EVALUATION OF THE PREDICTIVE RELIABILITY OF NATURAL GAS DISTRIBUTION MAIN LINES WITHIN THE FRAMEWORK OF THE GRDF INVESTMENTS PRIORITISATION STRATEGY

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Summary

The purpose of this study is to assess the reliability of natural gas main lines operated by GrDF in France on the basis of feedback data. The results of this study, as well as enabling network reliability to be assessed, are relevant input for prioritising renewal investments on the GrDF network.

Within this framework, this paper presents a statistical method for estimating the nature and speed of ageing on natural gas main lines.

This four-step methodology is based on feedback and a number of statistical methods and modelling tools such as classification techniques and parametric survival models.

1 Background and objectives

GrDF, a wholly-owned subsidiary of GDF SUEZ, brings together the Group's natural gas distribution activities in France. It operates a natural gas distribution network of almost 200,000 km.

CRIGEN (GDF SUEZ's Research & Innovation Centre on Gas and New Energies) provides methodological support to GrDF in the development of asset management and industrial safety policies.

As part of its asset management strategy, GrDF has acquired decision support tools to guide its investment programmes and assess their relevance.

A standard procedure has been developed to prioritise its facility renewal programmes. Using statistical analysis, it serves to guide renewal programmes nationally based on statistical analysis of failures (leaks) observed across the network.

2 Introduction

To support GrDF in its strategy, CRIGEN developed and implemented a method for assessing the predictive reliability of GrDF's natural gas main lines based on feedback.

The method can accommodate:

- regional particularities;
- different main-line materials and characteristics;
- small numbers of failures;
- periods when no failure data is available (censoring).

It is based on four steps for each GrDF main-line material and operating region:

Step 1: Identification of characteristics impacting the probability of failure.
Step 2: Estimation of the Weibull parameters.
Step 3: Estimator bias correction.
Step 4: Verification and prediction.

3 Input data

GIS asset data (Geographical Information System)

The input data relate to all main lines made of ductile iron, copper and steel in GrDF's eight operating regions. Polyethylene main lines, which are the latest additions to the network and make up the largest set of facilities in terms of length (around 70% of the network), are not covered by this study as they are not currently included in renewal plans due to their very low failure rate.

Main-line data can be grouped into three categories: technical characteristics, geographical location and operating data.

Technical data include:

- material;
- internal and external coating type;
- internal and external diameter;
- length;
- pressure;
- GIS identifier.

From a geographical viewpoint, the address, local central office and geospatial coordinates (X,Y) are provided for each section.

The third type of data relates to:

- commissioning date;
- operating condition (in service, abandoned, removed, pending).

Feedback data on failures

Feedback (FB) data have been collected since 2005 and the study takes into account failures that occurred up to 2012. The estimation is performed on failures recorded between 2005 and 2011. Those that occurred in 2012 are being kept for validation.

Failures due to human factors such as damage caused by third-party works are not included in the study. The data are also filtered according to defective or damaged equipment. It was decided to class as a "main line" any equipment of a tubular nature, i.e.:

- manifolds;
- couplers and connection fittings;
- pipes/tubes.

These two databases (assets and feedback) are not connected, and some preliminary work was required to link the failures to the facilities concerned. This approach enables each failure to be assigned to a group of sections known as a "cluster", based on the following criteria common to both databases: address, pressure and material.

However, some of the failures recorded could not be used in the modelling. To offset the bias resulting from these unusable failures, a specific correction was established in the prediction phase.

4 Methodology

1- Identification of characteristics impacting the probability of failure

A static model (logistic regression) and a dynamic model (survival curve equality test) were developed in order to identify the significant variables. The models were applied to each material and region, potentially resulting in different segmentations for the same material depending on the amount of data available in the region. However, the significant variables were the same for a given material.

Table 1 below shows the characteristics that have a significant impact on failures for each material.

Table 1: Characteristics impacting the probability of failure for each material

Material	Significant variables
Ductile iron	Sub-material (type of ductile iron)
Copper	Diameter
Steel	Pressure
	Coating

These criteria were used to group the main lines into families of facilities that were homogeneous in terms of reliability for each material and for each region. Models were then developed for each family.

