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Calibration and validation of fatigue design models for railway car bodies considering uncertainty

Sönke Kraft | **Helene Luise Blum** | **Christian Gomes Alves**

Institute for Vehicle Concepts, German Aerospace Center (DLR), Stuttgart, Germany

Correspondence
Sönke Kraft, Institute for Vehicle Concepts, German Aerospace Center (DLR), Stuttgart, Germany.
Email: soenke.kraft@rwth-aachen.de

Abstract

The fatigue design of railway vehicles is a requirement for resource- and energy-efficient lightweight design. A simulation-based design process makes high demands on the reliability of results. Therefore, this work focuses on the calibration of weld quality parameters for the simulation-based fatigue design of railway car bodies. Since the direct measurement of weld parameters is costly, an indirect Bayesian calibration approach is implemented, effectively combining limited testing with numerical simulations. Fatigue tests have been performed on the probe, component, and structure level for the load-bearing section of the Next Generation Train (NGT) car body within the SimbaCon (Simulation-based Conception) project at DLR. Based on the distribution of the measured life spans for component tests, the corresponding weld seam quality factors are calibrated using Bayesian calibration. The resulting weld seam qualities are used for the fatigue assessment of the complex car body structure.

KEYWORDS

Bayesian calibration, fatigue design, railway vehicles, welding

Highlights

- A process for a simulation-based fatigue design for railway vehicles is implemented.
- Component fatigue tests are performed to calibrate weld quality factors using Bayesian calibration.
- Fatigue testing and simulation of a lightweight car body structure are effectively combined.

Sönke Kraft, Helene Luise Blum, and Christian Gomes Alves are equally contributing authors.

1 | INTRODUCTION

Lightweight design can help to improve the resource- and energy efficiency of railway vehicles and contribute to a more sustainable mobility. One lightweight strategy aims at adapting the vehicle design to the real requirements in form of loads appearing during the life span of the vehicle. By considering loads close to the effective operating loads instead of generalized loads, structural components can be properly sized, avoiding oversizing and unnecessary weight. According to current standards, car bodies of railway vehicles are in general designed and dimensioned based on static equivalent loads as defined in EN 12663-1.[1] For realizing a vehicle design based on real operating loads, fatigue strength design has to be applied.

Since measurement runs and fatigue tests of complete railway vehicles require high efforts regarding costs and certification time, simulation-based fatigue design approaches have been developed.[2–4] Simulations shall replace at least partly fatigue tests on real structures during the design and certification phase. The virtual testing and certification[5,6] therefore leads to high requirements for the calibration and validation of the used numerical models, in order to guarantee the necessary accuracy and reliability of the simulation results. After selecting a suitable modeling approach (model type, mesh size), the parameters (material, welds) need to be adjusted.

Since the life span of the vehicle is influenced by numerous parameters, many of them characterized by uncertainties, a deterministic simulation using fixed parameter values is not appropriate. High safety factors are required in order to capture these unquantified uncertainties. They can be far too conservative, thus leading to oversizing and hindering lightweight design.

Instead, a probabilistic simulation process is implemented, considering the effect of the uncertainties and giving a probability density function of the life span as result. Thereby the failure probability for damage to appear at a lower than the required life span can be estimated. The quality of this estimation depends mostly on the knowledge about the input parameter uncertainties, which need to be quantified for the simulation process. Inaccurate or even impossible uncertainty quantifications lead to uncertainties in the life span distribution and failure probability estimation, requiring additional safety factors. The calibration of parameter uncertainties is therefore an important requirement for more reliable results. Main uncertainty sources are the varying loading conditions and the structural properties. Results of fatigue testing and simulations point out that structural damage appears first in welds, depending on the weld geometry parameters and qualities.[7,8]

In this work, performed within the DLR project SimbaCon aiming at a simulation-based design and certification of vehicles, the calibration and validation process is applied to the car body structure of the Next Generation Train (NGT).[9,10] The simulation of the fatigue life span of the car body structure requires a complex modeling chain including the modeling of the track geometry as main source for loads, the dynamic reactions of the vehicle running on the track, the structural loads due to the vehicle dynamics, and the resulting fatigue life span. To ensure reliable simulation results, the calibration of numerous model parameters is required in all steps of the chain including track geometry parameters, vehicle suspension parameters, and structural parameters, in particular welds where damages appear.

While for the quantification of some of the model parameter uncertainties reliable measurements are available (for example regular measurements of the track geometry parameters), other model parameters would require complex and costly test campaigns. This is the case for the weld parameters. In order to reduce the testing effort for the calibration of these parameters, indirect Bayesian calibration is applied based on work performed in previous works.[11–18] It aims at the effective use of limited component tests and corresponding models to calibrate the uncertainties of weld parameters, thereby improving the reliability of the probabilistic simulation of the fatigue life. In this work, based on a sensitivity analysis and a meta model, relevant parameters are identified and calibrated using the Bayesian approach.

In Section 2, the simulation-based fatigue design is outlined, focussing on the modeling of the welds. The calibration process, based on component fatigue tests, is described in Section 3. The focus is put on the sensitivity analysis and the calibration of parameter uncertainties, using the Bayesian approach. In Section 4, results are discussed.

2 | SIMULATION-BASED FATIGUE DESIGN

For the fatigue design of railway vehicles, various approaches can be found in literature, depending on the considered components, load signals and frequency ranges.[3,4,19–21] It can be distinguished between approaches in the time and frequency domain, with or without the consideration of eigendynamics of the structure. Due to instationary vehicle dynamic loads at low frequencies, the cumulative damage approach in the time domain is appropriate. Transient simulations, considering the eigendynamic of the structure, are required when excitation frequencies and eigenmodes of the structure are not separated leading to structural vibrations.

In this work, simulation results are compared with fatigue test results. For this purpose, the loads acting on the car body structure are analyzed using the Rainflow counting method in order to create block loadings applied both to the testing and the simulation.[22] The hystereses of the load-time signal are identified and classified in a Rainflow matrix according to their mean value and amplitude. The classes of this matrix form the blocks of the block loading. As recommended, the blocks are ordered by starting with the lowest mean value and increasing amplitude.

Resonance effects are not considered during testing and simulation. The validity of this approach is confirmed using modal analysis of the tested components.

The simulation process is based on multibody system (MBS) and finite element (FE) models, including an important number of parameters with possible effects on the life span. In the following, the modeling steps and the parameters that need to be considered for the calibration are briefly outlined.

2.1 | Modeling of operating loads on the car body

The resulting loads on the car body can be determined either from measurements or simulations. At DLR, multibody system simulations of the vehicle dynamics[9] and CFD simulations for the determination of pressure profiles in tunnels and during train encounters[23] were carried out for the NGT. MBS models in Simpack[24] are available for the middle car, the end car, and a shortened train of the NGT High Speed Train (HST). The upper part of Figure 1 shows the MBS model of the middle car.

The bogie concept[10,25] is based on independently rotating wheel pairs, which are installed in single wheel pair and double wheel pair frames. The propulsion of the train is distributed over all wheels with higher traction power installed in the two end cars. Since the independently rotating wheels do not have self-steering capability, a lateral guidance control based on opposed torques on the wheel pair is used. The operating loads from vehicle dynamics are obtained using measured track design and track irregularities as well as configured speed profiles. The track geometry parameters are measured by specific track measurement devices delivering precise input data to the simulation process.

2.2 | Modeling of stresses and damage

The stresses in the car body structure are computed using a linear elastic FE model with 2D shell elements, shown in the lower part of Figure 1. While the first bending mode of the car body structure appears at 17.7 Hz, the modal analysis of the tested car body section, analyzed by fatigue testing and indicated in Figure 2, reveals eigenfrequencies starting at 30 Hz. This is due to the higher stiffness of the car body above the running gears and the boundary conditions during testing. Since the frequency content of the loads is far lower, dynamic effects are neglected both in the fatigue testing and the corresponding simulations.

