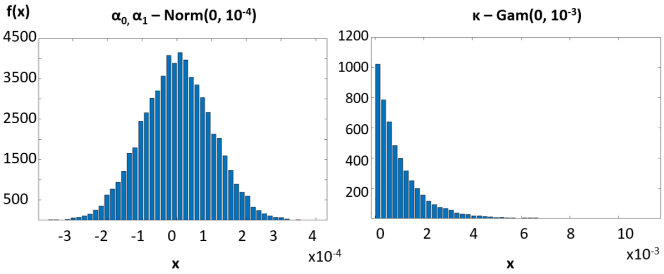

Figure 11 The prior distribution of the parameters [7]

During the simulation, previous data on the previously described transmission line were used, which covers half a year. The wind direction model is a first-class autoregressive Bayesian timeline model, in which with previous data were used to produce a predictive distribution for the near future. As the available data is divided into 10 minutes, it is advisable to make a 10-minute forecast, which requires all 10-minute data from the previous 6 days [10][13].

The model has 3 parameters, which are α_1, α_0, κ. To estimate their values, an ergodic Markov chain with stationary distribution must be created by Gibbs sampling. By increasing the number of iterations during the simulation, all three parameters will converge to a value that will be the final parameters of the model [10].

If the current value of the three parameters stored after each iteration, then the so-called trace plots can draw for MCMC simulation. As a result of Gibbs sampling, we obtained the desired posterior distribution of the parameters, from which the sampled data could be used to prepare the forecast.

All in all, although the simulation can be considered successful, as the Markov chain converged and the posterior distribution of the parameters was like as they were expected, the model needs further clarification to get more precise result [7][10].

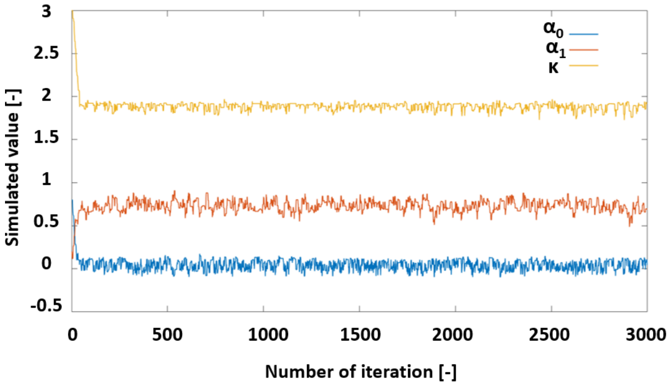

Figure 12 Trace plots of the MCMC simulation [10]

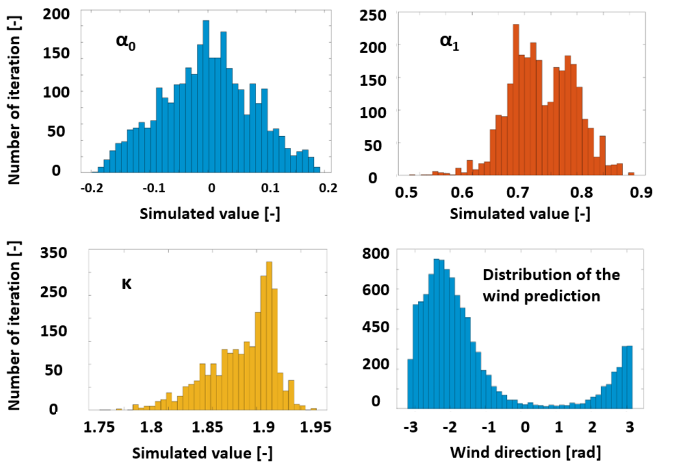

Figure 13 Posterior distribution of the 3 parameters and the wind prediction [7][10]

C. *DLR forecast by Monte Carlo ampling method*

Based on the hybrid DLR model, the distributions of environmental factors predicted by the MCMC simulation serve as the input for the conductor temperature model. However, as it was mentioned before, these simulations need to be clarified and due to reduce the simulation error artificial distributions were applied for this presented simulation. The aim was to determine the maximum load of the OHL with a 5% risk factor. According to Figure 6 the model required 2 input distributions, which were generated by Matlab. For the wind direction von Mises, while for the wind speed Weibull distributions were applied as it is shown in Figure 14 [7][10].

