

Ductile damage at MnS inclusions in 16MnCrS5 steel - influence of the phase environment

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ARTICLE INFO

Keywords:

Microstructural damage
Semantic segmentation
Scanning electron microscopy
Machine learning
Steel
MnS
Spherical nanoindentation

ABSTRACT

Forming-induced damage strongly affects the service life and mechanical properties of components made from 16MnCrS5 case-hardening steel. In this study, we quantitatively investigate how the local phase environment, specifically ferritic, pearlitic, and mixed regions, around damage sites associated with manganese sulphide (MnS) inclusions affects their nucleation and growth. Using a novel approach based on machine learning-driven segmentation of high-resolution scanning electron micrographs from in-situ tensile tests, we achieve reproducible and efficient identification of phases in ferritic-pearlitic microstructures and quantification of damage sites. Our results reveal that ferritic environments lead to increased damage prevalence when compared to mixed and pearlitic environments. In particular, the growth of damage sites is markedly facilitated when the local ferrite fraction is increased. We explain this with the low strain hardening capability of ferrite compared to pearlite, determined via spherical nanoindentation. In contrast, the nucleation probability is not strongly dependent on the immediate phase environment, as the yield strength of ferrite and pearlite are similar.

1. Introduction

Research on structural materials typically focuses on improvements of mechanical properties. In particular, when improving service life of components, the reduction of forming-induced ductile damage is of importance. Ductile damage, commonly characterised by voids within the microstructure, is known to compromise components' mechanical properties such as energy absorption during impact and endurance under cyclic loading conditions [1–3]. Consequently, maximising component performance requires minimising the prevalence of damage sites, usually quantified by their number or total area, during forming operations.

Typically, a high prevalence of damage sites is predominantly observed in materials that exhibit significant mechanical contrast between microstructural phases [4–6]. Irrespective of the exact mechanism of initiation or material system, damage formation is governed by the different mechanical properties and spatial arrangement of constituent phases. These can be inherent phases, as in dual-phase steels [7–10] or magnesium alloys [11]. In these cases, the mechanical contrast between the constituent phases leads to strain partitioning and subsequent nucleation of damage sites at phase interfaces or via fracture of the more brittle constituent phase [12,13]. In many other materials, however,

damage initiates not from main constituent phases but from particles, such as inclusions or precipitates [14–16]. Whether intentionally added or formed due to impurities [17,18], these inclusions can act as nucleation points for damage.

One example is case-hardening steel 16MnCrS5, which exhibits damage sites that are mainly attributed to the fracture of manganese sulphide (MnS) inclusions or delamination at their interfaces [19]. The damage behaviour and its negative impact on the mechanical properties of this steel are well described in the literature [20–23]. Generally, accelerated failure under fatigue conditions and reduction of impact energy are observed and attributed to damage that nucleates due to the different mechanical properties of MnS and the surrounding steel matrix. However, addition of Manganese and subsequent formation of MnS also provides benefits for manufacturing processes such as resistance to hot shortness [24,25].

In earlier work, we have shown that both the size and number of damage sites differ between individual MnS inclusions and depend on each inclusion's specific location within the steel microstructure [19]. Notably, this variation occurs even at identical levels of applied global strain. We hypothesise that this heterogeneous distribution of damage sites is partially driven by variations in local phase composition (ferrite

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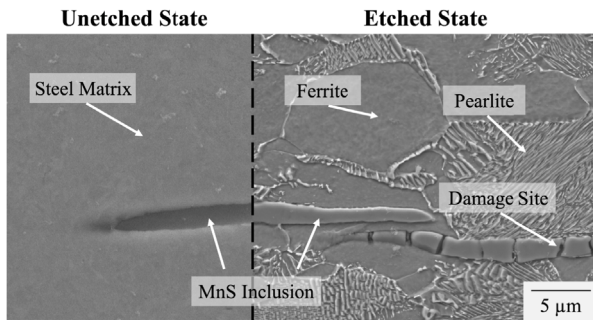