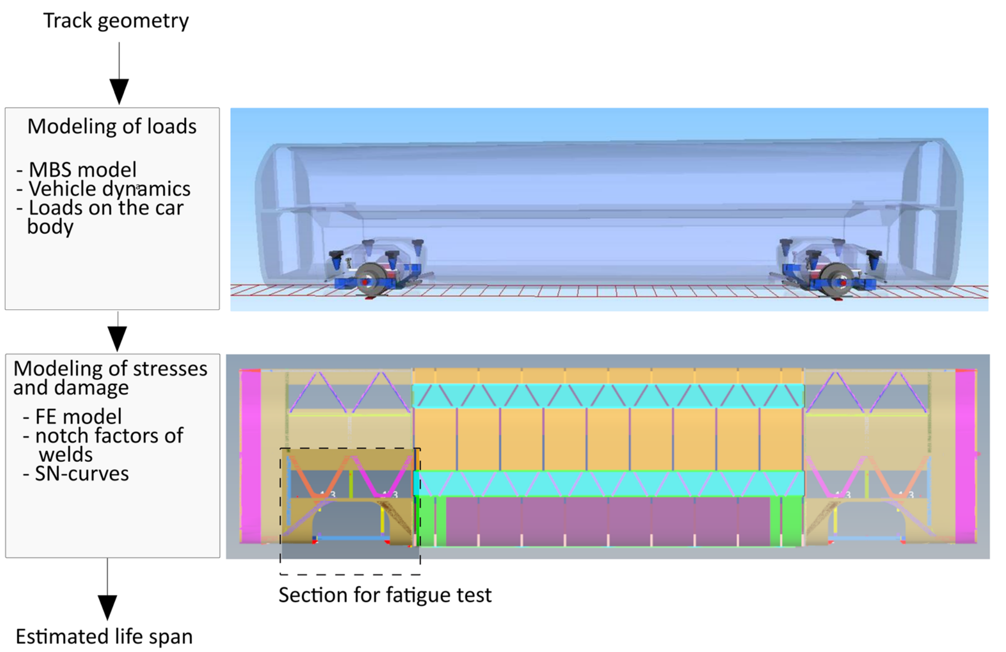

FIGURE 1 Simulation-based fatigue design of the car body including the modeling of the loads, stresses and damages. [Colour figure can be viewed at wileyonlinelibrary.com]

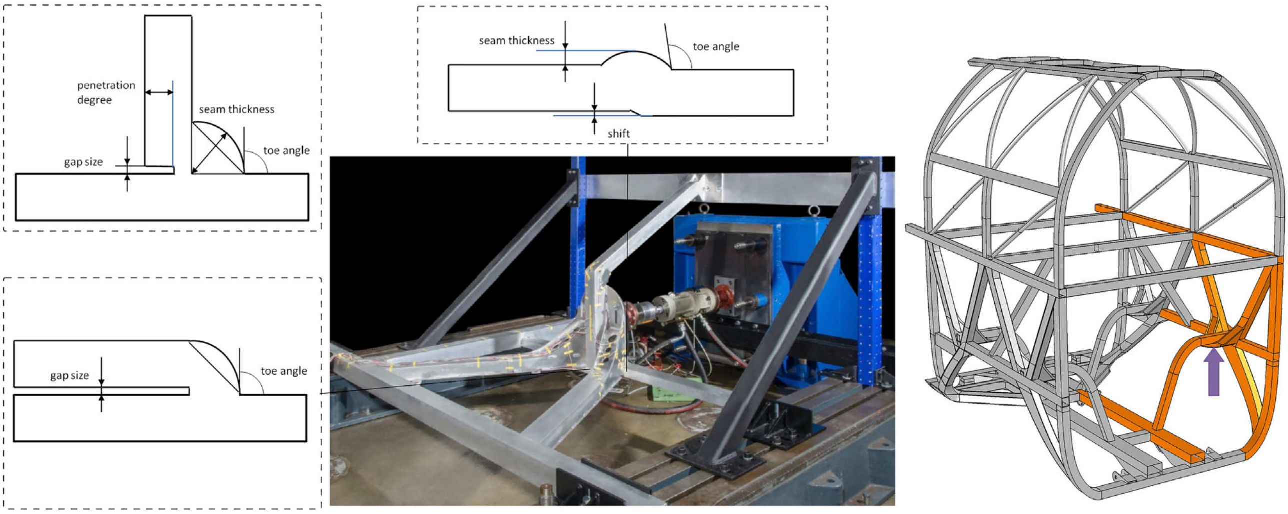

FIGURE 2 Car body section, on which fatigue testing is performed (indicated in orange) and the different weld seam types included. [Colour figure can be viewed at wileyonlinelibrary.com]

The damage is computed using the linear damage accumulation method according to the modified Miner rule.[22] For this purpose, the FE stresses of the different load cases are superposed and the equivalent stresses computed according to the DVS 1608[26] standard. The stress-time signals are then analyzed using the Rainflow counting methods and the damages computed from SN curves. For the fatigue assessment, the tool Femfat MAX[27] is used.

The modeling of the welds, where the highest damage occurs, is outlined in detail in the following section.

2.3 | Modeling of welds

Weld seams represent the most critical locations of the car body structure, due to their lower load bearing capacity under cyclic loading. Their modeling and parameterization therefore have significant influence on the reliability of the simulation results. Furthermore, the weld properties can vary significantly depending on the weld type and welding method, leading to uncertainty in the life span.[7]

The diversity of welded joints in the car body structure is illustrated in Figure 2 for the car body section, for which fatigue testing is performed. It includes a large number of weld seams with different joint types, weld types and geometric parameters. Butt welds and filet welds are most frequently used.

2.3.1 | Weld seam modeling concepts

For the modeling of weld seams in fatigue testing, approaches based on nominal, structural and notch stresses are available. Since the damage in the weld depends on the stresses in the weld root and weld toe, the computation of these weld stresses needs to be as accurate as possible. According to standards,[28,29] the life spans are computed using SN curves given for typical constructive details and notch classes.

The notch stress approach is local, the most precise one and based on the comparison of resulting and permissible notch stresses in weld seams. By using detailed 3D FE models of the weld seams for the computation of the notch stresses, higher modeling accuracy is obtained.[8] The notches of the FE weld seam model are rounded out using a defined theoretical radius (1 mm for steel) according to Radaj.[30] However, this approach is costly due to small mesh size and difficult to implement in practice for the complex structure of a railway car body.

Therefore, an approach has been developed by Femfat,[31] which is based on the computation of weld seam notch factors using FE fine models for different weld types.[32,33] Depending on the weld type, notch factors are computed for different load cases and at different assessment points. For the analyzed weld types component fatigue tests have been performed in order to determine the corresponding SN curves and Haigh diagrams. For this purpose, the endurable nominal stresses of the tests have been scaled using the computed weld seam notch factors to obtain the endurable notch stresses. The weld seam notch factors, SN curves, and Haigh diagrams are saved in a database.

For the fatigue design of a complex structure, a standard FE model without detailed weld seam modeling is used in order to compute the structural stresses. Based on the weld seam notch factors obtained from the FE fine models the structural stresses are scaled to obtain the notch stresses. The fatigue life is evaluated based on the corresponding SN curves of the database.

For the computation of the weld seam stresses transverse and longitudinal to the weld seam, the structural stresses are evaluated at a certain distance to the weld seam.[31] By interpolating the stresses of the FE elements surrounding the evaluation point, the effect of the mesh grid size is reduced.

2.3.2 | Influencing factors

Each weld seam type is parameterized by a certain number of parameters, as outlined in Figure 2. These parameters describe the geometry of the weld seam but also the overall weld quality. For the filet weld, the most frequent seam type in the car body section, the geometry is described by the weld toe angle, the weld seam thickness, the weld gap, and the penetration degree.[34]

In the database proposed by Femfat,[31] notch factors for weld geometries, corresponding to three different quality classes, are available. By interpolating the notch factors between the three given qualities, a continuous parameter variation can be performed for the sensitivity and reliability analysis.

For railway vehicles, six weld quality classes are defined in the standard EN 15085-3.[35] The required quality class depends on the loading conditions and safety requirements. The loading conditions arise from the utilization factor, computed as the ratio between the effective and admissible stresses. The safety requirements are based on possible consequences of failure.

The quality classes correspond to different levels of irregularities and defects in the weld seam. For aluminum, the weld quality classes refer to the three assessment classes B, C, and D given in standard DIN EN ISO 10042.[34] In the fatigue assessment based on the FE model, the weld quality is described by a scaling factor, applied to the permissible stress amplitude in the Haigh diagram. The resulting permissible stress is obtained by dividing the standard value with the scaling factor according to Femfat.[31] The value 1 corresponds to the standard quality class, values below 1 indicate an improved, and values above 1 a low weld seam quality.

3 | CONSIDERATION OF UNCERTAINTIES IN THE FATIGUE DESIGN PROCESS

As outlined in the previous section, the fatigue design is influenced by numerous parameters and modeling assumptions. A deterministic simulation is not able to quantify these influences, therefore requiring the introduction of high safety factors. By considering the influence of the parameter uncertainties, more reliable results can be obtained.[36] Figure 3 gives an overview of the different parameters and uncertainty sources of the simulation-based design process.