2- Estimation of the Weibull parameters

From among the various parametric models, likelihood ratio tests resulted in a Weibull distribution being selected for the estimation. This choice was further justified by the flexibility of the model, which is based on three parameters and enables all phases of the bathtub curve to be modelled (youth, useful life and ageing phases). As noted by (Lannoy and Procaccia, 2006), the Weibull model is commonly used in reliability to model ageing (deterioration of material characteristics over time).

Tests carried out on the position parameter resulted in it being set at 0, which means that deterioration begins as soon as the main lines are commissioned. The shape (β) and scale (η) parameters were then estimated by maximum likelihood.

Main lines that experienced no failures before 2011 were considered as right censored. However, the absence of information prior to 2005 could not be incorporated in the modelling as left censoring because there was no information to determine whether a main line had experienced a failure before 2005.

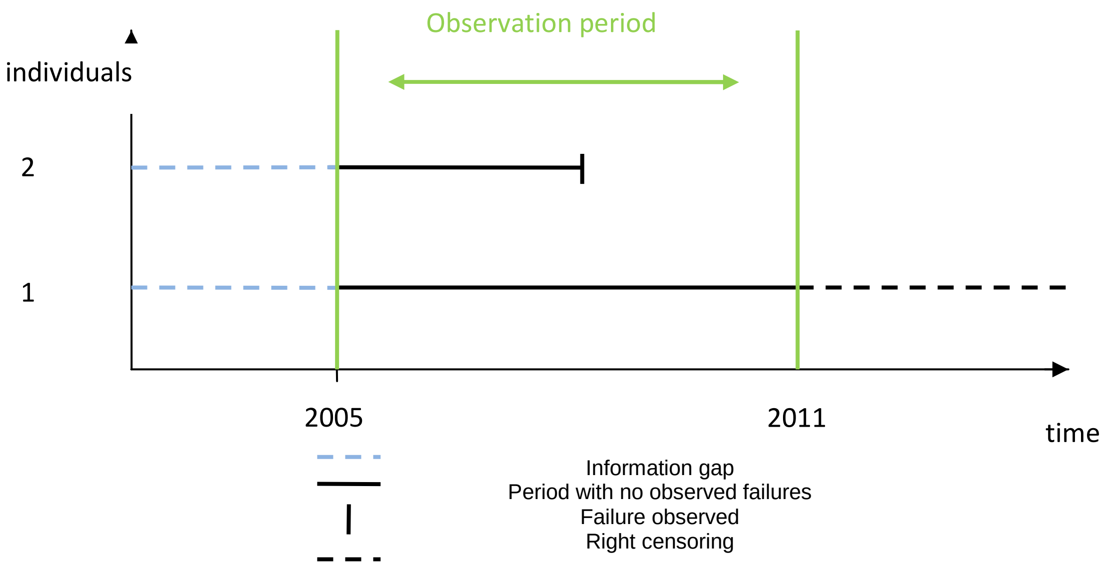
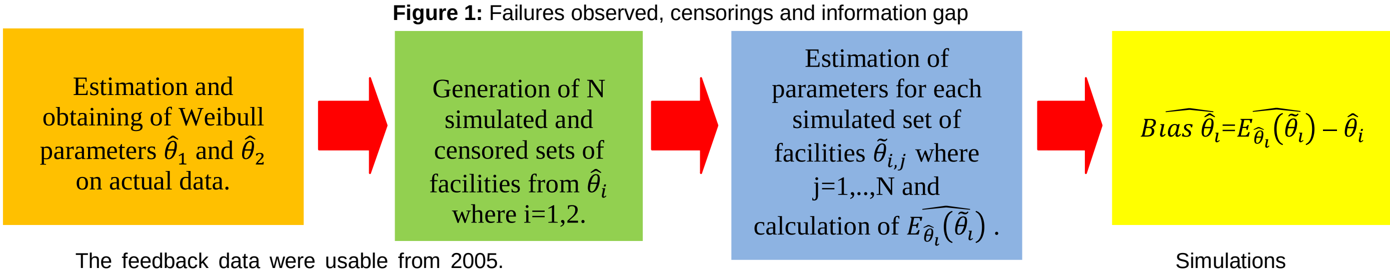


Figure 1: Failures observed, censorings and information gap



The feedback data were usable from 2005. Simulations were performed to determine the impact of the information gap on the quality of the estimators; the results suggested a significant bias. In what follows, parameters β and η will be referred to as θ_1 and θ_2 respectively.