For generation of Weibull and von Mises distributions 10,000 values were set, of which 2000 were randomly selected. These selected values were used for the temperature model. For the first iteration the real environmental and load parameters were used to compare the result with the measurement of the sensors. In this case, the current was 99 A and the mounted sensor measured 12.1□. In Figure 15 the result of the simulation is close to the real value so that the model validation was successful. From this first iteration step the risk factor is zero and a current can be increased to reach the 40 □ temperature limit. In further simulation steps the current value is changed iteratively until the risk factor reaches 5%.

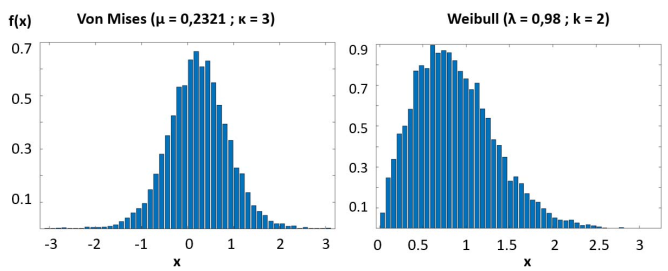

Figure 14 Distributions generated for the wind direction and speed [7]

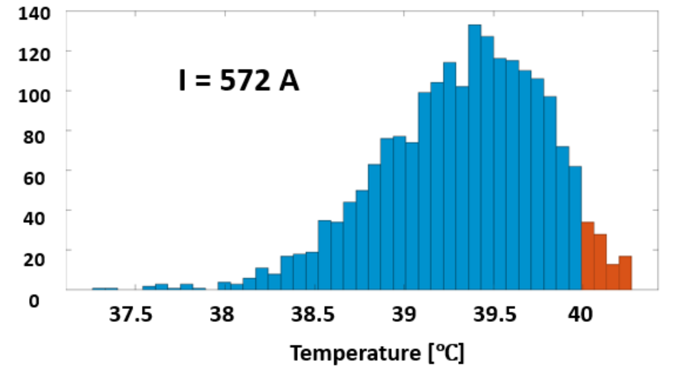

Figure 15 The DLR for the near future with 5% risk [7]

As a result of the simulation for this 10-minute period the transfer capacity was 572 A, due to in this case only 5% of the iteration step (marked with red) exceeded the maximum allowable temperature limit of the conductor. Since the SLR of the OHL is 530 A, this 572 A is almost 10% higher than the conventional rating of the transmission line [7][10].

VII. Conclusion

DLR is a novel method for increasing the ampacity of the existing line without any deeper modification of the grid. This can be achieved by real-time monitoring of the environmental and load parameters of the OHLs. The ampacity of each line is based on the thermal behavior of the conductors, but there are different approaches for the conductor temperature and transfer capacity calculation. In this article a short review was presented about the DLR models based on different approaches and case studies were carried out to show the operation of these models under real circumstances. In the first case study the physical, empirical models of the CIGRE and IEEE were compared to the BME Black box DLR model which is based on a neural network. After that, it was presented how Markov Chain Monte Carlo method could be linked to DLR calculation. In that section a prediction was made for wind direction with the implementation of Gibbs-sampling method. In the last section it was demonstrated how Monte Carlo sampling works in a hybrid, probability based DLR model if the predictions for the environmental parameters are known. In this simulation the DLR value was adjusted take into consideration that the risk factor cannot exceed 5%.

All in all, while there are different approaches of DLR calculation, it can be seen from the simulations that increase the ampacity of an OHL is possible and DLR could be an effective method. In this way a resilient, more reliable grid can be achieved while maintaining the level of existing safety and security.

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