Influences of the operation conditions including the track geometry, loading conditions, and maintenance operations have to be considered. Uncertainties arise from varying track geometry qualities, having an important effect on the damage as outlined in previous work.[37] The suspension properties of the vehicle determine the vehicle dynamics and the loads transmitted into the car body.

Since damage appears typically first in weld seams, in this work the focus is set on uncertainties of the weld parameters. Also modeling effects due to the mesh grid and the level of geometric detail are considered.

In order to consider these influences, sampling techniques based on input probability density functions (pdf) are applied for the simulation process.[38,39] Prior probability density functions are defined and calibrated using fatigue tests.

3.1 | Uncertainty sources

3.1.1 | Parameter uncertainty quantification

For the quantification of the parameter uncertainties, literature data, direct measurements, or indirect Bayesian calibration techniques can be used. The track geometry parameters used in the modeling of the vehicle dynamics are obtained from direct measurements using dedicated measurement vehicles.[37] For the calibration of the suspension parameters (springs, dampers, anti-roll bar, etc.), direct measurements in test benches are costly and often not practical. Bayesian calibration based on on-track measurements of vehicle dynamics (accelerations) has therefore been applied to the calibration of suspension parameter distributions in Lebel et al.[40]

Parameters of the parent material are known from literature.[31] Uncertainty is introduced by the scatter of the available SN curves, expressed by the survival probability (SP).[22] The main uncertainty in the fatigue design arises from the weld parameters.[39,41] The direct measurement of these parameters would require specific and costly measurements. Indirect Bayesian calibration is therefore applied. In order to identify the relevant weld parameters for the calibration process, sensitivity analysis is performed in a first step. In the second step, a suitable parameter set is selected and calibrated.

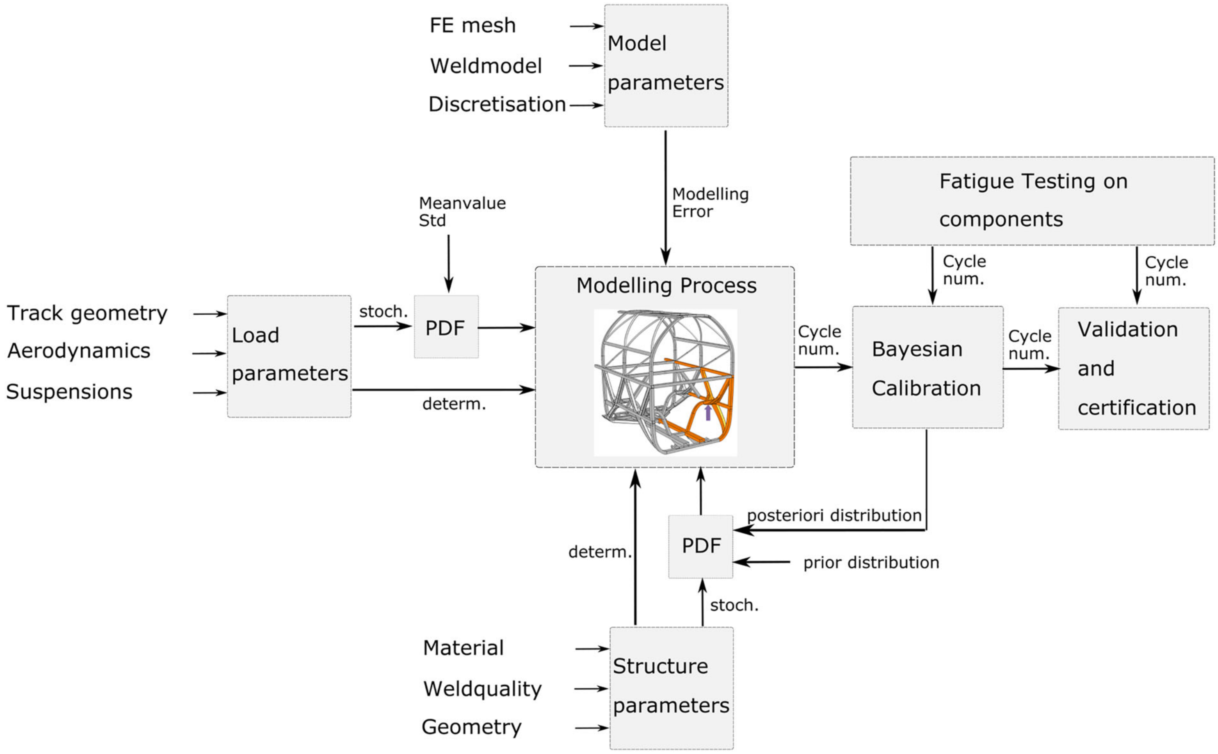

FIGURE 3 Reliability analysis of the fatigue design considering uncertainties. [Colour figure can be viewed at wileyonlinelibrary.com]

3.1.2 | Modeling uncertainty

The accuracy of the FE model depends on the mesh properties and the degree of geometric detail. The material behavior is linear elastic, and geometric nonlinearities are neglected. Since the considered car body structure is stiff and displacements small, this assumption is justified.

The grid size of the mesh can have a large effect on stress results, in particular at edges, corners, and weld seams. By analyzing the stress results while refining the mesh, a compromise between accuracy and computational effort is obtained. In singularities, the stress results do not converge and stresses cannot be evaluated. By interpolating stress results of several elements around the evaluation point, the mesh effect can be partly compensated.[31] In Table 1, the influence of the mesh size on the damage is illustrated for a welded aluminum t-joint (see Figure 5, right) with and without consideration of rounded profile edges. The more detailed model allows converging results while no reliable results are obtained for the simplified model. Probably this is due to the stress singularity created in the edge.

For the damage computation, the stress-time signals are transformed into stress spectra using the Rainflow counting method.[22] As a function of the amplitude and mean stress, the load cycles are attributed to the classes of the Rainflow matrix. Depending on the number of Rainflow classes, this can lead to discretization errors. For the maximum number of Rainflow classes in Femfat (64), discretization errors in the computed life span up to 4% are observed.

TABLE 1 Influence of the mesh size and the geometrical details of the model on the damage.

	Damage	
Element size	**Sharp edge** $R = 0$ **mm**	**Rounded edge** $R = 10$ **mm**
10 mm	$7.145 * 10^{-4}$	$2 * 10^{-2}$
5 mm	$1.885 * 10^{-4}$	$3.103 * 10^{-2}$
2 mm	$4.932 * 10^{-4}$	$6.392 * 10^{-2}$
1 mm	$6.607 * 10^{-4}$	$6.706 * 10^{-2}$

3.2 | Calibration and validation

For a reliable fatigue simulation, the uncertainties of the model parameters need to be quantified. If the uncertainty distributions are observable due to direct measurements, this information can be used for calibrating the model parameters. However, for the various weld parameters of the car body structure (seam thickness, toe angle, seam gap, penetration degree, porosity, etc.), direct measurements would be complex and costly in practice. Besides, for each configuration, numerous tests would be required to determine the uncertainty distribution of each weld parameter. The calibration based on literature data and previous knowledge may not reflect the used manufacturing and maintenance conditions and may impede the fit to the real fatigue behavior of the structure. To allow for the weld parameter calibration based on the observed structural behavior with limited testing effort, the inverse Bayesian approach is applied.

In deterministic calibration, parameter uncertainties are neglected. The calibrated parameter value can be obtained manually or from optimization approaches. Starting from an estimated initial parameter value, the distance between measured and simulated result expressed, for example, by least-squares is minimized using an optimization algorithm.[42,43] The parameter value is iteratively updated until the best fit between measurement and simulation is obtained.

The Bayesian calibration applies this inverse approach to probabilistic parameters. Staring from initial (prior) estimations of the input parameter uncertainties, the parameter uncertainty distributions are updated and uncertainties reduced based on measurement results. As a result, no deterministic values but the most likely uncertainty distributions of the parameters are obtained leading to a life span scatter best fitting the measured data.

3.3 | Calibration process

The calibration process is outlined in Figure 4. First, the damages that appear during the fatigue test of the car body structure are analyzed in order to identify the relevant joint types and weld shapes where damage appears first. For these configurations, which determine the life span of the car body structure, component fatigue tests are realized aiming at calibrating the corresponding weld parameters (weld geometry and overall quality). The calibration using component tests is based on the assumption, that the component test results are transferable to the car body structure.

