Fatigue Data-Based Design: statistical methods for the identification of critical zones

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Abstract: The reliability of safety parts is a major issue for an automotive manufacturer. Fatigue failure is, however, a phenomenon that is difficult to analyze because it depends on the one hand on the manufacturing of the part, its geometry and the mechanical properties of the various materials used, and on the other hand on the external loads it is subjected to. In order to better design safety parts against fatigue failure, numerical simulations and tests on real size prototypes are carried out by the design office. Deterministic fatigue criteria are then used to identify the critical zones of the part. If these criteria prove to be effective on experimental test data with standardized specimens, they are less effective for bench tests with prototypes: the variability inherent to tests on prototypes is poorly addressed by deterministic criteria, not to mention the errors due to numerical simulations. We then propose to use statistical methods on the one hand to improve the deterministic criteria; on the other hand to build new fatigue criteria.

Keywords: fatigue design, Dang Van criterion, multivariate analysis, classification.

1. Introduction

In mechanical design, fatigue is a highly scattered phenomenon that needs to be accounted for. When dealing with complex structures, fatigue cracks often occur at specific locations on mechanical parts. Especially the chassis of a vehicle has many welds. The majority of the cracks observed during the tests are related to a weld. To design correctly a mechanical part against fatigue, it is then essential to be able to identify these critical zones (*i.e.* zones that may lead to crack initiation).

In fatigue design, engineers resort to numerical modelling and finite element simulations to compute the stress distribution on a mechanical part subjected to external load. Then, critical zones are identified using a multiaxial fatigue criterion. When the design is satisfying, fatigue tests on real prototypes can be launched.

Fatigue tests often fail to correlate on numerical predictions. Therefore, the design has to be reviewed to deal with detected failure points, and a new test campaign has to be launched. These "back and forth" are expensive and strongly delay the development process.

It is thus interesting for engineers to have new prediction tools to better identify critical zones on a numerical model. In this work, our objective is to use statistical methods to define a fatigue criterion based on fatigue data.

In the section 2, we detail the fatigue database used in this study. The section 3 focuses on Dang Van fatigue criterion and the identification of material parameters using coupon tests. The section 4 illustrates how Dang Van fatigue criterion poorly generalize when applied to complex specimens. It is thus interesting to use additional features to characterize critical zones. Finally, in the section 5, we use supervised classification methods in order to define new statistical fatigue criteria.

2. Fatigue Database

We analyse a fatigue database consisting in both computations on numerical models and results from corresponding fatigue bench tests. We are then able to incorporate information from tests results on the numerical model. Thus, the purpose is then to extract knowledge from such a database. In other words, we want to be able to identify potential failure points on a new design not tested yet.

2.1 Numerical modelling

In mechanical design, engineers use numerical models to study the behaviour of a mechanical part subjected to external loads. After defining the geometry and the material properties, the mechanical part is modelled by a Finite Element Model that consists in a meshing of the part in small elements. It is then possible to simulate the internal stresses at each location of the mechanical part subjected to an external load.

In this study, we are interested in chassis' components (cradle models) subjected to different cyclic loads. For each Finite Element model and each load type, we have access to computations results: stress tensors defined on each element in the model. The loading is sinusoidal and proportional, thus we are only interested on the stresses computed at minimum and maximum instants on the load signal.

Instead of using stresses at minimum and maximum instants, we prefer mean and amplitude stress tensors that are more relevant in this context. In addition to stress tensors, we can compute a few other features based on the stress tensors: hydrostatic stress, principal stresses, shear stress, triaxiality…

As mentioned in the introduction (section 1), fatigue cracks often occur on welded joints and spot welds which are very specific locations on the mechanical part. We choose to focus on these specific zones.

2.2 Fatigue bench tests

Finite Element computations are usually used as a pre-validation tool. If the stress on each point of the structure meet some fatigue safety criterion, the design is ready to be tested in real conditions.

Hence, bench tests are performed on real prototypes. Usually, the number of identical prototypes tested ranges from three to seven. Tests are performed using the same load as for the numerical model but with a different severity. Moreover, load amplitude is increased during tests following Locati protocol (accelerated life tests, cf [1]). Test reports contain photos of observed cracks along with the number of cycles before failure (*i.e.* observation of crack initiation).

We are then able to identify the weld responsible for crack initiation and report the information on the numerical model (cf Figure 1). This association between numerical models and fatigue tests is the baseline of our database.