Figure 2: Estimation of bias

The bias is realistically assumed to be independent of the true value of the parameter, or in any case not very sensitive to that value. It can therefore be estimated on the basis of simulated data under the value of the parameter estimated on the actual data, i.e. $\hat{\theta}_1$ and $\hat{\theta}_2$. A bias exists when $\widehat{E_{\hat{\theta}_i}(\tilde{\theta}_i)} \neq \theta_i + o_p(1)$ where $\widehat{E_{\hat{\theta}_i}(\tilde{\theta}_i)} = \frac{1}{N}\sum_{j=1}^{N}\tilde{\theta}_{i,j}$ and $o_p(1)$ is a random variable that tends towards 0 when N→ ∞. This random term refers to the fact that $\hat{\theta}_1$ and $\hat{\theta}_2$ are estimators.

Estimator bias correction

The estimation is improved by performing a bias correction. This consists of subtracting from the estimators their estimated biases such that:

$$\theta_{i,0} + o_p(1) = \hat{\theta}_i - \text{Bias}(\hat{\theta}_i),$$

Where θ_{i0} are the unknown parameters that generated the failures in the set of facilities and $o_p(1)$ is a random variable that tends towards 0 in probability (under $\theta_{i,0}$) when p→ ∞, p being the dimension of the set of facilities, and, since the set of facilities is large, we get: $\hat{\theta}_i - \text{Bias}(\hat{\theta}_i)$ close to $\theta_{i,0}$.

The difficulty arises from the fact that, with a non-zero bias assumed to be non-constant, the estimator bias is no longer Bias $\hat{\theta}_i = E_{\hat{\theta}_i}(\tilde{\theta}_i) - \hat{\theta}_i$ but Bias $\hat{\theta}_i = E_{\theta_{i,0}}(\tilde{\theta}_i) - \theta_{i,0} + o_p(1)$.

To obtain the bias, it is therefore necessary to retrieve the parameters $\theta_{1,0}$ and $\theta_{2,0}$ that generated the failures in the set of facilities. To obtain an estimation of these parameters, an algorithm was developed. It proceeds by iteration until convergence, convergence being reached when the bias is stabilised. The estimator precision is obtained by translating the prediction interval of $\hat{\theta}_i$ onto the corrected estimator $\underline{\theta}$.