For this work, component tests are performed for butt joints and t-joints representing typical structural elements of the car body structure at which damage appears. For each joint, several fatigue tests are performed in order to analyze the scatter of the measured life cycles until damage. For detecting damage both in the car body structure and in the component tests, changes in the structural stiffness are monitored during the test based on the applied load and the deformation of the structure. In addition, strain gauges are used to identify changes in the structural behavior of the car body.

The measured life spans of the component tests are used as input to the inverse approach for quantifying the weld parameter uncertainties. The initial (prior) uncertainty distributions of the model parameters are updated using Bayesian technique by optimizing the fit between simulated and measured life span scatters.

The calibration parameters must be those that determine the scatter of the life spans. These parameters can be as follows:

1. physical weld seam parameters (gap size, weld seam thickness, etc.) or
2. global weld quality parameters without direct physical meaning (scaling factor)

The selection of the adequate calibration parameters is made based on the results of the sensitivity analysis

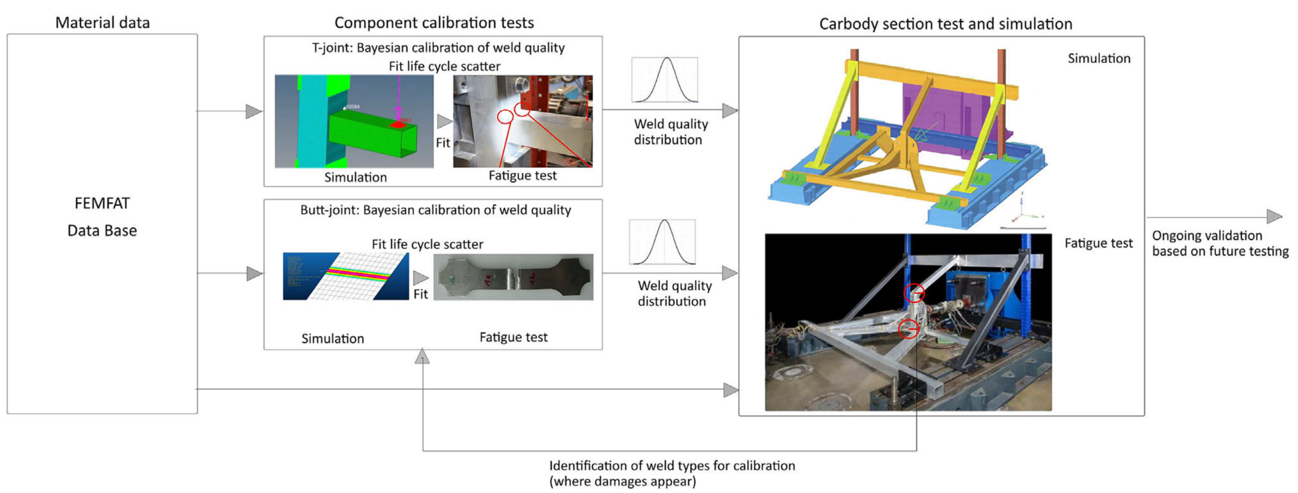

FIGURE 4 Calibration process for weld parameters. [Colour figure can be viewed at wileyonlinelibrary.com]

and component tests. Based on these results, a global weld quality parameter is used for the Bayesian calibration. This weld quality parameter covers all physical weld seam properties, including the geometric discrepancies and the overall quality of the weld.

In principle, the Bayesian calibration process can be applied to any set of parameters including geometric weld parameters. However, since the variation of the life span is determined by uncertainty sources in addition to the weld geometry parameters, the calibration of the geometric parameters could lead to nonphysical results due to compensation effects. In the absence of specific weld measurements, calibrated weld geometry parameters cannot be validated against measured values. Instead, the goal of the calibration to increase the likelihood of the simulation to reproduce the observed life span scatter can be ensured by calibrating the global weld quality parameter. In conclusion, by using the most probable values of the geometric parameters based on previous knowledge (reliable literature data), the explanatory force of the physical model is ensured. The observed uncertainty of the life span is added to the simulation using a global quality parameter including all uncertainty sources.[12]

The calibrated weld quality parameter uncertainties are then used as input to the fatigue simulation of the car body structure. By merging the calibration results of the component tests, a virtual design process as used, for example, in aircraft applications[6,44,45] can be implemented. The reliability of the simulation needs to be validated by comparisons with additional fatigue tests of the car body structure.

The steps of the calibration process are outlined in the following sections.

3.4 | Sensitivity analysis

In order to identify the relevant weld parameters, influencing the life span of the structure, numerical sensitivity analysis is applied first.[46] Each parameter is varied individually around a working point of the system with all other parameters fixed. The consideration of coupling effects within a global analysis would require additional datasets.

The sensitivities are obtained by modifying the notch factors computed from detailed FE models of the welds. For every weld geometry parameter (see Figure 2), notch factors are available for three weld qualities (standard, improved, and degraded) according to the investigations made by Femfat.[31] The analysis is thus performed by interpolating the notch factors between these values using a bilinear function. By analyzing the damage computed for the three weld seam qualities, a linear relation is observed for the weld seam gap and the weld quality. For the weld seam thickness, the relation is nonlinear. In the latter case, the bilinear approach can lead to errors in the sensitivity analysis and the creation of additional notch factor data sets from detailed FE models is recommended for future work.

The values of the weld parameters for the low, standard and high quality are summarized in Table 2 for a thickness of 10 mm. Between the values given in the Femfat Database and in the DIN EN 10042, some discrepancies are observed.

The detailed FE models have been created for three quality levels of each weld geometry parameter, while the other parameters are fixed at their nominal value. Consequently, the available notch factors do not describe the effect of parameter combinations.

The scatter of the life span obtained in the numerical sensitivity analysis is compared to the scatter observed in the component fatigue tests, outlined in the following section. The aim is to include all parameters which determine the life span scatter into the model. For the two test series of the t-joint with constant weld geometry parameters each (within the framework of the manufacturing tolerances), a relevant scatter of the life span is observed, which is thus not explained by the considered geometry parameters. To include this uncertainty effect on the life span scatter in the model, a global weld quality parameter is used for calibration.

TABLE 2 Weld parameter values for the sensitivity analysis.

		Weld quality			
Parameter	**Type**	**Low**	**Standard**	**High**	**Data source**
Seam thickness (mm)	Local	7 (8)	10	15 (13)	Femfat (EN 10042)
Toe angle (°)	Local	90	100	110	Femfat (EN 10042)
Seam gap (mm)	Local	5	1.67	0	Femfat (EN 10042)
Penetration degree (%)	Local	0	50	50	Femfat
Quality class (-)	Global	0.7	1	1.5	Femfat

3.5 | Fatigue component tests

The probability density functions of the weld parameters, which are identified as relevant by the sensitivity analysis, need to be quantified using calibration. This can be done either by direct measurements or by solving an inverse calibration problem. Since direct measurements of the weld parameters are costly or even impossible with nondestructive methods,[41,47] the inverse Bayesian calibration using measured loads and life spans is sought.

According to Figure 4, component calibration fatigue tests and one fatigue test of the car body structure are performed. For the parent material, comprehensive datasets are available from literature including SN curve data with confidence intervals (survival probability).

The scatter of the life span of the butt welds is analyzed using a series of fatigue tests under a sine excitation with approximately constant amplitude and mean value. The probes are produced manually without introducing any intentional geometrical variation. The weld seam geometry parameters are not evaluated. Based on the available dataset including the amplitude and mean value of the load as well as the corresponding number of cycles until damage, the weld quality parameter of the corresponding simulation model is calibrated.

The most frequent weld type in the car body structure is the filet weld in t-joints. For the calibration, two series of fatigue tests are performed for a t-joint aiming at analyzing and calibrating the weld parameters under realistic load conditions in a representative component of the car body structure (Figure 5, left). This shall ensure the transferability of the calibration results to the car body structure simulation. The effect of possible additional residual stresses in the car body structure due to the manufacturing process could not be considered.

The two test series represent different weld qualities. Based on these tests, the finite life section of the component SN curve is analyzed, using the pearlstring approach.[39] Unlike the test-horizon approach, this approach is adapted, if only few prior knowledge is available about the component SN curve. Based on prior simulation and test results of the SN curve, the amplitude and mean load for the first test can be selected such that the result is situated in the core area of the finite life fatigue curve. The following fatigue probes are then tested at higher and lower amplitude levels, keeping the R-ratio constant. Thereby, unusable fatigue tests in the high cycle fatigue and low cycle fatigue area are avoided.