Fig. 1. MnS inclusion in 16MnCrS5 case-hardening steel, showing constituent phases in the unetched (left) and etched (right) states.

vs. pearlite), surrounding each MnS inclusion. Unlike dual-phase steels, where interactions between two inherent constituent phases primarily govern damage formation, the heterogeneous microstructure of 16MnCrS5 contains three distinct phases: ferrite, pearlite and the inclusion phase MnS. As a result, more complex interactions contribute to damage formation. The significance of MnS position in relation to damage has also been recognised by other researchers evaluating individual inclusions [26,27]. However, no quantitative framework directly linking an inclusion's local microstructural environment to its propensity for nucleating and growing damage has yet been established. Developing such a framework is crucial to gain a deeper understanding of the mechanisms governing damage evolution in these multiphase alloys.

In this study we address this gap by investigating how local phase environments affect initiation and growth of inclusion-induced damage sites in multiphase microstructures. In particular, we propose that ferritic regions, being softer than pearlite and accommodating greater strain, facilitate increased damage prevalence around MnS inclusions. Our central scientific question is: Does a higher proportion of ferrite adjacent to MnS inclusions lead to greater damage? Furthermore: Is this effect manifested through more frequent nucleation events, accelerated void growth, or both?

To answer these questions, we quantitatively assess how ferritic, pearlitic, and mixed-phase environments influence the number fraction, area fraction and mean size of voids associated with MnS inclusions. Our analysis provides information at both macroscopic (mm) and microscopic (μm) scales, focusing on statistical trends as well as individual MnS inclusions and their associated damage sites. We achieved this by acquiring high-resolution panoramic scanning electron microscopy (SEM) images at different strains during an in-situ tensile test of an etched 16MnCrS5 case-hardening steel sample. For subsequent automated evaluation across large image datasets, we trained two neural networks based on the nnU-Net architecture [28], enabling segmentation into ferrite, pearlite, MnS inclusions, and damage sites. This approach extends time-efficient statistical analysis previously applied to unetched samples [19,29–32] by incorporating all constituent phases of 16MnCrS5 (see Fig. 1). Finally, to complement our statistical findings, we interpret observed trends using mechanical property measurements obtained via spherical nanoindentation within individual phases.

2. Materials and methods

2.1. Case-hardening 16MnCrS5 steel

Microstructure segmentation and damage quantification were conducted on a case-hardening 16MnCrS5 steel that had been produced by continuous casting. The chemical composition of the steel, previously determined in [33], is provided again in Table 1.

The flow curve of the material has also been previously determined in [2,34] and shows an ultimate tensile strength of approximately 600 MPa and a uniform elongation of approximately 20% true strain.

Its typical ferritic–pearlitic microstructure (visible only after etching) is shown in Fig. 1. MnS inclusions are elongated due to the continuous casting process and embedded in the steel matrix without obvious preferences for pearlitic or ferritic interfaces. MnS inclusions can reach lengths of several tens of micrometres but typically have diameters up to $2\mu\text{m}$ (Fig. 1). When tensile loading is applied parallel to the long axis of the MnS inclusions at ambient temperature, these inclusions typically fracture, resulting in the nucleation of damage sites. This damage initiation mechanism physically separates segments of an MnS inclusion as elastic strain is relieved; continued deformation separates the segments further, as illustrated in Fig. 1. All experiments were performed on the as-received material. Aside from the in-situ tensile tests themselves, no additional forming steps or heat treatments, including case hardening, were carried out.

2.2. Sample preparation

To prepare samples for in-situ tests, dog-bone-shaped specimens were machined from a 16MnCrS5 steel billet using electrical discharge machining. The sample geometry (Fig. 2) featured a sheet thickness $h = 1.5\text{ mm}$, gauge length $l = 3.56\text{ mm}$, and gauge width $w = 1.5\text{ mm}$.

