FORECASTING REAL-TIME RATINGS FOR ELECTRICITY DISTRIBUTION NETWORKS USING WEATHER FORECAST DATA

Andrea MICHIORRI
Durham University – UK
andrea.michiorri@dur.ac.uk

Philip C. TAYLOR
Durham University – UK
p.c.taylor@dur.ac.uk

ABSTRACT

Currently the operators of electrical distribution networks face a number of challenges, such as load growth, the proliferation of distributed generation and ageing infrastructure. This is drawing attention to techniques which will allow more efficient asset utilisation and facilitate network dynamic management. Power system component real-time ratings are a cost effective solution for increasing network power transfer capacity. Instantaneous ratings can be used for this purpose, but distribution network operator decision making capability regarding network power flow management would be enhanced by the adoption of rating forecasts. Therefore this paper presents an investigation into the technical challenges and potential benefits of power system component rating forecasts. Weather forecasts are used with power system component thermal models and a state estimation technique for calculating rating forecasts at different time horizons.

1 INTRODUCTION

The rating of power system components is influenced by external parameters such as wind speed or air temperature, but the possibility of exploiting any increase in rating is problematic due to the variability of these external parameters. The technique referred to as "real-time ratings" involves real-time measurement of component temperatures and external parameters, such as air temperature or wind speed, in order to estimate component real-time ratings. Durham University is participating in a collaborative project with AREVA T&D, Imass, PB Power and ScottishPower EnergyNetworks, which aims to develop, install and test a power output control system for distributed generation informed by dynamic thermal ratings. Within this research, dynamic thermal ratings are defined as a time-variant rating which can be practically exploited without damaging components or reducing their lifetime. Actual environmental parameter measurements are used as the input to steady state thermal models and it is assumed that there are no outages (planned or unplanned) present within the electrical power system. Previous research [1] has demonstrated the suitability of real-time ratings for distributed generation power output control. This paper describes research with a different approach: weather forecasts are used for producing rating forecasts for different time horizons. A number of perceived benefits are expected to be yielded by this approach: Firstly a reduction in the number of on-site weather stations would be possible since the necessary information could be gathered from meteorological offices. Secondly the availability of rating forecasts would enhance the decision making capability of distribution network operators regarding network power flow management. Decisions would be informed by both the instantaneous ratings as well as rating forecasts for different time horizons. Another innovation described in this paper is the utilization of an estimation technique, in order to assess the error associated with rating forecasts. The knowledge of the error associated with the use of state estimation techniques would potentially increase the distribution network operator's confidence in real-time rating systems. This paper is structured in the following way: Firstly a survey of related work is presented. Then the methodology used in the research is described and the data used for the simulations and the case study are presented and finally simulation results are given and conclusions are drawn.

2 RELATED WORK

This work aims to combine two different areas of research: power system component real-time ratings and forecast techniques. Research has been carried out on the two topics, but not on their combination. The concept behind real-time ratings is described in [1]. The description of an application of a real-time rating system for the transmission network in the region of Madrid is provided in [2]. In this case, a low number of weather stations are used to estimate wind speed and direction over a wide geographical area and these estimations are used for calculating the real-time rating of an overhead line. The Electric Power Research Institute (EPRI) developed a similar system in the late 1990s considering overhead lines as well as other power system components. In [3] and [4] the system and field test results are reported. It was found that for a complete network, rating increases of up to 15% of the static value were possible. Forecast techniques have been applied to predict energy demand and wind power production. In [5] different techniques for load demand forecasts such as ARIMA modelling, adapted exponential smoothing and weather forecasts were compared and it was found that the combination of weather forecasts and exponential smoothing provide a better approximation for load demand forecasts beyond one hour ahead. Another approach, described in [6], bases the energy demand forecast on weather ensemble forecasts- a method which provides a probability distribution of the possible weather parameter values. This method is considered for a time horizon of up to 10 days. Regarding wind power forecasts, in [7] the system used in the on-line management of the Spanish transmission system is described. It makes use of several models and of adaptive estimation for the parameters. The final prediction is then obtained as a weighted average of the results of the

different models. From the analysis of the research described above, it is possible to highlight the requirement for work in the area of components real-time rating forecasts. This paper aims to suggest a possible methodology for filling this gap.