For the calibration process, the probability density function respectively the confidence interval of the SN curve are required. Assuming that the confidence interval of the SN curve is constant within the finite life area, all experimentally derived results can be shifted along the 50% SN curve to a defined reference load. The 50% SN curve is obtained by linear regression, as illustrated in Figure 5 (center).

The first test series is performed for symmetric filet welds with high quality. In the second series, the weld quality is degraded by manufacturing asymmetric weld seams with a smaller and thus more critical weld toe angle. By comparing the SN curve of the two test series, the influence of the weld quality is studied.

3.6 | Bayesian calibration approach

In the Bayesian calibration, the parameters are not described by deterministic values but probability density functions. The approach thus allows quantifying input

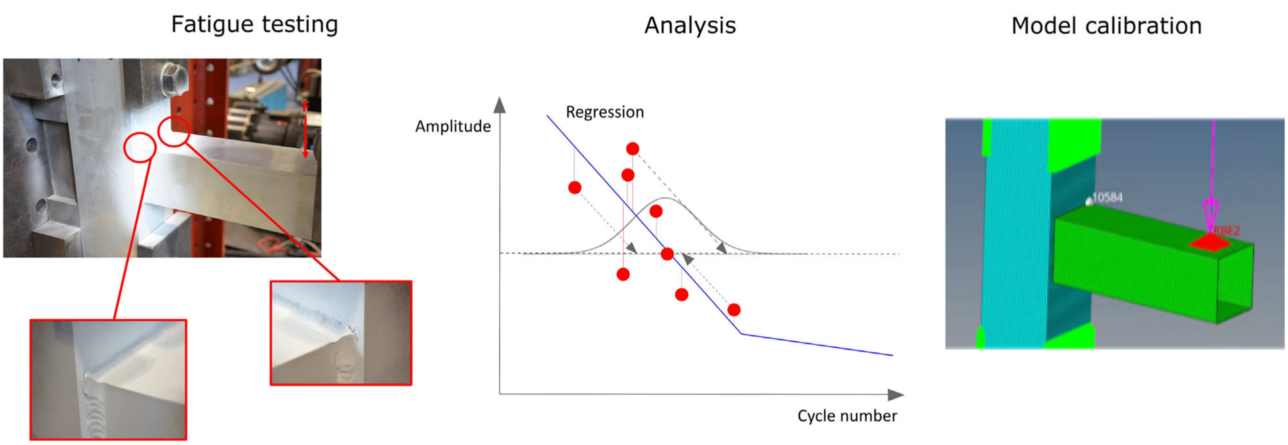

FIGURE 5 Fatigue test of the t-joint (left), computation of the life span distribution from test samples (center) and FE model (right). [Colour figure can be viewed at wileyonlinelibrary.com]

distributions for probabilistic simulations in the reliability analysis (Figure 6).

Starting point of the calibration is a priori estimation of the parameter distribution, which shall be calibrated by fitting the distribution of the simulated life cycles to the distribution of the measured ones. Based on this prior estimation of the probability density function and the results of the fatigue tests, an improved posteriori distribution is obtained.

Considering a normal distribution of the weld seam quality factor, the prior is given by the mean value and the standard deviation. The mean value is set to 1, corresponding to the standard weld quality as defined in the Femfat database. For the standard deviation, no initial information is available and a value of 0.1 is selected for the prior.

Mathematically, the computation of the posteriori distribution requires the likelihood $L(y,\Omega)$ of the measurement data y and the parameters to calibrate Ω. It expresses the similarity between the measured and the simulated life span distribution as a function of the weld parameters Ω. Contrarily to the simulation model itself, the weld parameters Ω are considered as an input to the likelihood function, while the inputs to the simulation model, in this case the acting loads, are considered as fixed parameters.

Based on the likelihood $L(y,\Omega)$ and the priori distribution of the weld parameters $d(\Omega)$, the posteriori distribution of the weld parameters $d(\Omega,y)$ is obtained according to the Bayesian theorem[15] as follows:

$$d(\Omega,y) = \frac{L(y,\Omega)d(\Omega)}{m(y)} \tag{1}$$

By using the normalization constant $m(y)$, the probability density function of the posteriori distribution integrates to 1.

The solution of the Bayesian theorem has in general no closed form and needs to be approximated using stochastic sampling methods. In this work, the random walk Metropolis Hasting algorithm is used. Due to the required number of model evaluations, the solution of the Bayesian equation is computationally expensive. The use of the FE model is therefore restricted. By replacing the FE model by a simpler surrogate model, the sampling can be realized. However, the surrogate model needs to be trained and validated based on the physical model, allowing sufficient accuracy.

3.7 | Uncertainty propagation and reliability of the fatigue design

The identified parameter uncertainties are propagated through the simulation process and lead to uncertainties in the computed life span of the car body structure. Based

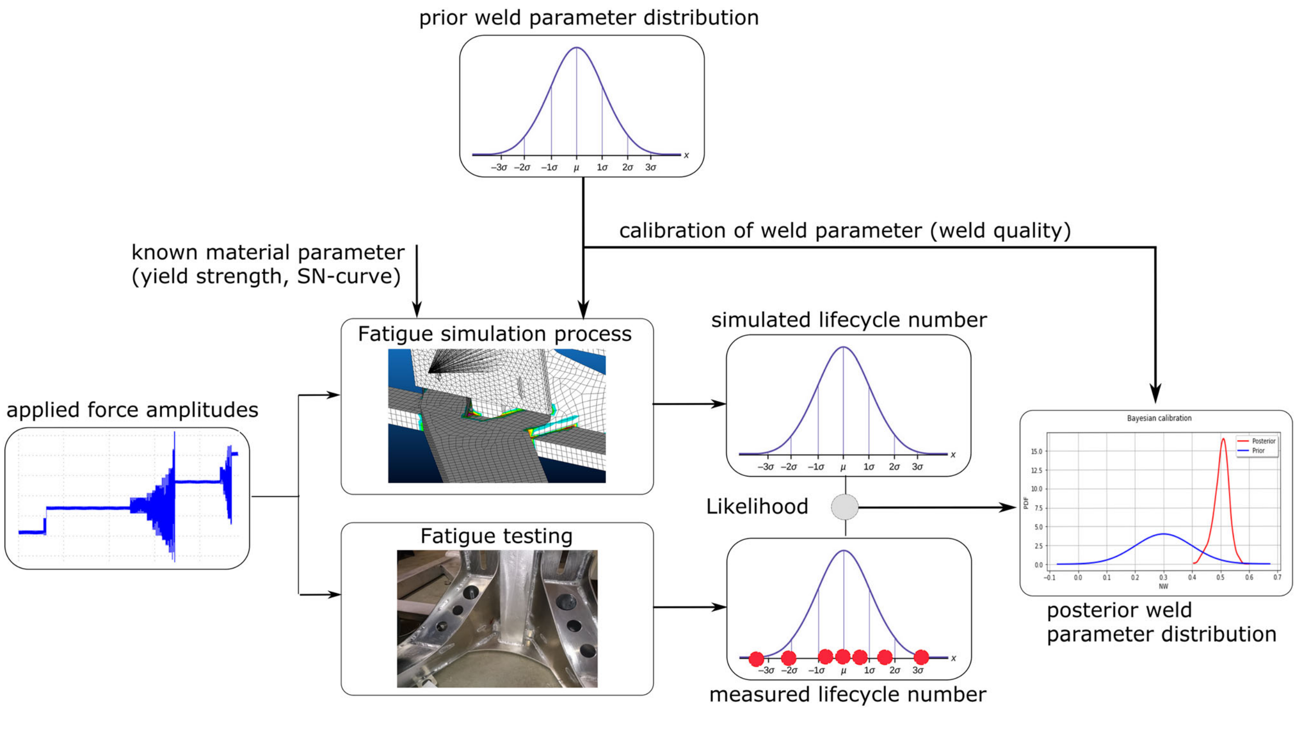

FIGURE 6 Bayesian calibration process for weld parameters based on fatigue test results. [Colour figure can be viewed at wileyonlinelibrary.com]

on the obtained probability density function, reliability analysis is performed and the simulation compared to test results.

The reliability analysis aims at identifying the failure probability that the car body does not reach the required life span. In the same way, the safety margin of the simulation compared to measured results can be quantified by computing the probability that the simulated life span exceeds the measured result.