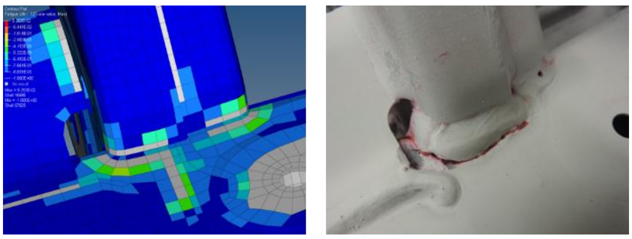

Figure 1: Crack initiation on a welded joint (right) and corresponding zone on the numerical model (left)

2.3 Fatigue database

Based on the various tests, the following data are available: $(x_i\,;y_i)_{1\le i\le n}$. where x_i in $\mathbb{R}^d$ and y_i in $\{0;1\}$. For each element i, the vector x_i contains the information resulting from the Finite Element simulation (e.g. local stresses applied on the weld, its geometry) and details about the test (severity). The binary variable y_i is a flag indicating whether a crack initiation has been observed ($y_i = 0$) or not ($y_i = 1$).

This study uses a reduced database containing three Finite Element models and test reports, which represent $n = 3397$ observations. Only 47 observations are crack initiations. We are therefore dealing with an imbalanced database. The number of features is $d = 31$ (including features that will be defined in the section 4).

In addition, we have results on fatigue coupon tests (cf [2]). Four elementary geometries of welded structures are studied under different load types. The results of these tests will be used to define a probabilistic fatigue criterion in the section 3.

3. Definition and calibration of a fatigue criterion

Generally, deterministic fatigue criteria are used to identify critical zones. A fatigue criterion is an evaluation, on each element of interest in the model, of the degree of criticality of this element based on the calculated stresses. It is known that the initiation of fatigue cracks is mainly related to shearing (tangential stresses) and that the normal tensile stresses accelerate (in extension) or delay (in compression) their appearance (cf [3], chap. 2).

3.1 Dang Van criterion

The Dang Van criterion is commonly used as a fatigue criterion in the french automotive industry (cf [1]). For a zone of the piece, let us note τ the critical shear stress and ph the corresponding hydrostatic pressure. We consider Dang Van's line

$$\boldsymbol{\alpha_m} \cdot \boldsymbol{ph} + \boldsymbol{\tau} = \boldsymbol{\beta_m} \qquad [\mathbf{1}]$$

where α_m and β_m are material constants (cf Figure 2). If the point (ph, τ) is above the straight line then the stress at this point is above the endurance limit of the material. Therefore, the zone is critical because the risk of cracks in a finite time is non-zero. If the point (ph, τ) is below then the stress at this point is lower than the endurance limit and therefore the risk of cracking in a finite time is zero (cf [4]).
The material constants α_m and β_m are usually identified using uniaxial fatigue tests in traction and torsion. In practice, the endurance limit of the material is estimated to $N_c = 10^6$ cycles.

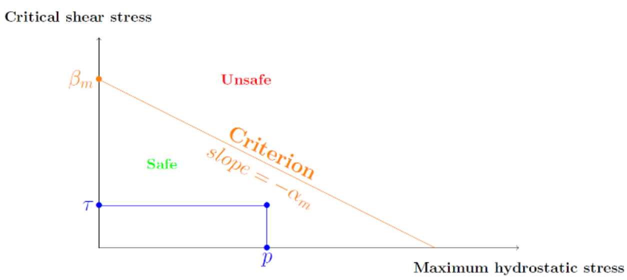

Figure 2: Dang Van criterion. A zone is safe (resp. unsafe) if $(\boldsymbol{ph}, \boldsymbol{\tau})$ below (resp. above) the straight line.

3.2 Coupon tests

Following Fayard's study on welded joint modelling, we have access to fatigue tests on simple welded specimens (cf [2]). Our objective is to identify the parameters (α, β) for Dang Van criterion applied to welded joints. For each test j performed, a load F_j is applied and thanks to a finite element model, we know the local stresses (ph_j, τ_j) on the spot where the crack has initiated. We also observe N_j the number of cycles before failure (lifetime).

3.3 Identification of fatigue parameters

Thanks to coupon tests, we are able to identify material parameters α and β for welded joints. The identification relies on a statistical model between the lifetime N and the local stresses (ph, τ). Parameters are estimated using maximum of likelihood method.

4. Additional features for the identification of critical zones

We are now interested in designing complex mechanical parts against fatigue. Focusing on welds where the majority of failures are observed, we note that the criterion defined in the section 3 fails to identify all the critical zones. A crack is observed in many zones classified as non-critical by the Dang Van criterion. Therefore, additional features are needed to better characterize critical zones.