3 METHODOLOGY

The research described in this paper adopts the following approach: Component thermal models available in literature are used for calculating component rating for particular weather conditions. A state estimation technique based on Montecarlo method is used for giving a more complete description of the possible states of the system, providing the minimum, maximum, average and standard deviation of the rating forecasts according to the possible forecasted weather conditions. Historical weather forecast data from the National Oceanic and Atmospheric Administration (NOAA) [8] is used as inputs to these models.

3.1 State estimation

In this section a description of the algorithm responsible for the state estimation is given. The aim of this algorithm is to provide a reliable estimation of circuit ratings described by an appropriate cumulative probability function. The circuit has been divided in several parts, for taking into account different soil roughness and line orientation. This makes it possible to calculate descriptors such as the minimum, maximum, average and standard deviation of the rating estimation. The algorithm developed is briefly illustrated in Figure 1, where it is possible to see the following steps:

1. Forecasted weather data is read from an external source (in this case the database "a"). This data, comprising the minimum, maximum, average and standard deviation of each parameter in the given period, is described in Section 3.3.
2. A set of values for weather parameters is calculated in the following way: From the data read in "1" the parameters of a cumulative probability function are calculated. In this case the Beta probability function is used. A random value for the probability is selected and from the cumulative probability function the corresponding parameter value is found. This is repeated for each weather parameter.
3. For each component of the circuit the rating is calculated using the models described in Section 3.2.1. The result is stored temporary in "b".
4. The circuit rating is calculated selecting the minimum rating of each component. The results are temporarily stored in "c".
5. The steps from 2 to 4 are repeated for a fixed number of times N.
6. The precision of the result is compared with a predefined value. If the result is not acceptable, a new value for N is calculated and the steps from 2 to 5 are repeated
7. Circuit ratings stored in "c" are analysed in order to calculate the minimum, maximum, average value and standard deviation for each time horizon.

