Application of Monte Carlo Methods in Probability-Based Dynamic Line Rating Models

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Abstract. Due to the growing demand for electrical energy, the use of alternative transfer capacity-enhancing methods such as Dynamic Line Rating (DLR) become more and more significant. However, there are some challenges regarding the prediction of the DLR value, which are still unresolved. In the last few years several DLR pilot projects have been constituted resulting a big database of the measured environmental and load parameters. One aim of this article is to introduce how different Monte Carlo methods could be applied in probability-based DLR models to predict the DLR value and the operational safety risk factor. Based on simulations, it is possible to implement a smart DLR system in the future, which will be able to set the model parameters from time to time using big data. In order to demonstrate the advantages, relevance and limitations of the Monte Carlo simulations, a case study is presented for a genuine transmission line.

Keywords: Dynamic Line Rating, DLR, Monte Carlo methods, MCMC, transmission line, probability-based models.

1 Introduction

Today one of the most current issues is to meet growing energy needs while reducing expenditure and maintaining operational safety in the transmission system. To meet these requirements, Dynamic Line Rating (hereinafter referred to as DLR) calculation method can be used to increase the transmission capacity of suitable transmission lines cost-effectively. The essence of DLR is that it monitors the changes of the environmental parameters in a real-time manner, and constantly adjusts the ampacity to the current state in contrast to the conventional transfer capacity calculations. In case of using DLR method it is important to have appropriate quantity of real-time data available for the calculations and provide a precise DLR prediction for the system operator in real time. The main advantages of the DLR prediction are that it encourages the integration of the renewable energy sources into the grid and makes the system more flexible, so that disastrous black-outs can be avoided. In the first sections of the article the possibility of Monte Carlo simulation is detailed. In the second part of the paper a simulation is carried out to show how the model works under real circumstances and what are the application limits. In this simulation, half year of recorded data are used to determine and tune the main parameters of a probability-based DLR model using

Markov Chain Monte Carlo (MCMC) simulation. After it, a general Monte Carlo sampling is applied to determine the DLR value at a given operational risk factor value. [1][2]

2 Relationship to Industrial and Service Systems

Several pilot projects have been started in recent years in which sensors and weather stations are installed on conductors and power line towers. In most cases sensors take place on the conductor, due to these devices needs direct contact to measure the temperature of the wire while weather stations are installed on the steel structure of the high voltage towers. These devices continuously record environmental and load data in real-time, thus forming a big data system that can be used to perform further computations and explore statistical relationships between these parameters. DLR calculation based on real-time measurement is radically different from the currently used transfer capacity-determining methods. Until now, the ampacity calculation of a transmission line was based on the so-called static way, which means that the transfer capacity is calculated from the worst-case scenario of the environmental factors. Accordingly, in this way the real capacity of each transmission lines cannot be exploited. [3]

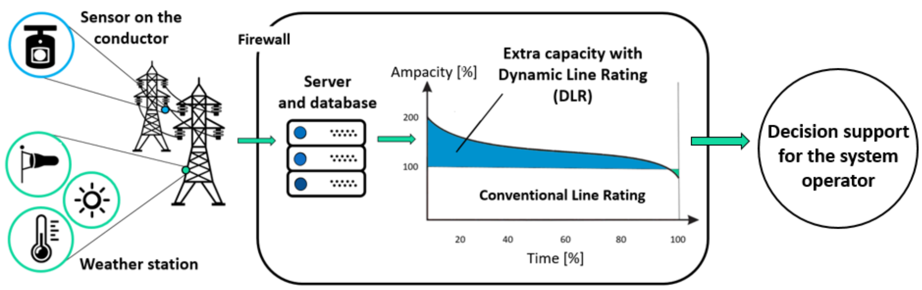

Fig. 1 Concept of Dynamic Line Rating system

Measured data from the sensors and weather stations are transmitted wirelessly to a central server which forwards them to a database. In this way it is possible to use these data for further calculations such as setting the parameters of the different environmental factors (wind speed, wind direction etc.) in the prediction models by using MCMC methods. Due to the use of the data of the weather stations a more accurate temporal and spatial resolution could be achieved in the different predictions.