4.1 Limits of Dang Van criterion

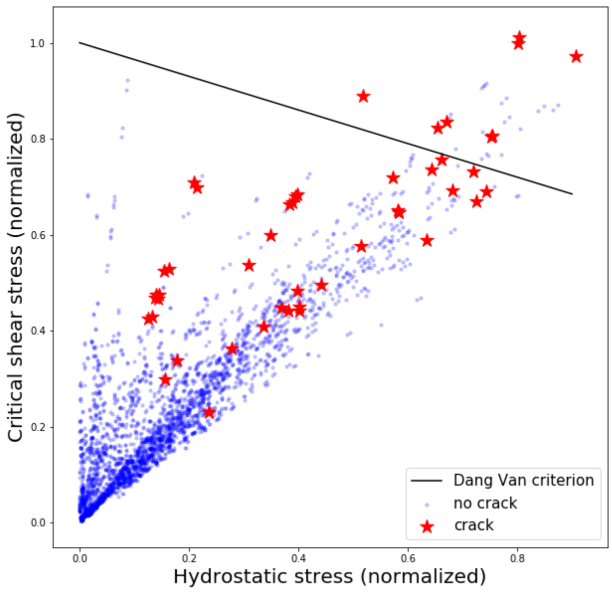

Figure 3: $\boldsymbol{ph - \tau}$ Dang Van diagram: from the bench tests, we observe cracks (represented as red stars) on areas predicted to be safe by the Dang Van criterion.

We use the database defined in the section 2. Among the d variables describing individuals, we have access to maximum hydrostatic stress and critical shear stress. Tests are not performed at constant amplitude and with same severity. Thus stresses are corrected in order to correspond to the equivalent stress that would have initiated a crack after $N_c = 10^6$ cycles. The method to compute equivalent stresses relies on Miner-Palmgren linear damage accumulation rule and is not detailed here (cf [5]).

In Figure 3, we observe the dataset in $ph - \tau$ Dang Van diagram. The Dang Van fatigue criterion identified in the section 3 is reported there. It is clear that several cracks are not identified with this criterion. Instead, some cracks even appears far below the border.

4.2 Additional features

The simulation of the Finite Element Model provides many variables in addition to shear rate and hydrostatic pressure: stress tensors, invariants and gradients. It can be thought that taking these variables into account can improve the identification of critical areas.

When looking at several crack examples, it seems that crack often happen at geometric singularities. At these specific points, it is known that the results given by the Finite Element Model are less reliable. Moreover, different shapes of welded joints exist that can have different fatigue behavior. Therefore, we define the following variables taking into account both the geometry of the weld and its neighboring:

- Weld size, curvature;
- Distances to the nearest welds in the structure, hydrostatic and shear stresses for the nearest welds;
- Distances to the nearest edges, hydrostatic and shear stresses for the nearest edges.

We now assume that each individual i in the dataset is characterized by an input vector x_i in $\mathbb{R}^d$ and that d is the number of features including those defined in this section ($d = 31$).

4.3 Multivariate analysis

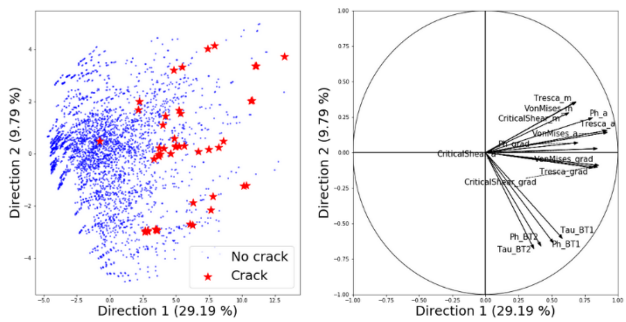

Figure 4: First and second principal components and correlation circle

Dang Van's criterion is based only on two variables of $X = (x_i)$. The Principal Componant Analysis (PCA) allows us to apprehend the variability of the X cloud and the correlations between the different variables of X (cf [6]). The first principal plane concentrates around 40% of the variability of X (see Figure 4): the first axis expresses a “size effect” as all the variables are positively correlated with. In particular, the amplitude, mean and gradient values of the stress. The second component is associated with “Ph_BT1”, “Ph_BT2”, “Tau_BT1” and “Tau_BT2”. They are neighboring variables representing stresses on the two closest edges.

Unfortunately, it is impossible to separate the cracked from the uncracked zones, neither in the first principal plane, nor in the further dimensions (not shown). While PCA allows us to identify correlations between variables, it does not allow us to classify areas with a crack. We can think that some variables are missing to make this classification: for example, the residual stresses due to welding.

5. Classification for fatigue predictions

Since fatigue criterion based on welded coupon tests generalizes poorly on complex mechanical parts, our idea is to use supervised classification techniques to identify critical areas using X data. As shown in the section 4, the two variables ph and τ cannot discriminate efficiently failure points from non-failure points. However, additional variables defined in the section 4 may help predict crack initiation risk.

