FORECAST OF FAULTS DURING HEAT WAVES IN A MEDIUM VOLTAGE GRID AND CRISIS MANAGEMENT

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ABSTRACT

In France, the Paris area has one of the densest power distribution networks in the world. In summer, during heat waves the number of outages on the underground medium voltage grid can increase dramatically.

From an operational point of view, it is important for the DSO management (ERDF) to be able to forecast the number of outages likely to happen during high temperature spells in order to anticipate staff needed to repair the faults and avoid faulty cables piling up, which would weaken the grid resilience.

Also, on the long term, it is useful to pick out which feeders are most likely to be subject to outages in order to prioritize investments on the grid.

ERDF has developed (big)-data analytics and data mining capabilities to improve its performance and integrate 21st century technologies in distribution power management. One of the first operational outcomes is the forecast of outages on the medium voltage grid in Ile de France during heat waves.

This paper describes the predictive model used by ERDF in Paris area during summer 2015 and its integration in the crisis management processes set in place.

INTRODUCTION

On the medium voltage grid, resilience is assured through redundancies and the ability to reconfigure the grid in order to make sure that a minimum amount of customers stay without power when faults happen on some cables. In France, this task of reconfiguring supply schemes is assumed by regional system capacity management teams.

When the number of faulty cables increases during a short period of time, redundancy decreases across the grid and so does its resilience. Being able to anticipate the number of defaults likely to happen is therefore decisive in order to organise the multi step operations required to repair the fault as quickly as possible and regain maximal redundancy.

ERDF in Ile de France has developed an operational tool used by management to anticipate the amount of defaults likely to happen during heat waves and improve its ability to manage these critical periods when a high number of defaults happen in a short period of time.

FAULTS AND HEAT WAVES

It has been observed that the number of defaults on the medium voltage in Paris area increases dramatically during heat waves. The chart below shows the monthly number of defaults across the period 2001-2013 on Parisian network.

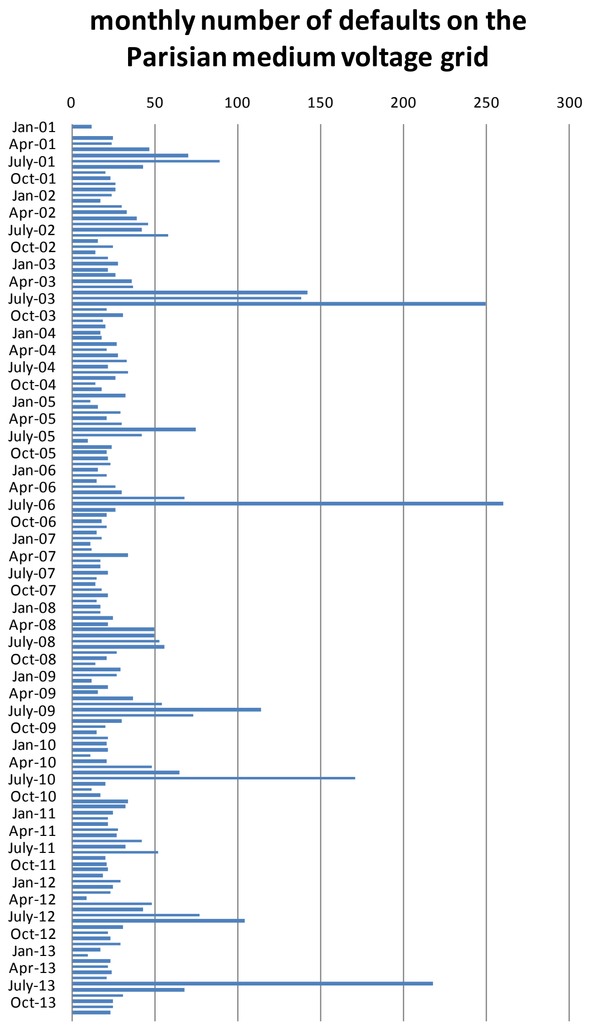

Figure 1: monthly number of default on Parisian medium voltage network over the period 2001-2013

On the above chart, one can clearly visualize and imagine the so called “crisis” when up to 250 defaults happen in one month. In France people usually remember the summer 2003 as the real scorcher but maybe less other years with shorter heat waves.