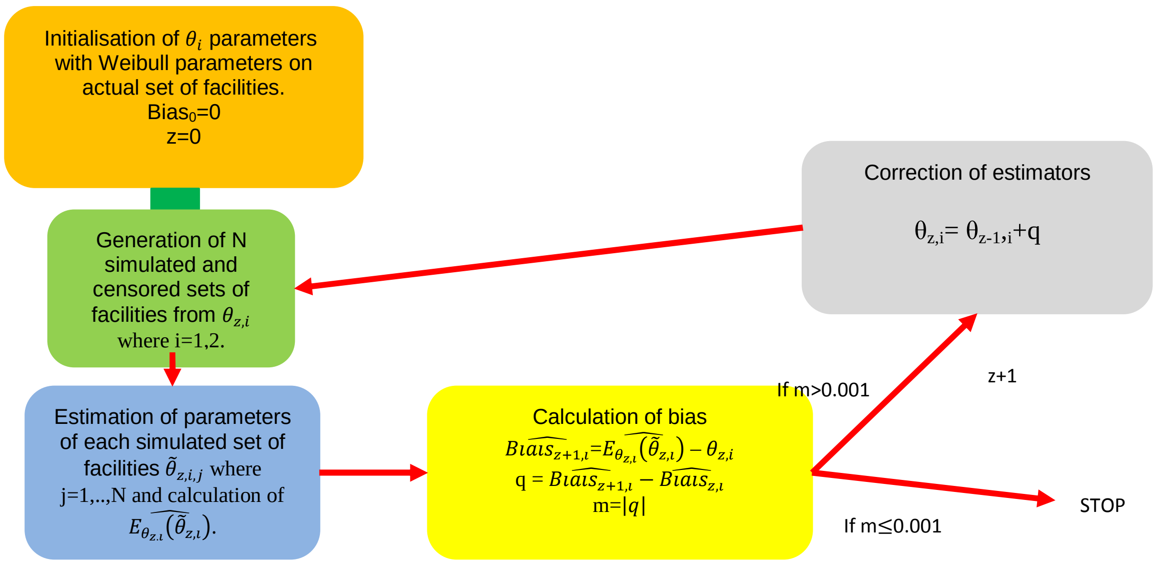


Figure 3: Bias correction algorithm

3- Validation of corrected estimators

As stated above, the estimation of Weibull parameters in a set of facilities containing an information gap has the potential to be heavily biased. To evaluate the improvement made by the correction, it is possible to study the bias of the corrected estimator.

Method

To study the bias, a set of facilities comprising around 200,000 metres of main line is used, on which failures are generated according to a known data-generating model. Given the time taken by the correction procedure, a single case will be studied.

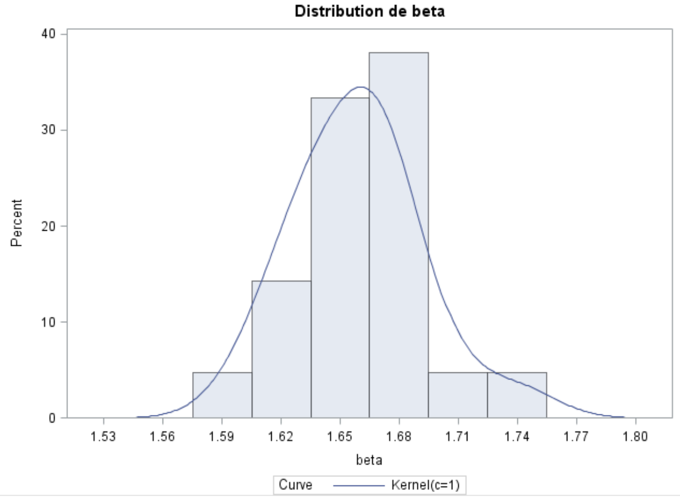
The failures generated in the set of facilities are obtained with beta=1.5 and eta=50000. For a set of facilities of this dimension, the estimated parameters change very little from one simulation to another. The correction is therefore applied to the estimated parameters, in order to obtain a distribution of the corrected estimators.

The correction is performed with a stopping rule of 0.001 for beta, 0.005 for eta and with 10 simulations for calculating the expected value. The values of these parameters were chosen to enable the correction to be performed relatively quickly. A greater number of simulations and a more precise stopping rule would improve the correction but would require a very long calculation time for sets of facilities which may exceed 1 million metres in length.

Results

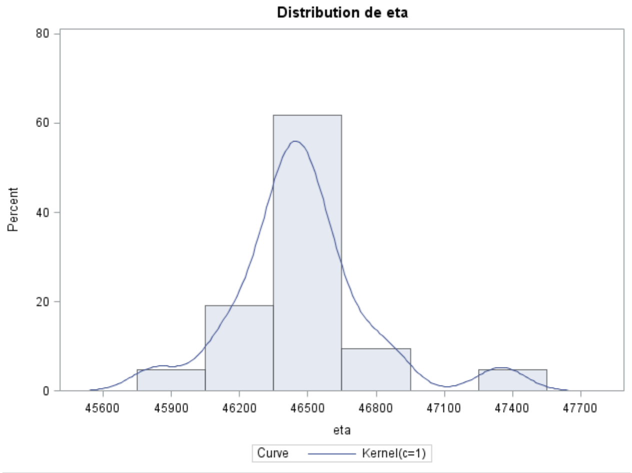
The distribution is based on 20 points.

The average of the corrected estimators for beta is 1.66. The bias is now therefore 10%.



[Beta distribution]

The average of the corrected estimators for eta is 46,472. The bias is now therefore 7%.



[Eta distribution]

The correction therefore substantially corrects the bias, which here falls from 430% to 10% for beta and from 52% to 7% for eta. It even seems possible to eliminate the bias entirely by refining the stopping rules, although this would entail a compromise in terms of the time taken.