3 Probability-based DLR Models

Although in the literature mostly deterministic models are presented such as CIGRE or IEEE ones, several probability-based models have been developed in recent years. One of their major advantages is that these models work with distributions describing environmental and load conditions more accurately. Another big advantage of them is that a risk factor could be associated for such probabilities, which contains additional information for the system operator. However, these models are appropriate for the determination of conductor temperature and DLR, the real challenge is to predict these values. [3][4]

3.1 Prediction Models

The conductor temperature is significantly influenced by five factors. Four of them are environmental variables (wind speed, wind direction, ambient temperature and solar radiation) and the last one is the load variable (current of the conductor). In order to calculate the conductor temperature and the DLR, it is necessary to give prediction for these environmental variables. [3][4]

Table 1 The main properties of forecasting models

Predicted variable	Prediction model	Distribution	Tune of the parameters
Wind speed	Probability-based	Weibull	Expectation-Maximization
Wind direction	Probability-based	von-Mises	Markov-Chain Monte Carlo
Solar radiation	Deterministic	-	-
Ambient temperature	Deterministic	-	-

In case of ambient temperature and solar radiation there is no need for probability-based prediction models, due to the high accuracy of the meteorological predictions. However, in case of wind speed and wind direction the temporal and spatial resolution of the meteorological predictions are not proper, therefore different time series models can be used to get more precise results. [3]

3.2 Bayesian Approach

These wind prediction models contain various parameters that need to be tuned from time to time based on historical big data. At this point, applying Bayesian approach can lead to result for these model parameters. The essence of Bayesian approach is to determine the posterior distribution of the parameters based on the measured data and the a-prior knowledge. The Bayes formula is described by **Error! Reference source not found.**. [5][6][7]

$$P(\theta \mid Y) = \frac{P(Y \mid \theta)\, P(\theta)}{\int P(Y \mid \theta)\, P(\theta)\, d\theta} = \frac{P(Y \mid \theta)\, P(\theta)}{P(Y)} \tag{1}$$

Where Y is an observed variable, θ is a parameter of the model, $P(\theta)$ is the a-prior distribution of the parameter, $P(\theta \mid Y)$ is the posterior distribution of the parameter and $P(Y, \theta) = P(Y \mid \theta)\ P(\theta)$ is the joint distribution. However, in most of the cases the $P(Y)$ is unable to be calculated or even estimated, but MCMC method or EM (Expectation-Maximization) method could lead to result. [5][6][7]

4 Monte Carlo Methods

The Monte Carlo method is a collective term, which means a variety of procedures, techniques and sampling forms. The common feature of these methods is that they are based on random number generation, thus facilitating the resolution of analytically difficult problems. In case of DLR, different Monte Carlo methods can be applied for the prediction of the parameters and for the calculation of the operational risk factor. [6]

4.1 Markov Chain Monte Carlo (MCMC)

The essence of MCMC methods is that the posterior distribution of the parameters of the first-order time series models can be determined. As its name indicates, this method is based on the characteristics of Markov chains. [6]

Markov chain is a series of probability variables over a state space where the probability of being in each state depends on only the previous state. If a Markov chain is aperiodic and irreducible it is called ergodic, so that it has a stationary distribution named π. Directed graphs where every change in the states has a probability forming a matrix (named P) are good representations for these kind of chains. However, the operation of MCMC contrasts with Markov chains, since in this case the P matrix is not known, but the π distribution to which the process converges is clearly declared. [5]

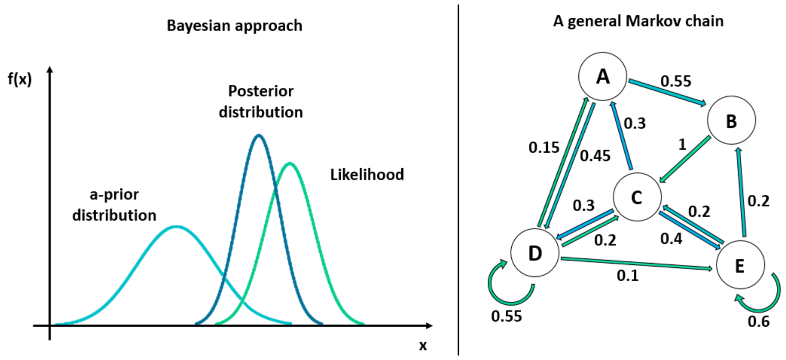

Fig. 2 Bayesian approach of model parameters and a graph representation of a general Markov chain based on [11]

There are various algorithms for the construction of Markov chains. The most common is Metropolis-Hastings and its special case named Gibbs sampling. The latter is also used in the algorithm in the wind direction prediction model. [5][6][7]

4.2 Monte Carlo Sampling (MCS)

Using MCMC and EM methods, a full prediction of wind direction and wind speed for the time $t + 1$ can be specified. From the meteorological data there is a deterministic prediction for solar radiation and ambient temperature. If these parameters are known for the time $t + 1$, then the temperature of the wire could be calculated by using the CIGRE model. [4][7]

$$c_p m \frac{d\theta_C}{dt} = P_j + P_S - P_r - P_C \tag{2}$$

Where c_p is the heat capacity of the conductor [J/kg·K], m is the specific mess of the conductor [kg/m], $d\theta_c$ is the change in the temperature of the conductor [K], dt is the period of the change in conductor temperature [s], P_j is Joule-heating [W/m], P_S is solar heating [W/m], P_c is convective cooling [W/m] and P_r is radiative cooling [W/m].