Once machined, the samples were metallographically prepared to obtain a flat surface suitable for SEM imaging. To this end, each sample was initially ground with silicon carbide (SiC) sandpaper up to a grit size of 4000 and subsequently polished mechanically with water-based diamond suspensions ($3\mu\text{m}$ and subsequently $1\mu\text{m}$) and water as a lubricant. As a final polishing step, the sample surface was polished with an oxide polishing suspension (OPS), followed by etching in 3% nital for 9 s to reveal the pearlitic phase.

2.3. In-situ tensile test

After mechanical preparation, the sample was mounted in the chamber of the SEM (Clara, Tescan) and the surface was imaged using panoramic imaging with a secondary electron (SE) detector at an acceleration voltage of 10 kV and a beam current of 1 nA. In total, 150 images were acquired per strain state, each covering an area of $100\mu\text{m} \times 100\mu\text{m}$, at a resolution of $100\mu\text{m}/3072\text{ px}$ and an overlap of 15% on each side. These images were subsequently stitched to generate a single panoramic image encompassing approximately 1.1 mm^2 . Following initial imaging of the sample surface, the sample was transferred to a micro-tensile stage (Proxima, microMECHA) and deformed incrementally to a plastic strain of 3%. After each deformation step, the same surface region was re-imaged using the panoramic SEM approach. This procedure was repeated at further plastic strains of 4 more times at plastic strains of 5%, 8%, 10% and 14%. To compensate for specimen elongation during deformation and to maintain consistent coverage of the chosen region at increasing strain levels, the number of images per panoramic scan was gradually increased up to 180 images at the highest strain level. This adjustment resulted in a total imaged area of about 1.3 mm^2 at (14%) final strain, which was still within the regime of uniform elongation.

2.4. Image segmentation using neural networks

To enable segmentation of the microstructure into its constituent phases and to quantify damage sites, two separate neural networks, both based on the nnU-Net architecture [28], were trained and fine-tuned using the acquired SEM data. Hereafter, these networks are referred to as phase-net and damage-net, according to their respective purposes. In total, three different datasets were prepared for training purposes and annotated using the Computer Vision Annotation Tool (CVAT) [35]. The characteristics of these datasets are summarised in Table 2 and more information on the design choices of the neural networks is given in the supplementary materials.

Table 1
Chemical composition of 16MnCrS5 case-hardening steel (in wt.%).
Source: From [33].

Element	C	Si	Mn	P	S	Cr	Mo	Ni	Al	Co	Cu	Nb	V	Fe
Wt. %	0.20	0.17	1.24	0.03	0.03	1.05	0.04	0.14	0.03	0.01	0.16	0.01	0.01	Bal.