3.7.1 | Sampling methods

For the reliability analysis, sampling methods are applied.[48] The commonly used Monte-Carlo sampling covers the complete range of the input parameters and allows evaluating the mean value and variance of the life span distribution. The failure probability $P(F)$ that the life span is below the required value l_{target}, thus $P(F) = P(l < l_{target})$, is given by the fraction of samples for which $l < l_{target}$ corresponding to the P-th percentile of the distribution. Due to the concentration of samples in the area of high probabilities, a large number of samples has to be computed for evaluating low failure probabilities requiring sufficient samples with $l < l_{target}$. Otherwise the failure probability is estimated with large error or even becomes 0. By using meta modeling, which replaces the costly FE model, high sample numbers can be realized. However, the meta model is trained and calibrated based on a limited number of FE samples and introduces an unknown error to the failure probability estimation.[49]

In order to obtain a more precise estimation of the failure probability, adapted sampling methods exist, which focus on the distribution around the failure probability. The subset sampling[48] transforms the computation of the rare failure probability into a series of more frequent failure events using conditional probabilities. By using importance sampling,[50] a larger fraction of samples is situated in the region of the failure probability.

3.7.2 | Car body fatigue test

The simulated life span distribution is compared to the result of a fatigue test of the car body section (Figure 2). Due to the cost for manufacturing and testing of the car body structure, only one fatigue test could be performed, so that knowledge about the measurement uncertainty is not available. It is analyzed with which probability the simulation-based design gives a higher life span than the actually measured one.

In the test, the structure is excited only by the vertical air spring force. The sensitivity analysis in Kraft and Lüdicke[37] indicated that this force has the highest influence on the damage in the car body structure. The load-time signal is obtained from MBS simulation of the NGT and transformed into a load spectrum using Rainflow counting. The load is then applied as a sine with frequencies between 1 and 4 Hz. The application of the load spectrum is repeated with increasing amplitude (see Table 4) until damage in the structure in form of cracks appears. The damage is detected by monitoring stiffness changes, which are measured using strain gauges.[51]

3.7.3 | Validation

A comparison of the calibrated weld quality with measured weld quality in the car body structure is not possible. First, measurements of the weld parameters are not available. Second, the selected calibration parameter has no direct physical meaning but covers all weld properties, which have an impact on the life span. For the component tests, the reliability of the simulation is ensured by fitting the simulated to the measured life span distributions. In order to validate the simulation results for the car body structure, additional fatigue tests should be performed.

4 | RESULTS

Based on the outlined methods, fatigue tests and simulations are performed and analyzed. The potential for using the approach in a virtual design and certification process for railway car body structures is evaluated.

4.1 | Butt joint component test

The influence of the butt weld seam quality on the life span is analyzed for welded probes (Figure 4). Bayesian calibration is applied for the calibration of the corresponding simulation model based on the fatigue test results of 8 probes. Table 3 gives the input forces (amplitude and mean value) as well as the number of cycles until damage.

The observed scatter of life spans due to varying properties of the welds is considered in the calibration process. The fatigue tests are reproduced by the simulation-based fatigue design process described in Section 2. The global weld quality parameter is introduced as an uncertain model parameter in the simulation and used for calibration.

TABLE 3 Fatigue testing of welded probes.

Probe number	Amplitude (N)	Mean value (N)	Number of cycles (-)
1	3135	3835	1,161,885
2	3190	3860	1,025,860
3	3175	3835	1,102,179
4	3145	3845	1,515,304
5	3175	3810	1,228,880
6	3165	3800	1,340,296
7	3175	3825	1,077,852
8	3190	3860	1,061,452

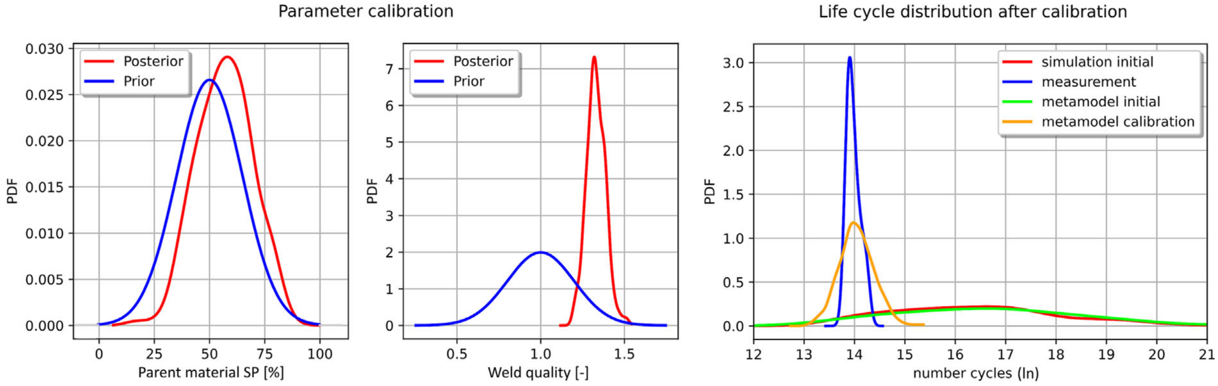

FIGURE 7 Prior and posteriori distribution of the parent material survival probability (SP) and butt weld quality (WQ) (left) and distributions of the life cycles for the initial FE and meta model, as well as the measurement and the calibrated meta model (right). [Colour figure can be viewed at wileyonlinelibrary.com]

4.1.1 | Sensitivity analysis

The influences of the force amplitude and mean value as well as the parent material SN curve uncertainty and the weld seam quality are analyzed using a multilinear regression analysis. For this purpose, the input parameter distributions are defined and Monte-Carlo sampling is performed. As priori distribution of the weld quality, the default value 1 and a standard deviation of 0.1 are assumed. The yield strength and stiffness of the material are considered as constant.

The standard regression coefficients (SRC) of the obtained samples indicate nearly linear behavior with a R^2 value of 0.99 and the paramount influence of the weld quality parameter on the life span.

4.1.2 | Calibration

For the calibration, the parent material influence and the weld quality are taken into account. Considering the large number of samples required for the calibration, the sensitivity data set is used for the training and validation of a meta model. A polynomial chaos model of order 3 gives the best validation result with a R^2 value of 0.99.

By fitting the measured and the simulated distributions of the life cycles using the log likelihood, the model parameters are calibrated. The obtained posteriori distribution is shown in Figure 7 (left). Based on the calibration result, the Monte-Carlo sampling is repeated. The life cycle distributions of the measurement as well as the initial and calibrated model are computed using kernel fitting techniques and compared in Figure 7 (right). The calibration allows adapting the simulation to the measurement.

4.2 | T-joint component test

For the welded t-joint, the influence of the weld parameters on the damage is studied by experimentally determining the component SN curves for the two test series with different weld geometries. A pulsating tensile sine force with varying amplitude is applied to the crossbeam of the t-joint.

Based on simulation results, the starting amplitude for the pearlstring method is selected at 1.0 kN, leading to approximately 100,000 life cycles. Then the amplitude is increased and lowered from this value. Figure 8 shows the experimentally derived life spans for the two test series together with the corresponding SN curves with 50% survival probability obtained from linear regression. The experimentally derived life spans are shifted along the SN curve to the reference amplitude for computing the probability density functions needed in the calibration. A clear effect of the two weld seam qualities is observed. At the same time, each test series shows a relevant scatter.

4.2.1 | Sensitivity analysis

The influence of the geometric filet weld parameters is studied using the numerical model by varying the notch factors between the good and the low weld quality using bilinear interpolation according to Table 2. Figure 9 shows the resulting component SN curves as a function of the weld geometry parameters. The spread of the SN curves is expressed by the percentage of variation with respect to the standard value indicating that the weld quality parameter has the highest influence on the damage. Among the geometry parameters, the weld seam thickness and the gap size are equally relevant.

Contrary to the literature, no effect of the toe angle is observed. This result can be explained by the dependency of the weld thickness to the toe angle. The positive effect due to an increasing weld toe parameter is compensated by the smaller weld seam thickness due to the more concave shape. The results outline the limitations resulting from the local analysis without considering dependencies and coupling effects.

Based on the numerical sensitivity analysis and the result of the t-joint component tests, the global weld quality parameter is selected for Bayesian calibration. It includes both the life span scatter due to uncertainties in the geometry parameters and the scatter observed in the component test for constant weld geometries due to uncertainties sources, not described by the physical model.