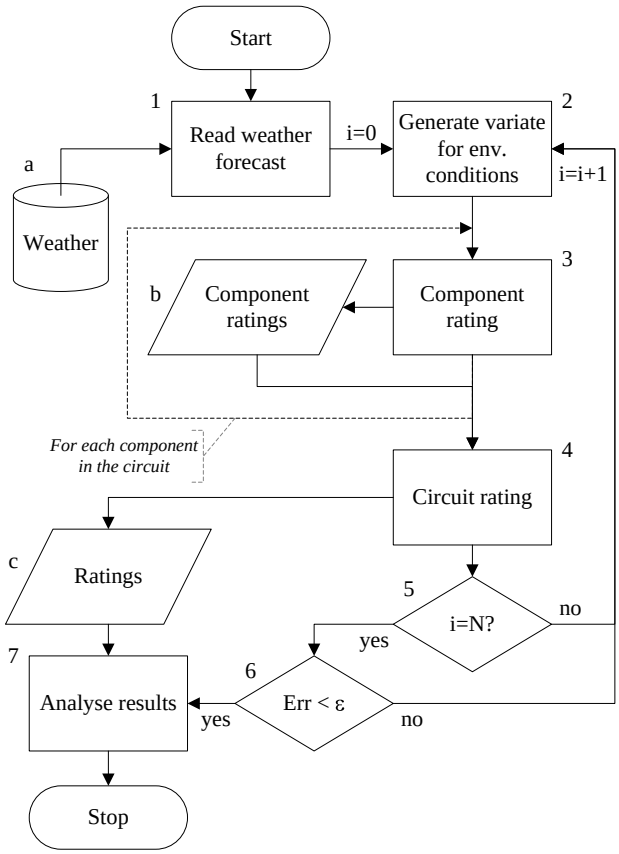

Figure 1: Montecarlo simulation basic flow chart

3.2 Models

3.2.1 Overhead line rating

The fundamental idea behind component ratings is that the operating temperature limit of the component must not be exceeded in order to avoid damaging the component. For overhead lines in particular, a temperature rise leads to a reduction in conductor tension and to an increase in the sag. Typical values for maximum conductor temperature are between 50 ºC and 90 ºC. Component temperature is not a constant value but depends upon the energy balance between the heat produced inside the component and the heat exchange on its surface. The energy dissipated depends on the load, however the heat exchange is mainly influenced by the temperature difference between cable and the environment and by other external factors such as wind speed or solar radiation. Considering the heat dissipated by the Joule effect (I^2R), the heat exchanged by convection (Q_c) and radiation (Q_r), and the solar radiation (Q_s), the energy balance for an overhead line conductor is described in Equation (1).

$$I^2R + Q_s = Q_c + Q_r \quad (1)$$

Different methods have been suggested for the calculation of each one of these parameters. In this research the methodology previously described in [1] was used.

3.2.2 Environmental condition interpolation

The inverse distance interpolation technique [9] allows environmental conditions to be determined over a wide geographical area using a reduced set of inputs. In this case meteorological inputs are the weather forecasts from the NOAA at a height of 10m from the ground. Wind speed is corrected with the method described in Section 3.2.3. Wind direction, air temperature and solar radiation values were included within interpolations but did not require the application of a correction factor. At each point in the geographical area (k) the value of the parameter (Z) representing the environmental condition can be estimated as a weighted average of the parameter values known at i points. The weighting factor is a function of the distance between the points as shown in Equation (2).

$$Z_k = \frac{\sum_i \frac{1}{d_{i,k}^2} Z_i}{\sum_i \frac{1}{d_{i,k}^2}} \qquad (2)$$

3.2.3 Wind speed correction

Ground roughness influences wind speed profiles and may lead to differences between the wind speed estimated at a given height and location and the actual wind speed passing across an overhead line. This may be corrected using the wind profile power law given in Equation (3). The wind speed (w_s) at two different heights (z_1 and z_2) is linked with the ground roughness through the exponent K_{shear}. Values of K_{shear} for different ground types may be found in [10].

$$w_s \;\; z_1 \;\; = w_s \;\; z_2 \;\; \cdot \left(\frac{z_1}{z_2} \right)^{K_{shear}} \qquad (3)$$

Using Equation (3) the forecasted wind speed is extrapolated to a reference height (in this case 100 meters) to remove ground roughness dependence. The values from different forecast locations may then be interpolated, using Equation (2), to provide a wind speed forecast estimate at the reference height for a particular geographical location. The ground roughness at this location is then taken into account and Equation (3) is used to estimate the wind speed across the overhead line.

3.3 Data

For the study described in this paper, weather forecasts from the NOAA [8] for the test area in Wales with a time step of 6 hours have been used. Data is described in Table **1**.

Table 1 weather forecast for 18/09/2008 on test area

	Time horizon [h]				
	0	**6**	**12**	**18**	**24**
Ws [m/s]	1.8	2.5	1.7	1.2	3.4
Wd [deg]	178	196	189	301	216
Ta [°C]	10.3	9.8	16.1	12.9	12

The Montecarlo simulation does not require simple parameter values, but a description of their probability, with the minimum, maximum, average and standard deviation. These values can be obtained with ensemble forecasts or time series analysis. In this study the precision of the forecast for different time horizons has been estimated from the precision of the forecast for each parameter in the period between 08-18/08/2008.

Table 2 Forecast error minimum, maximum average and standard deviation

		Time horizon [h]			
	[%]	**6**	**12**	**18**	**24**
Ws	**min**	-28.30	-17.78	-30.19	-38.55
	max	13.79	50.00	27.27	83.33
	st dev	14.24	21.60	18.17	38.96
Wd	**min**	-1.94	-3.33	-2.78	-8.33
	max	15.83	1.67	20.83	23.61
	st dev	5.00	1.44	6.70	8.11
Ta	**min**	-15.86	-9.93	-20.27	-16.22
	max	1.57	4.80	31.07	15.84
	st dev	6.07	5.78	12.06	8.51

The network studied is part of the Manweb distribution network situated in an area attractive to prospective wind farm development. It is composed of a 132kV Lynx overhead line conductor with a maximum operating temperature of 50°C connecting two towns 7 km apart. The line passes through the two towns in an area characterised mainly by the presence of grass and inhabited areas. This is important since the different in ground roughness influences the value of wind speed as calculated in Equation (3). In Figure 2 a representation of the network studied is provided.