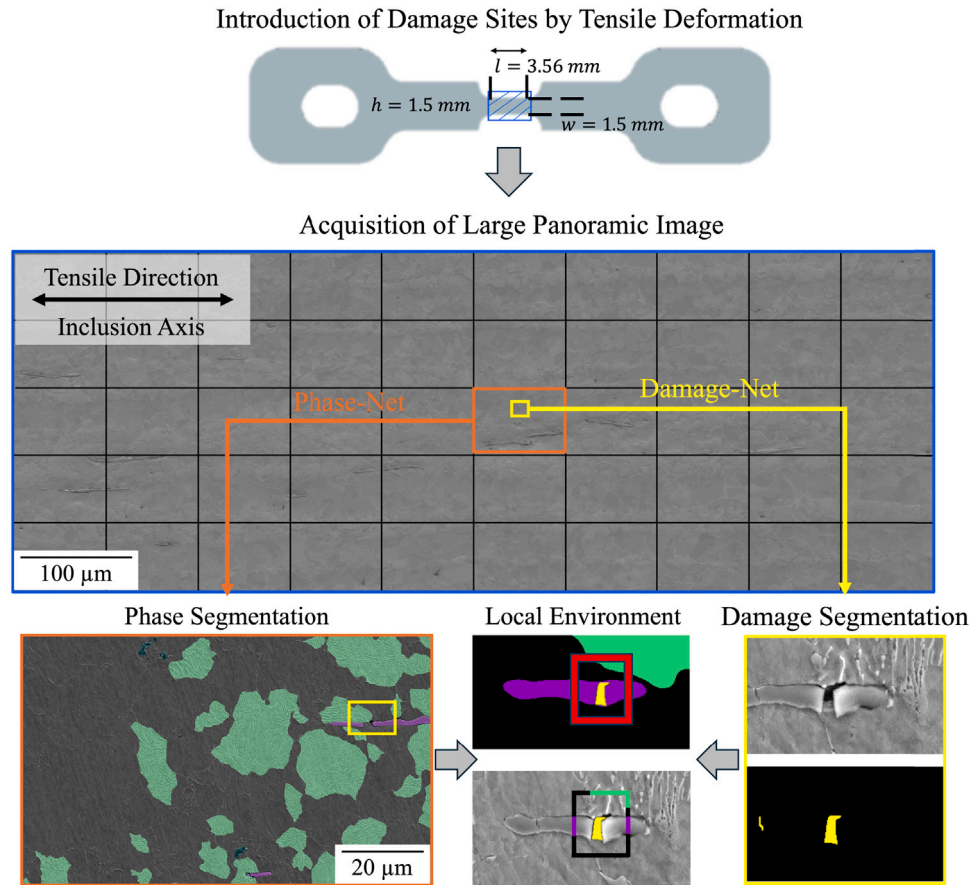


Fig. 2. Workflow for determining the influence of local phase environments on damage behaviour in 16MnCrS5 steel. From top to bottom: samples are machined, deformed incrementally via interrupted tensile tests, and imaged after each step using high-resolution panoramic SEM. The resulting images are segmented by two neural networks, one for microstructural phases (orange arrows) and one for damage sites (yellow arrows). Combining these results enables evaluation of the local microstructural environment surrounding each damage site. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Summary of datasets used to train both neural networks.

Dataset	Deformation mode	Number of images	Classes	Networks
Set 1	Tensile tested	70	Ferrite, Pearlite, MnS	Fine-tuning phase-net, pre-training damage-net
Set 2	Tensile tested	119	Damage	Fine-tuning damage-net

During in-situ testing, plastic deformation is visible on the surface as slip steps, which are considered as artefacts in the context of microstructure segmentation. Thus, to ensure consistent segmentation accuracy across all strain levels, the training dataset included images with both low and high densities of surface artefacts. To this end, images were randomly selected from those acquired at strains of 3% and 10% to represent a broad range of deformation states. For dataset 1, a total of 70 images were manually labelled for microstructural constituents and used as ground truth. This dataset was used both for the training of phase-net and the pre-training of damage-net. Dataset 2 comprised 119 manually labelled images, reflecting the fact that damage sites occupy only a small fraction of each image. During network training and evaluation, 80% of each dataset was allocated to training/validation, while the remaining 20% was reserved for testing. After

training, phase-net segments the microstructure into distinct classes: “Ferrite”, “Pearlite” and “MnS”, directly corresponding to microstructural features shown in Fig. 1. Damage-net, on the other hand, was specifically trained to identify damage sites and assigns a single class labelled “Damage”. The output from damage-net enables localisation of all present damage sites as well as quantitative assessment including total void area and number of individual sites, required for evaluating damage prevalence. By combining spatial information provided by both phase-net and damage-net outputs, it becomes possible to determine the local microstructural environment surrounding each MnS inclusion and associated damage site. Importantly, both networks operate simultaneously on the same captured SE images, as illustrated in Fig. 2, producing independent segmentation results. Further information