The chart below shows the link between temperature and monthly number of defaults on the same data set as in Figure 1:

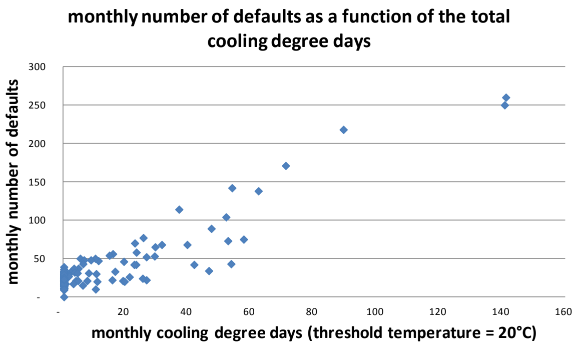

Figure 2: monthly number of defaults as a function of the monthly cooling degree days

MODELLING

Choosing the explicative features

Prior modelling and statistical analysis, discussions with operational staff and material experts has been decisive to pick up the explicative features of the model *a priori.*

Temperatures

It has been known that defaults happen mainly during heat waves: some experts mentioned that the temperature has to stay high during several days, other that the maximum daily temperature has to get above a given level or that night temperature is not below another level. Another expert insisted on the importance of radiation, in the heat transmission from the pavement to the underground cables.

We therefore kept as explicative features, the average, minimal and maximal daily temperatures of the Day for which we want to Predict the number of defaults (D_P) and of the five days before it.

To take into account radiation effect in the heat transmission we also took the average daily temperature at the fourth power over the same six day period.

Other features

Another effect, called “early season clean up” by operational staff, is described as the fact that a hot spell happening early in the summer tends to trigger a high number of defaults whereas a hot spell late in the summer when some have already happen earlier in the season tends to have a lower impact: once the weak equipment has had a default it will be out of order and then replaced so can’t have another default.

We therefore took as explicative feature the number of defaults happening over several period of time prior D_P. We actually consider seven periods : the five years prior to the current year, the fortnight and the day prior D_P.

The last feature considered was the height of the sun in the sky depending on the day (sun is higher and day are longer in June than in August). This last feature improved the model for the two operational regions outside the city of Paris but had no beneficial impact on the model for Paris itself: an explanation could be that the density of buildings and the shadow they provide prevent the sun from having a too big impact on the number of defaults.

Statistical model

Poisson regression

Poisson regression is well adapted to model count data. A characteristic taken into account to choose this kind of model compared to other models which could be more accurate but more complex was the simplicity of the analytical formula. This makes it easier to get the model accepted by operational staff and to keep an understandable meaning of the features.

The chart below shows the distribution of daily numbers of defaults for Paris city over the period 2001-2013.

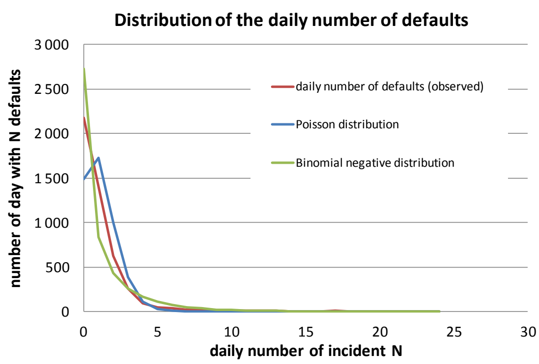

Figure 3: distribution of daily numbers of defaults for Paris city over the period 2001-2013

To fit the model we have used a Poisson regression. Poisson regression assumes the response variable y (the number of defaults for a given day) has a Poisson distribution, and assumes that the logarithm of its expected value μ can be modeled by a linear combination of the predictive features x_i:

$$P(y = k \mid x_1, \dots, x_i, \dots, x_p) = \frac{e^{-\mu} \mu^k}{k!},$$

with

$$E(y \mid x_1, \dots, x_i, \dots, x_p) = \mu = exp\left(\beta_0 + \sum_{i=1}^{p} x_i \beta_i\right)$$

Fitting the model means finding the values for the coefficients β_i

Solving the collinear problem

Trying to fit directly the model with the predictive features described previously doesn't work. This is due to the fact that the temperature features are highly correlated together. To overcome collinearity issues we have used a method inspired from *Aguilera et al.* (2005) [1] which consists of doing a Principal Component Analysis of explicative features prior to fitting the Poisson regression on selected principal components.

Operational model

The statistical model has been implemented in an operational model available on the company intranet. Twice a day, temperature forecast for a eleven day period ahead are used to calculate a forecast of the daily number of defaults over this period. This allows adjusting to change in weather forecast. Depending of how far ahead is the day D_p for which we make a prediction, the values of features are real or forecasted, as shown in the figure below.