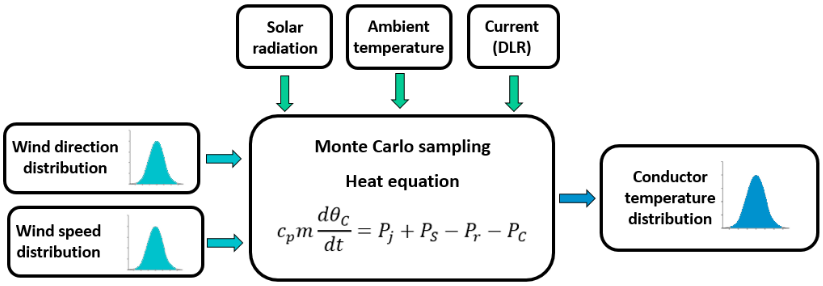

Fig. 3 Schematic diagram of the conductor temperature model

Since the wind direction and wind speed are represented with a distribution it is possible to sample from them using Monte Carlo Sampling method. The essence of MCS is that the wind speed and direction values that are more likely to occur are sampled more frequently. Thus, the result of the calculation is a distribution for the conductor temperature on which an operational risk factor can be defined. [7][8]

For each wire there is a maximum temperature value for which the particular conductor has been designed. By dividing the number of instances in which this maximum temperature was exceeded with the number of the simulations, an operational risk factor can be determined with the use of **Error! Reference source not found.**. [7][8]

$$P(\theta_c > \theta_{max}) = \frac{N_f}{N} \tag{3}$$

Where N_f is the number of times when the maximum temperature has been exceeded and N is the number of all simulations.

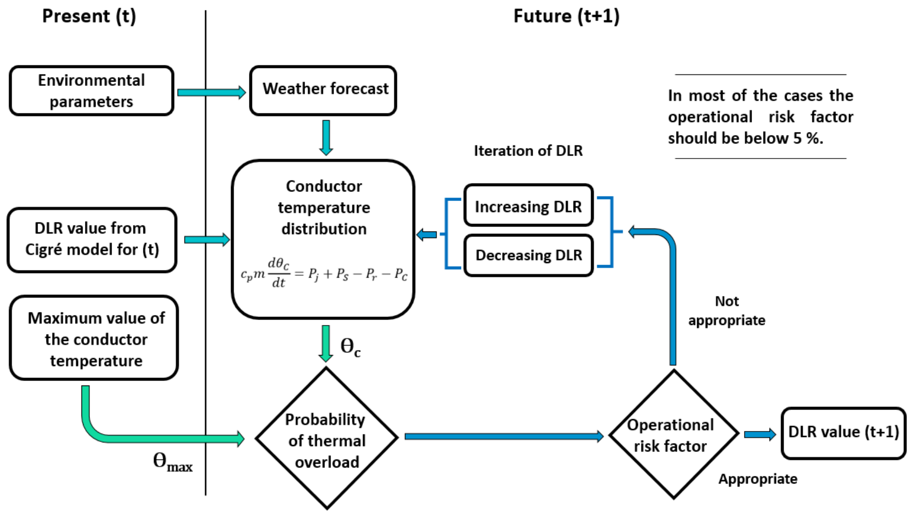

Fig. 4 DLR forecasting based on a probability-based model based on [8]

However, in reality, a reverse situation arises because a system operator strictly defines the safety factor and the ampacity of the line should be adjusted to it. In this way, the DLR value for the time $t + 1$ can be determined.

5 Case Study

While the mentioned models are known for a while, there are quite a few real-time simulations that make broader validation more difficult. As a result of DLR pilot projects, it is possible to find out the limits of the practical application of a probability-based DLR model by presenting a case study. The major aim of the case study is to predict DLR value with the operational safety factor 95 % for 15 minutes ahead. In order to calculate this value there is a need for a 15-minute weather forecast. The wind direction is predicted by MCMC method, the wind speed is estimated with Weibull-distribution, and for the ambient temperature and solar radiation there are exact forecast from meteorology. [9]

The case study included the parameters and measurement data of a 110 kV transmission line in Eastern Central Europe. On the line an ACSR wire 240/40 mm^2 is installed, and the main parameters are in Table 2. The static line rating of the line is 530 A.