4- Verification and predictions

The estimators obtained in this way are verified by making a prediction for the period 2005–2011 and for the period 2012 then comparing the results with the number of failures that actually occurred during these periods.

The predictions are primarily corrected by the coefficient obtained by regression of the stationary series of unusable failures on the stationary series of the dimension of the set of facilities. Both series are stationary in order to avoid capturing a correlation due solely to time.

The regression is performed on the dimension of the set of facilities because on the majority of sets of facilities it is possible to capture a significant correlation between these two variables. This also allows us to have a correction capable of making predictions over a time period for a chosen dimension of a set of facilities.

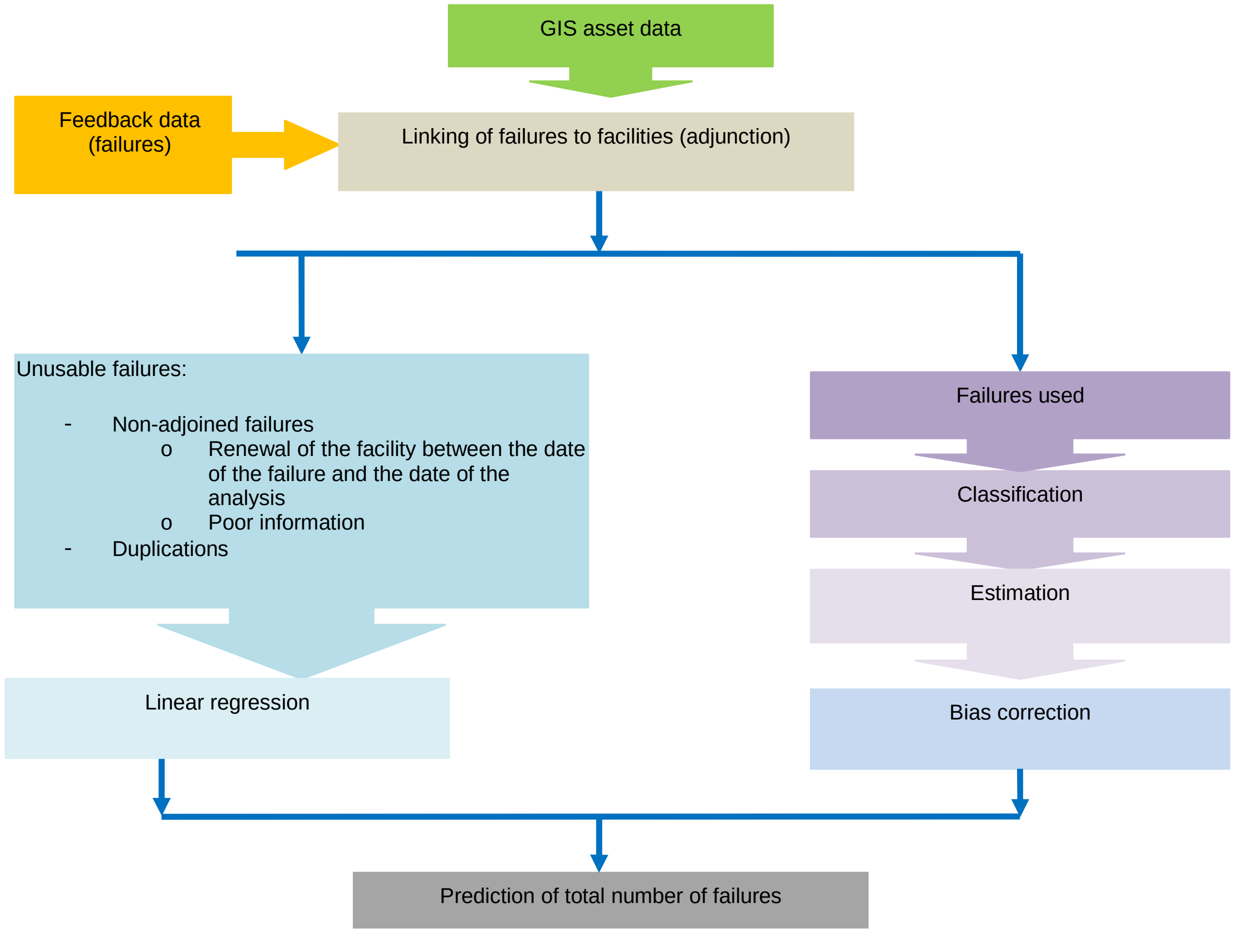


Figure 4: Methodology for estimating the reliability of gas main lines

We observe that the error rates for the retrieval of 2005-2011 data are in the order of 0 to 20%. This analysis allows us to verify the reliability of the model in relation to the input data. For example, in the case of steel, the error rates vary as follows according to the GrDF operating region (except for region 5, where the number of incidents was not sufficient to estimate the model parameters):

Table 2: Error rates for the retrieval of feedback data

GrDF operating region	Error rate
1	3%
2	3%
3	20%
4	13%
6	10%
7	11%
8	14%