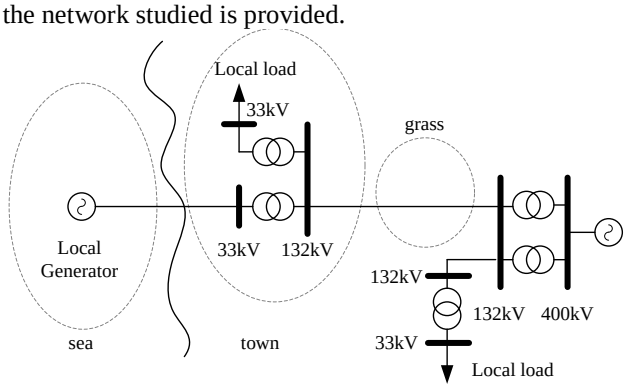

Figure 2: Network and site schematic representation

4 RESULTS AND DISCUSSIONS

The simulation results are shown in Table 3 and Figure 3, where the rating forecasts for the whole day are represented from the reference time of midnight. Two main considerations arise from the observation of these results: As expected, the error increases with the distance of the forecast from the reference time. At 6pm the possibility to have a real time rating below the value of the static seasonal rating is forecasted.

Table 3 Rating forecast in MVA for different time horizons

	Time horizon [h]				
[MVA]	**0**	**6**	**12**	**18**	**24**
min		108	109	75	85
max		142	134	141	152
aver	138	133	122	98	130
st dev		9	9	24	17

In this case the minimum forecasted rating in the late afternoon corresponds with the daily peak for the power transfer on the line. If the line utilization increased because of an increased connection of distributed generation, this would create a problem and the necessity to curtail part of the generation. On the other hand, the ability to forecast this situation and to quantify its probability, would allow appropriate decisions for generation control to be taken. Considering the different precision found for different time horizons, it is recommended to take into account this parameter, along with the distance from the forecast reference time, when developing control strategies for power flow management.

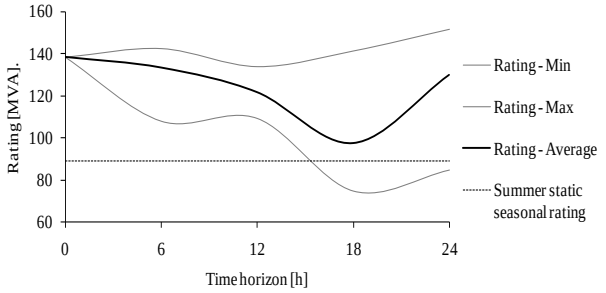

Figure 3: Rating forecast

5 CONCLUSION

In this paper a methodology for overhead line rating forecasts has been presented. This is based on the research regarding distribution network real-time rating estimations developed at Durham University. Weather forecasts were used with component thermal models and a state estimation technique based on the Montecarlo method in order to calculate a probability distribution for each circuit component's rating for different time horizons. The results have then been collated for calculating line rating probability distribution, and metrics such as minimum, maximum, average and standard deviation of the rating forecasts. The simulation highlights that the estimation precision tends to decrease with the distance from the reference time. It was also shown how a possible rating lower than the static seasonal rating was forecasted 18 hours ahead of the reference time. The work presented in this paper on rating forecasts is expected to enhance distribution network operator decision making capabilities regarding network power flow management. This is because decisions may be informed not only by instantaneous rating estimates, but also by the forecasted ratings for different time horizons. Work is continuing in this area to realise the potential of forecasted real-time ratings for electrical distribution networks.

6 ACKNOWLEDGMENTS

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