Table 2 The main parameters of the overhead-line

Parameter	Value	Parameter	Value
Type of the conductor	ACSR 240/40 mm^2	Emission factor	0.55
Maximum temperature	40 °C	Resistance at 25°C	0.120 Ω/km
Outer diameter	21.9 mm	Resistance at 75°C	0.144 Ω/km
Outer strand diameter	3.45 mm	Average mass per unit lengths	0.987 kg/m

The line is equipped with a sensor that measures the temperature of the conductor in every 15 minutes with direct temperature measurement method. On the steel structure of the tower there is a weather station that includes an anemometer, a thermometer and a solar radiation measurement point. The weather station also provides real-time data in every 15 minutes. The operating temperature range of the sensor is between – 40.0 °C and + 85.0 °C and its power supply is a current transformer. The conductor temperature measurement resolution is 0.5 °C, while the temperature measurement deviation is ± 2.0 °C in range from - 20 °C to + 100 °C. The communication with the datacenter is based on GSM/GPRS protocol. [10]

5.1 Wind Direction Prediction with MCMC

The wind direction model is a first-order autoregressive Bayesian time series model, so that MCMC method could be proper to make a prediction for the next 15 minutes. For the simulation, all 15 minutes of the last 6 days have been examined. [7][8]

In the wind direction model there are 3 parameters $\alpha_1, \alpha_0, \kappa$. The α_1, α_0 has a normal a-prior distribution, while κ has a gamma a-prior distribution. For the MCMC simulation it is necessary the define the log-posterior distributions of each parameter in order to simulate the posterior distributions. According to the log-posterior distributions MCMC algorithm constructs the Markov chain with Gibbs-sampling. [6][7]

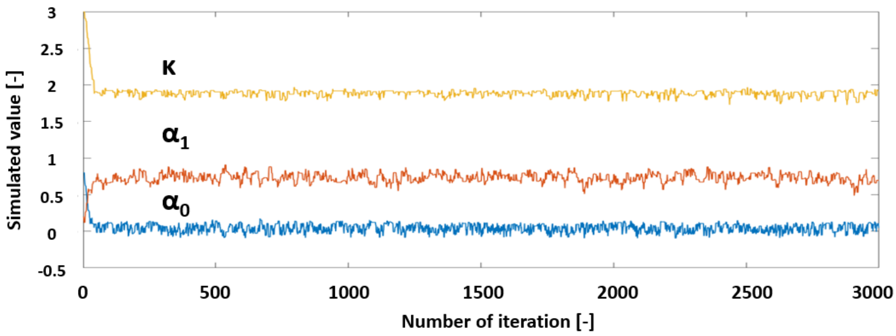

Fig. 5 Trace plots of the parameter as a result of MCMC simulation [11]

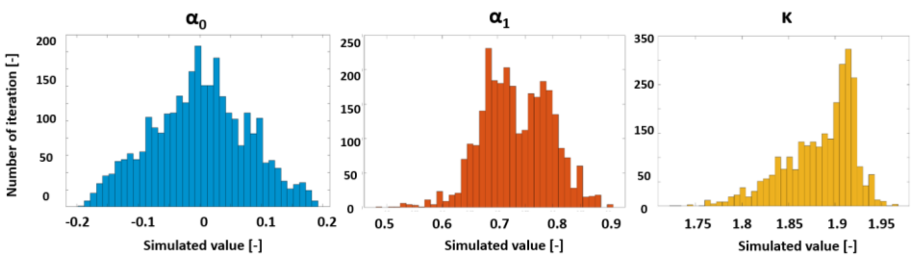

Fig. 6 Posterior distribution of the parameters at iteration number of 3000 [11]

According to Fig. 5, it can be seen from the trace plots that the MCMC simulation is successful, and the convergence of the parameters is independent from the starting value. From the trace plots the posterior distributions are illustrated in Fig. 6.

Using these parameters, it is possible to make a prediction for the wind direction. This predicted wind direction fits a von Mises distribution with a mean value 229°. However, the expected mean value of the wind direction was 13°. Although, it is also important to mention that this 13° was a struggler value, the five former and later wind direction was between 210-240°. The reason is why struggler values could occur is that in this area there is no dominant wind direction resulting extremely stochastic changes in the wind. Based on this statement, the model needs further clarification if the wind speed is under 5 m/s.