The error rates for the prediction of incidents in 2012 are in the order of 0 to 30%. This analysis allows us to verify the robustness of the model in terms of its predictive ability. For example, the table below gives the error rate in predicting the number of failures on steel main lines compared with feedback reports of failures in 2012. However, note that in regions 4 and 7 the number of failures observed in 2012 was particularly small compared with the previous years; this explains the model's inability to give a good prediction.

Table 3: Error rates for prediction compared with feedback data

GrDF operating region	Error rate
1	14%
2	28%
3	6%
4	56%
6	13%
7	81%
8	-7%

5 Results

Several reliability models have been developed for each region, resulting in:

- 14 models for ductile iron main lines, according to sub-material;
- 4 models for copper main lines, according to diameter class;
- 17 models for steel main lines, according to pressure class and external coating type.

Using these different models, it is possible to predict a number of failures and a failure rate per unit of length over a given time frame (e.g. 5 years) and to compare the results obtained within the same region for different main-line materials or the results between different regions.

The figures below give some examples of results derived from the models. Figure 5 shows, for the ductile iron main lines in region 2, the number of failures observed in the period 2005-2013 and the number of failures predicted by the model for the period 2012-2018. It also gives a breakdown of the number of predicted failures according to the ductile iron sub-material (2GS and K9).

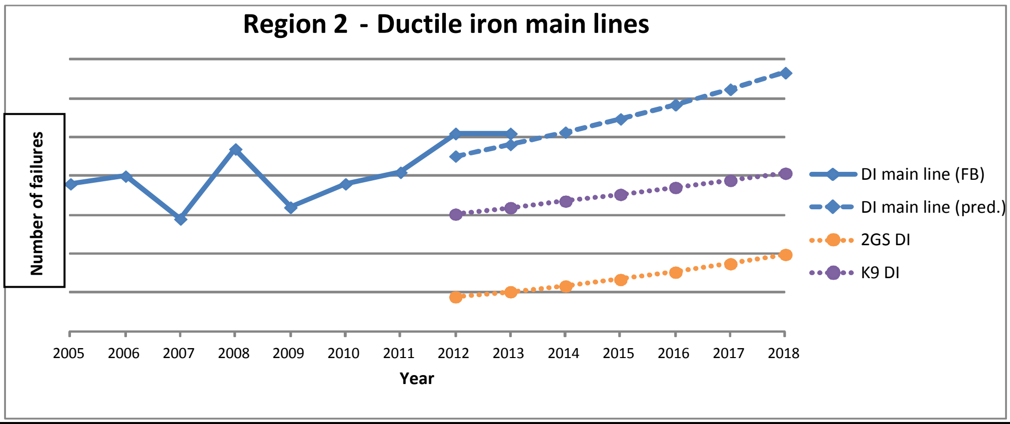


Figure 5: Example of results for the ductile iron (DI) main lines in region 2 (the number of failures is hidden for confidentiality reasons).