4.2.2 | Calibration and validation

Starting with the priori distribution of the weld quality and the material SN curve survival probability, Monte Carlo sampling is performed. The multilinear regression analysis between the input parameters and the damage indicates a relatively linear system behavior with a R^2 value of 0.92. The standard regression coefficients indicate that the amplitude has the highest influence on the damage, followed by the weld quality parameter. Since the amplitude is known during measurements and not of interest for the model calibration, the calibration is applied to the weld quality parameter and the parent material SN curve.

For the meta model, a polynomial chaos model of order 3 with a sufficient number of training samples gives the best validation quality.

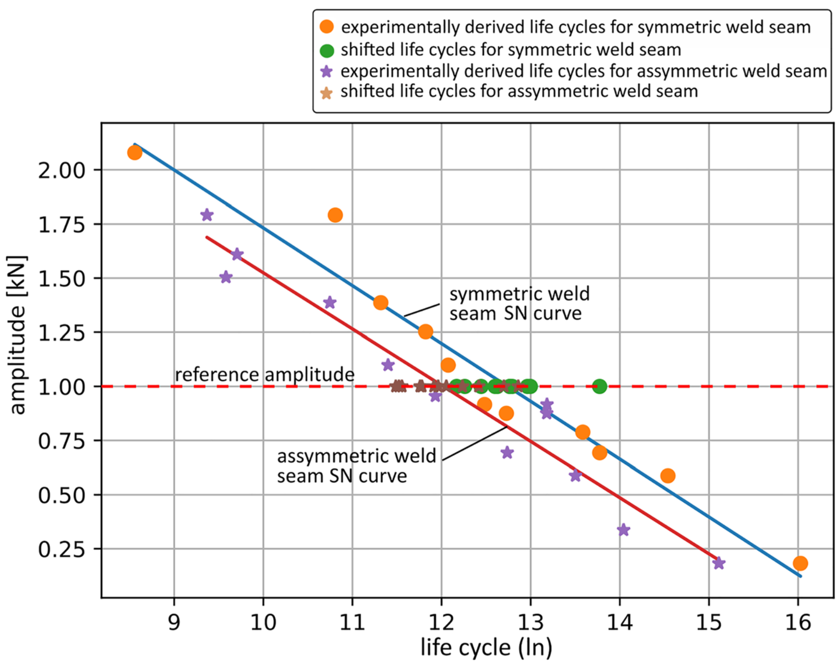

FIGURE 8 Measured life cycles and 50 % SN curve for the two fatigue test series of the welded t-joint. [Colour figure can be viewed at wileyonlinelibrary.com]

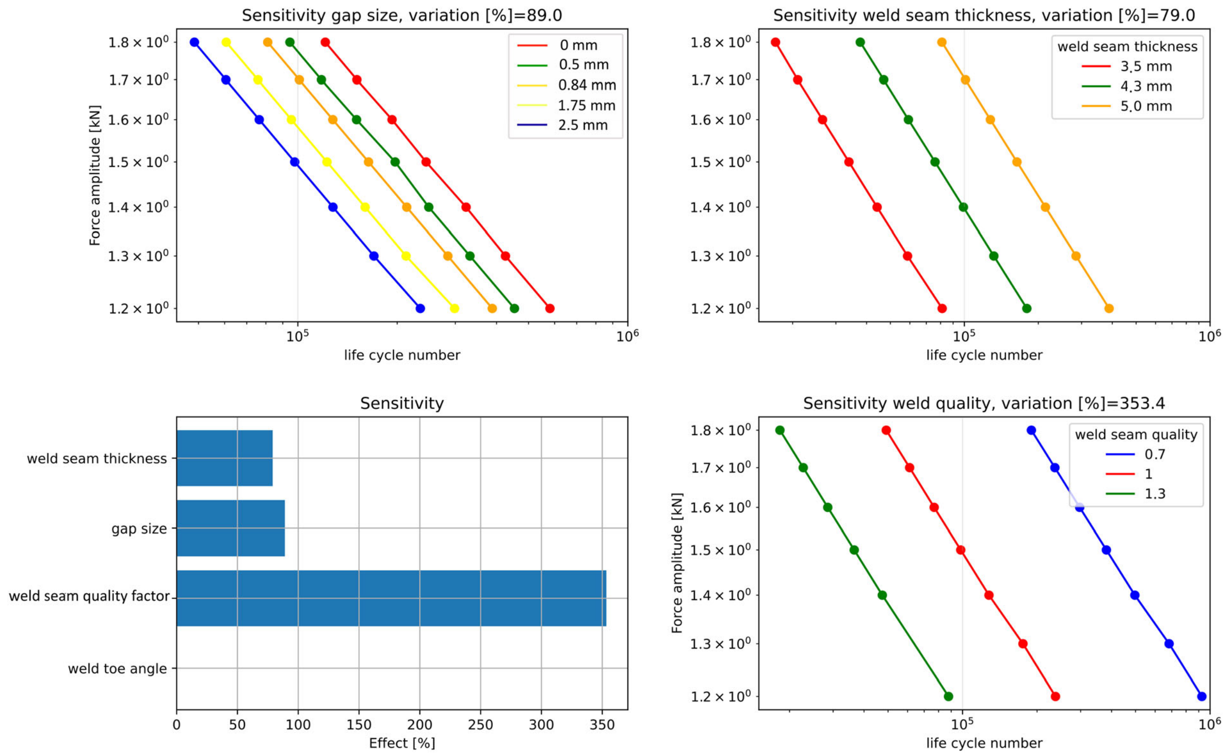

FIGURE 9 Simulated influence of the weld parameters on the SN curves and SRC regression coefficients. [Colour figure can be viewed at wileyonlinelibrary.com]

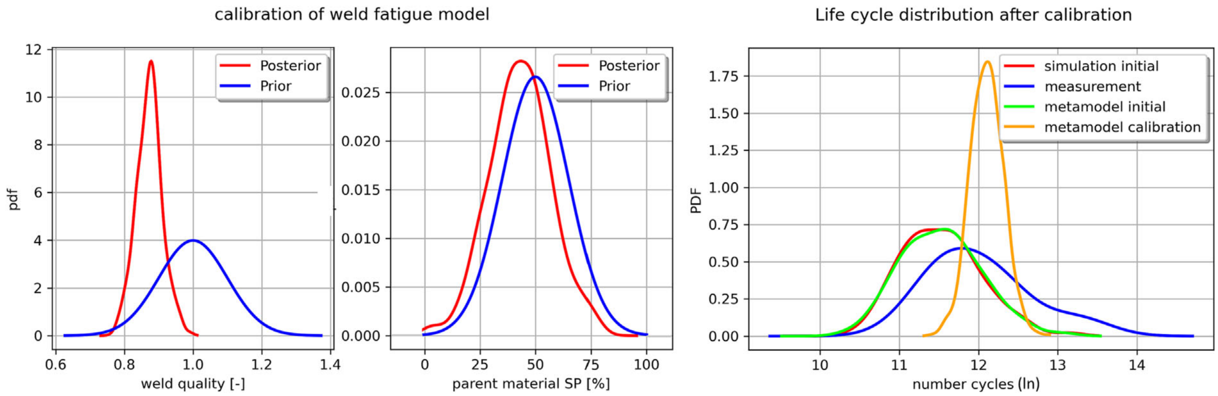

FIGURE 10 Priori and a posteriori distribution of the weld parameters (left) and comparison of measured, initial and calibrated distribution of the life span (right). [Colour figure can be viewed at wileyonlinelibrary.com]

As priori distributions in the Bayesian calibration standard weld quality with normal distributions are assumed: The weld quality parameter is defined at 1 with a standard deviation of 0.1 and the material SN curve at 50% with a standard deviation of 15%. From the fatigue tests (Section 4.2), force amplitudes and corresponding life cycles at nearly constant mean force are applied to the calibration.

The results of the calibration are given in Figure 10 (left). It is found that only the weld quality parameter is updated while the material SN curve distribution remains nearly unchanged. This can be explained with the much higher sensitivity of the weld seam quality on the life span.

Based on the calibrated model parameters, the Monte Carlo sampling of the SN curve is repeated and the probability density function of the measured and simulated life spans are computed and compared in Figure 10 (right). The measured distribution shows a large spread reducing the quality of the calibration. By measuring SN curves at fixed mean values, this spread could be reduced in future calibrations.