5.1 Supervised classification

Formally, given features x_i in $\mathbb{R}^d$, we want to be able to predict whether a weld may crack ($Y_i = 0$) or not ($Y_i = 1$). This is a classic supervised classification setting.

We implement different machine learning techniques (cf [7]) to address this problem:

- Logistic Regression with Lasso regularization (LR);
- Support Vector Machines (SVM);
- K-Nearest Neighbors (KNN);
- Random Forests (RF).

Hyperparameters are tuned using K-Fold cross validation with five folds.

5.2 Performance evaluation

Given a trained classifier, we are now able to compute a probability $\hat{p}_j$ for a new individual j to result in a crack ($y_j = 0$). Then, choosing a threshold p, we will predict “crack” if $\hat{p}_j \geq p$ and “no crack” else. The two interesting metrics in this context are:

- Recall: the percentage of correctly identified cracks;
- Precision: the percentage of true cracks among crack predictions.

The first metric is obviously more important: ideally, we would like to identify (almost) every failure. However, predicting every point as a crack will result in a perfect recall but a poor precision.

We do not choose any threshold p for now. In order to assess the performances of a model independently of the chosen threshold, we measure the area under the ROC curve (Receiver Operating Characteristic).

5.3 Scenarios

We compare two different scenarios:

- The performances for each classification method using only maximum hydrostatic stress and critical shear stress as features (Dang Van variables, Table **1**).
- The performances of each classification method using every available features (All variables, Table **1**).

5.4 Results

Results are presented in Table **1**. As a comparison, classifying only using Dang Van criterion gives a score (area under ROC curve) equal to 0.91. Classification methods applied with the two variables involved in the criterion cannot improve performances. Even if mean scores improve for every methods when all variables are used in classification, there is no evidence that this improvement is significant. Classification methods implemented here only use a reduced database with a few number of “crack” instances and the estimations of performances have a great variance. Therefore, we need to apply this methodology on a richer database in order to see whether there is a significant gain in using additional variables.

	LR	**SVM**	**KNN**	**RF**
Dang Van variables	0.92 +/- 0.02	0.92 +/- 0.02	0.91 +/- 0.04	0.91 +/- 0.02
All variables	0.94 +/- 0.04	0.93 +/- 0.02	0.92 +/- 0.02	0.95 +/- 0.02

Table 1: Mean (+/- standard deviation) area under ROC curve (5-fold cross validation)

6. Conclusion and perspectives

To design mechanical parts against fatigue, Dang Van's criterion is used to identify critical areas. In this study, we show that this deterministic criterion is not effective on bench test data for real size parts. Instead of relying on coupon tests, we used directly fatigue data from real-scale components to identify a statistical fatigue criterion. We applied different classification techniques to address this problem. This methodology has several benefits. On the one hand, additional variables can be taken into account: this offers new ways of characterizing failure points. On the other hand, the statistical models are trained directly on complex mechanical parts: hence, it can better generalize to other complex specimens.

Results presented in the section 5 tend to support the benefits of supervised classification applied to fatigue data. Still, this study relies on a reduced fatigue database. New datasets are therefore needed to confirm this trend. Furthermore, when we perform classification, we are not facing a standard supervised learning problem. The main challenge is that the observation (crack or not) does not match exactly what we are trying to predict (critical or not). The absence of crack does not imply an absence of danger. This problem appears to be a special case of classification with noisy labels known in the literature as PU Learning, namely “Learning from Positive and Unlabeled Data” (cf [8]). As a future perspective, it would be interesting to investigate these techniques.

7. Acknowledgements

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8. References

[1] P. Beaumont, Optimisation des plans d'essais accélérés : application à la tenue en fatigue de pièces métalliques de liaison au sol, 2013.

[2] J.-L. Fayard, Dimensionnement à la fatigue polycyclique de structures soudées, 1996.

[3] J. Schijve, Fatigue of Structures and Materials, Springer Netherlands, 2009.

[4] P. Ballard, K. D. Van, A. Deperrois et Y. V. Papadopoulos, «High cycle fatigue and a finite element analysis,» *Fatigue Fract. Eng. Mater. Struct.,* vol. 18, n° %13, pp. 397-411, Mars 1995.

[5] A. Fatemi et Y. L., «Cumulative fatigue damage and life prediction theories: a survey of the state of the art for homogeneous materials,» *Int. J. Fatigue,* 1998.

[6] B. Escofier et J. Pagès, Analyses factorielles simples et multiples, Dunod, 2016.

[7] T. Hastie, R. Tibshirani et J. Friedman, The Elements of Statistical Learning - Data Mining, Inference, and Prediction, Springer-Verlag New York, 2009.

[8] J. Bekker et J. Davis, «Learning from positive and unlabeled data: a survey,» *Mach. Learn.,* 2020.