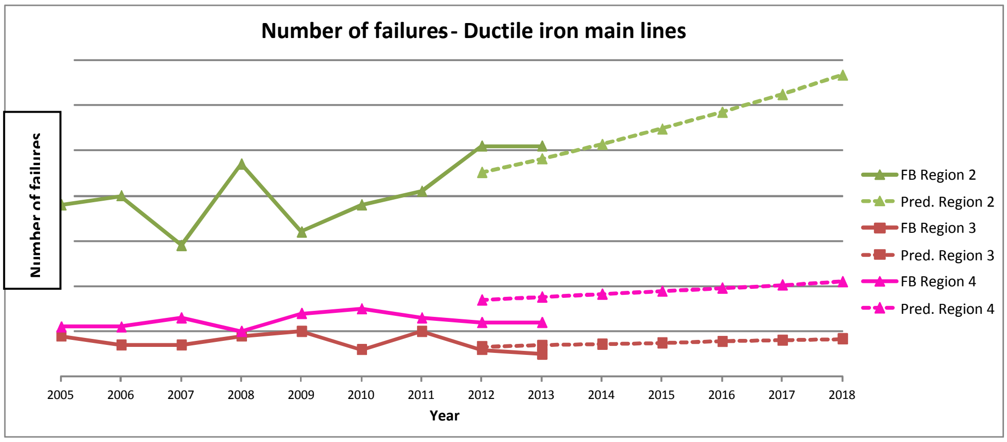


Figure 6: Example of comparison of results between regions (the number of failures is hidden for confidentiality reasons).

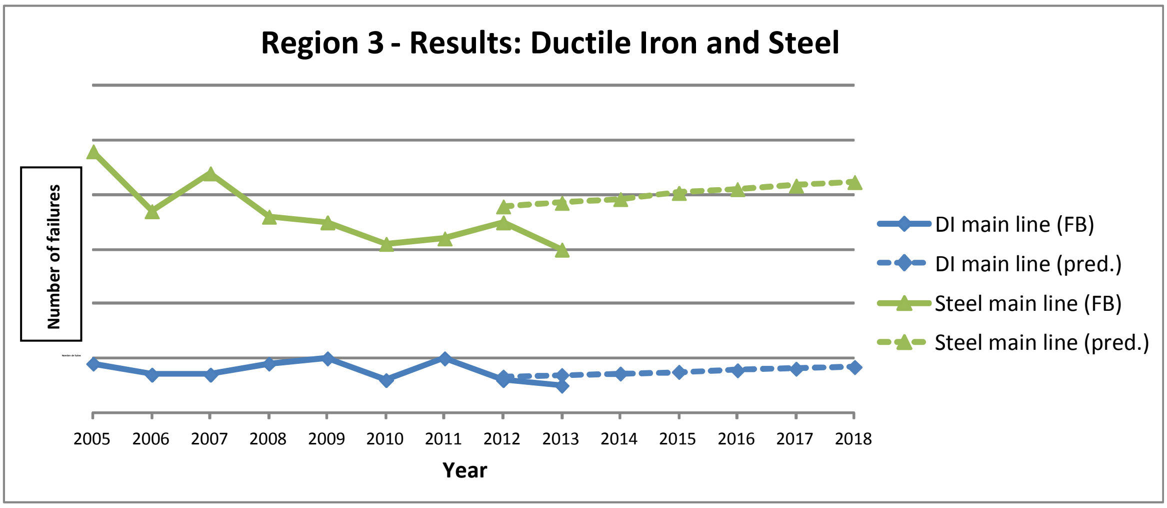


Figure 7: Example of comparison of results between different materials for region 3 (the number of failures is hidden for confidentiality reasons).

6 Conclusions

Thanks to the studies conducted on network main lines, GrDF now has reliability models that factor in:

- regional particularities;
- the impact of different technical characteristics on reliability;
- changes in reliability over time (ageing evaluation).

These models make it possible to estimate for a given set of main lines the number of failures that could occur over a given time period (e.g. predicted number of failures over 5 years). This enables a failure rate to be estimated per unit of length over the same period. These estimations are input for guiding investment choices.

The future scope of this work lies in a number of areas, most notably:

- **Evaluation of uncertainties**: the uncertainty associated with the results is very difficult to estimate due to the very long calculation time needed to perform multiple simulations. Additional studies are required in order to have an accurate estimate of the uncertainties in the results with acceptable calculation times.

- **Development of decision support indicators**: based on the various results obtained, a set of indicators could be established to facilitate decision support. A particular focus would be spatial decision-making with cartographic representations of the results: for example, displaying the number of predicted incidents per geographical area or the predicted incident rates per unit of length.

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