4.3 | Car body structure fatigue testing

4.3.1 | Testing

For the validation of the simulation-based fatigue design of the car body, a representative section of the car body structure has been tested, as outlined in section 3.7.2. The same load spectrum as for the fatigue test is applied to the simulation. It is composed of several blocks, where each block is given by the scaled load spectrum of the vertical air spring force. The complete load spectrum of the fatigue tests and simulation is summarized in Table 4. The higher number of cycles in the first block compared to the second, despite the lower number of runs is due to the fact that small amplitude cycles have been removed from the load spectrum after the first block in order to reduce the duration of the test.

After applying the 5,565,500 cycles of the load spectrum, cracks were detected in welds of the suspension support structure. Based on the measurement result, the weld quality and the material SN curve are defined as a variable input parameters to the simulation. All other model parameters including the geometry of the structure, the material properties and the applied loading are considered as exactly known, deterministic parameters.

4.3.2 | Static model validation

For the static validation of the model, strains are measured at 27 positions on the car body structure using strain gauges. The results are compared with the computed strains at a given static load. The focus is put on high strain values measured in areas with possible fatigue damage. Due to the used mesh size, significant strain gradients between neighbor elements are observed, leading to uncertainty in the simulated strains. For the highest measured strains, comparisons are given in Table 5 for a load of 37.75 kN.

4.3.3 | Fatigue model validation

The validation of the fatigue behavior is performed by comparing the location and the number of life cycles until damage. The simulated life cycle number varies according to the randomly selected input parameters. By applying a sampling method, a probability distribution is obtained and compared to the measured life cycle number in Figure 11.

The location of the damage in the simulation is in accordance with the fatigue test result. Cracks appear in welds at the air spring support structure. Since only one test could be performed, a validation of the life span considering measurement and simulation uncertainties is not possible. However, by defining the measured life cycle number as threshold event on the simulated distribution, the probability that the real structure fails earlier than the simulated life span is estimated between 10% to 12%. For the validation of the simulated life span distribution, additional fatigue tests for the car body structure should be performed.

4.4 | Discussion of the results

The available detailed FE models reproduce the physical behavior of welds with high precision and have been validated in literature. The use of these models in the car body model requires the calibration of numerous

TABLE 5 Static validation based on strain gauges.

Strain gauge	Measurement (mm/mm)	Simulation range (mm/mm)
1	3.2E−4	2.3E−4 to 3.1E−4
2	5.7E−4	3.3E−4 to 3.6E−4
3	6.6E−4	6.6E−4 to 6.7E−4
4	6.1E−4	4.3E−4 to 7.3E−4

TABLE 4 Load spectrum of the car body structure fatigue test.

Part	Mean scale	Amplitude scale	Repetitions	Number cycles
1	1	2	84	2,109,744
2	1	2	92	688,896
3	1	5	100	748,800
4	1	10	55	411,840
5	1	15	38	282,400
6	1	10	100	747,450
7	1	15	77	576,370

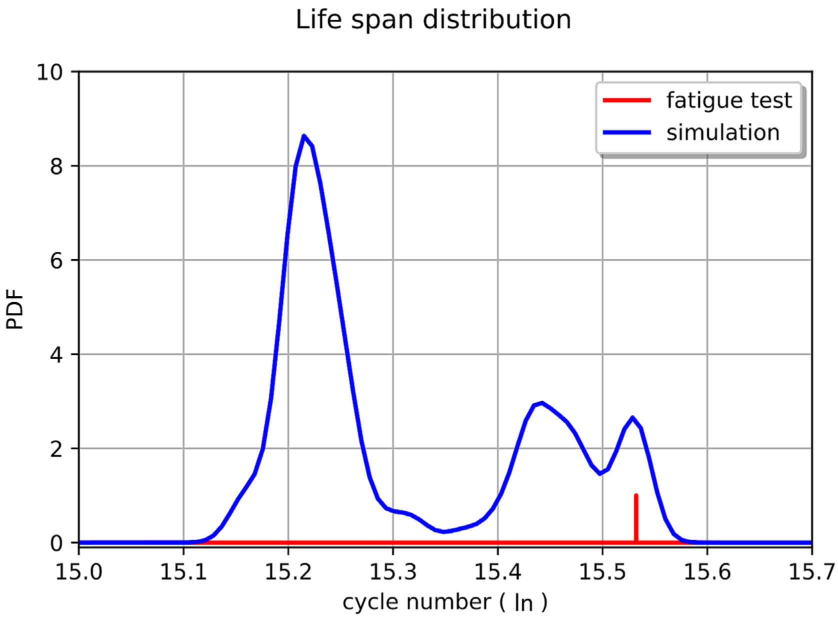

FIGURE 11 Estimation of the life span for the car body section and fatigue test result. [Colour figure can be viewed at wileyonlinelibrary.com]

parameters. A direct measurement of these parameters would be costly and is not feasible. Relying only on literature data for the parameters values and their uncertainties might not reflect the manufacturing and maintenance conditions under use.

To tackle these issues, the applied Bayesian calibration approach combines in an efficient way a small number of component tests with a meta modeling approach. The Bayesian calibration can be applied to any set of model parameters, using priori distributions. In the absence of measurements, these priori parameter uncertainty distributions are based on literature data. By making the choice of calibrating a global weld quality parameter instead of several individual weld geometry parameters, all uncertainty sources are considered, including weld quality uncertainties not included in the physical model, that is to say not described by the geometry parameters. Possible compensation effects in the calibration of several geometry parameters are avoided, keeping in mind that the calibrated uncertainties of the weld geometry parameters could not be validated in the absence of specific weld geometry measurements. By using well-established literature values for the geometry parameters the explanatory force of the weld model is recognized. The goal to increase the likelihood that the simulation reproduces better the observed scatter of the life span is reached by calibrating the uncertainty distribution of the overall weld quality parameter.

The relatively simple setup of the component tests ensures the precise application of loads reducing unknown preloads due to the assembly process of the structure. The distribution of the observed life span is thus due to uncertainties of the material and weld parameters, allowing for a more precise calibration than in the complex car body structure. Nevertheless, additional fatigue test should be performed to validate the transferability from the component tests to the complete structure of the car body, considering that additional uncertainty sources impact the life span of the car body structure, including unknown preloads which have been neglected in this work considering the high dynamic loads acting on the car body.

5 | CONCLUSIONS

Replacing static loads with dynamic operating loads for the fatigue design of railway car bodies allows improving the structural design with respect to real load conditions. The potential of lightweight design can be fully utilized in order to design resource- and energy efficient vehicles.

Fatigue design of railway vehicles based on real-life testing is costly or sometimes even impossible to perform. Simulation tools shall replace testing at least partly, forming the basis for a virtual design and certification of the vehicle. This leads to high requirements for the simulation process, in particular the calibration and validation of the results. Considering the numerous loading, structural and material parameters, some of them characterized by large variations, the quantification and propagation of uncertainties is required.

In this work, a Bayesian calibration process for the car body structure is outlined, aiming at identifying relevant uncertainty sources and calibrating the corresponding probability density functions. Since weld seams have a critical influence on the life span, the calibration focused on weld parameters. The direct calibration of the weld parameter uncertainties based on specific measurements would be very costly or even impossible in practice. The definition of parameter uncertainties without calibration might lead to unreliable results, not covering all uncertainty effects on the life span scatter. Therefore, an inverse approach using Bayesian calibration has been implemented. The most likely uncertainties of the model parameters are obtained by fitting the simulated to the measured life span distributions.

The calibration parameter has been selected based on the numerical sensitivity analysis and the component fatigue tests. First, the sensitivity analysis showed, that the fatigue resistance of welds depends on several geometry factors. Second, the observed scatter of the life span is not only determined by the physical weld geometry parameters included in the model. Furthermore, in complex structures like a car body, physical parameters of a specific weld type are not homogenous within the structure. Based on these outcomes, a global weld quality parameter is used for the Bayesian calibration, allowing considering all uncertainty sources in the modeling process. The application of the Bayesian calibration approach to different parameters sets is proposed for future work.

The calibration of the global weld quality parameter is performed for joint types and weld shapes, which are relevant for the damage of the car body structure. The distribution of the weld quality parameters obtained from the component tests are then used as input to the fatigue simulation of the car body structure. This transfer of the calibration results from the component test to the car body structure (or another application) implies that the uncertainty sources including, for example, manufacturing and testing conditions are similar. If, for example, different welding techniques are used, the transferability of calibration results between applications is not ensured. Therefore, the transferability of the calibrated weld quality parameter remains a task for future work.

In conclusion, this work outlined how FE modeling of welds, a limited number of component fatigue tests and the Bayesian calibration approach can be used to increase the reliability of the fatigue simulation of a complex rail vehicle structure.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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