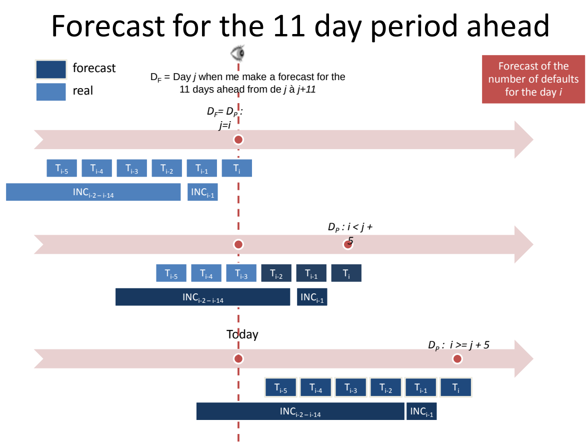

Figure 4: illustration of the forecast over the 11 day period ahead

The model is a web site available on the intranet of the company. It has been developed with open source technologies (PHP + MySQL).

Results

Three models have been calibrated, one for each operational region of ERDF in Ile de France : Ile de France Ouest, Ile de France Est and Paris

The models have been operational since May 2015. They over performed any previous model used in the company.

The picture hereafter shows the number of daily outages in Ile de France for June and July 2015 compared with the last forecast done for each day (the morning of each day) and the forecast done three day before, which is consistent with team planning.

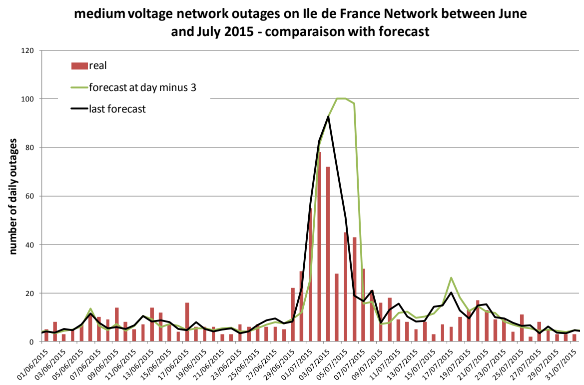

Figure 5: actual and forecasted outages on the medium voltage network of Ile de France during the heat wave of early July 2015

CRISIS MANAGEMENT ORGANISATION

In order to manage efficiently period when a lot of defaults happen on the underground networks, ERDF operational regional management teams have put in place a specific organisation.

Better understanding of the phenomenon allows to optimise resource management during the different phases:

- **Anticipation :** better understanding of size and duration of potential waves of defaults enables anticipation of the amount of internal or sub contacted resources which might be needed during these periods
- **Pre mobilization :** this phase starts as soon as exceptional weather conditions are announced. The model shows the forecast for an eleven day period ahead. It also shows the change of forecast between the day of forecast (D_F) minus five, D_F minus two and D_F which helps to understand trends in the change of forecast.

During this phase, staff operations are planned. To fix an outage several operations have to be serialized: localization of the outage, de-energization of the cable, civil works, reparation of the damaged equipment and re-energization of the cable. It's also important to anticipate the resources needed at the call center which will face a high number of calls during the wave of default.

- **Crisis management :** during the wave of defaults, resource requirement is updated in real time to make sure the right amount of resource is allocated to each step and that no bottleneck happens in any of the steps. This allows to minimise the number of cables out of order at the same time and to maintain the medium voltage grid resilient. Temperature forecast are actualided twice a day which enable greater reactivity to changing weather conditions

- **Back to normal :** thanks to the model it is possible to know when the situation is likely to go back to normal in term of number of outages and therefore to adjust resource requirement until all the system is back to normal. The model shows forecasted and actual number of outage.

CONCLUSION

In this paper we have described how resilience of medium voltage grid is improved through better prediction of defaults in order to better manage resources needed to repair the faulty cable. This project has been successful thanks to a close collaboration between operational staff, experts, IT and Statistics teams. The model has proved to be a success and very useful last summer. Some improvements are still studied on the statistical model itself and on the IT architecture side.

Further work under process aims to indentify which cables are most likely to have an outage in order to optimize investments and decrease the size of the waves of outages during the so called “crisis”.

REFERENCE

[1] Aguilera *et al.*, 2005, "Using Principal components for estimating logistic regression with high-dimensional multicollinear data", *Computational Statistic & Data*, vol. 50, Issue 8