5.2 Predicting DLR Value with an Operational Safety Factor of 95 %

Due to the inaccuracy in wind direction prediction, artificial distributions were generated in Matlab for also wind speed and wind direction based on the weather station measurements. The aim of this section is to present the tune of the DLR value using Monte Carlo Sampling from these distributions at a given operational safety level.

For this simulation, **Error! Reference source not found.** was applied where the time step was 15 minutes. The first simulation was carried out to validate the model using the real-time measurement of the sensor. The SCADA system measured 99 A for that period, and the temperature of the conductor was 12.1 °C. The maximum conductor temperature of the conductor is 40 °C.

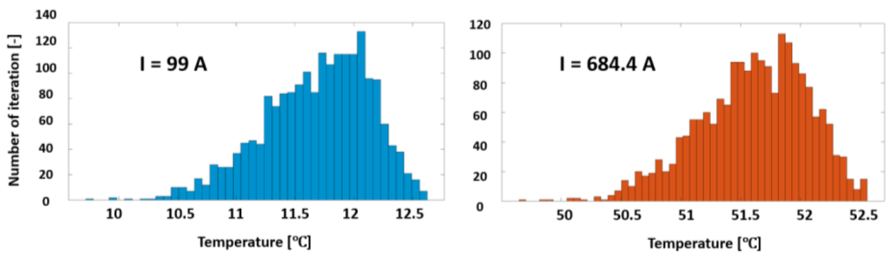

Fig. 7 The distribution of conductor temperature at 99 A and 684.4 A [11]

The first section of Fig. 7 shows that the simulated temperature approximates the measured value well, so that the model can be applied for further simulations. The second section of Fig. 7 shows the simulated temperature for time $t + 1$ with DLR value calculated for time t. According to this, the reduction of current is necessary due to the high operational risk factor value.

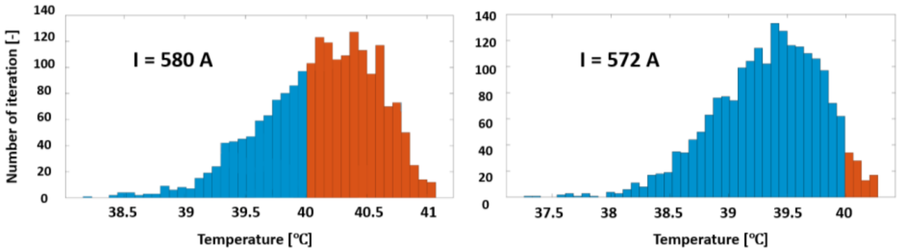

Fig. 8 The distribution of conductor temperature at 580 A and 572 A [11]

In Fig. 8, it can be seen how operational risk factor decreases with the change of the current value. According to the simulations, the 95 % of operational safety level is achieved at 572 A, so that the real DLR value for the time $t + 1$ (next 15 minutes) is 42 A more than the static line rating. This is a nearly 10% significant increase in the transfer capacity.

6 Conclusion

In the last few years several DLR pilot project were started resulting great amount of measured data about the environmental and load parameters. The main aim of this article was to present how probability-based DLR models and different Monte Carlo simulation could be linked under real circumstances. It can be stated that Monte Carlo methods are proper for the prediction of environmental parameters and also for the calculation of the operational risk factor. If the operational risk factor is determined by the system operator the prediction of the DLR value for the next 15 minutes is also possible.

In the first part of the case study it was demonstrated how the parameters in the wind direction model can be tuned by MCMC method. While these simulations are promising, it is worth to mention that there are some applicability limits. If the wind speed is under 5 m/s or the territory does not have a dominant wind direction the level of the prediction accuracy decreases significantly. In the second part of the case study the major aim was to make a prediction for the DLR value in the next 15 minutes, while the operational safety factor maintains at 95 %. As a result of the simulation, the transfer capacity become higher with 42 A than the 530 A static rating, which is almost 10 % increase in the ampacity.

Generally, Monte Carlo methods could be linked to DLR calculation, but the models and simulations need to be fine-tuned in the future. Overall, it can be said that the results of the simulations are a good basis for further research.

Acknowledgement

This work has been developed in the High Voltage Laboratory of Budapest University of Technology and Economics within the boundaries of FLEXITRANSTORE project,

which is an international project. FLEXITRANSTORE (An Integrated Platform for Increased FLEXIbility in smart TRANSmission grids with STORage Entities and large penetration of Renewable Energy Sources) aims to contribute to the evolution towards a pan-European transmission network with high flexibility and high interconnection levels.

Supported by the ÚNKP-18-2-I New National Excellence Program of the Ministry of Human Capacities

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