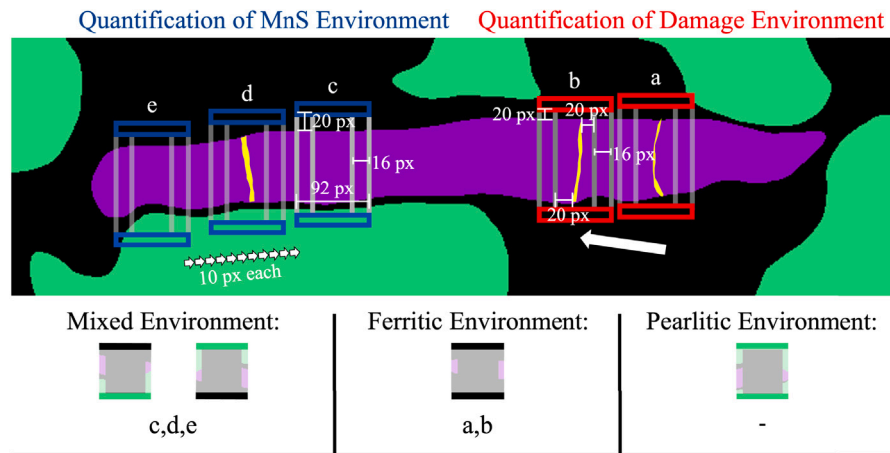


Fig. 3. Visualisation of the workflow to quantify microstructural environment around detected damage sites (a, b) and all possible environments (c–e), which includes environments around detected damage sites as well (d). Arrows visualise step size between recorded windows in both processes. Schematic representations below show the three environmental classes: mixed, ferritic, and pearlitic environments; green indicates pearlite, black indicates ferrite, purple indicates MnS inclusions. The non-transparent pixels are considered for the calculation of phase environment. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on network design decisions and their reasoning can be found in the supplementary material.

2.5. Determination of local environment

Once the positions of both damage sites and microstructural constituents have been identified through segmentation, the local environment surrounding each individual damage site is determined. For this purpose, two rectangular regions are constructed above and below each damage site. To capture damage site environment accurately, the dimensions of each rectangle are scaled according to the size of its respective damage site. Rectangular shapes were chosen to enable evaluation parallel to the tensile direction and to simplify analysis. In order to construct both rectangles, first their horizontal boundaries are set in a way that the left edge begins 20 pixels to the left of the leftmost point of the damage site and the right edge ends 20 pixels to its rightmost point. Similarly, in height, the lower boundary of the upper rectangle is set 20 pixels above the uppermost point of each damage site, while the upper edge of the lower rectangle is set 20 pixels below the lowest point of each damage site. The thickness of each rectangle is consistently set at 16 pixels. These dimensions ensure that labelling artefacts at MnS interfaces are excluded from analysis and that representative areas from local microstructures are evaluated. An example of the construction, along with its dimensions, is illustrated in Fig. 3a and b. The image provided is showing an MnS inclusion, its associated damage sites, and the surrounding microstructural environment after segmentation. The colours represent different segmentation classes: purple indicates MnS inclusions, green denotes pearlite, black represents ferrite, and yellow marks damage sites.

These rectangles provide a quantitative assessment of the local microstructural environment by calculating the proportion of each phase as a percentage of total pixels within the region. However, to simplify subsequent analysis, the environments surrounding damage sites are categorised into three distinct types: *ferritic*, *pearlitic* and *mixed* environment, which are also depicted schematically in Fig. 3. Each rectangle is analysed individually to determine its phase composition. If more than 50% of the pixels are identified as pearlite, the region is designated as pearlitic.

Beyond classifying regions around damage sites, this approach is also applied to areas adjacent to all MnS inclusions. For this purpose, two additional rectangles are constructed for each inclusion, each with a fixed width of 92 pixels and a thickness of 16 pixels. The rectangles extend from 20 pixels below the lowest point to 20 pixels above the

highest point of each MnS inclusion. To evaluate phase distribution along the inclusion length, these regions are shifted in 10 pixel increments Fig. 3c–e. Note that some regions may overlap with previously assessed damage site environments Fig. 3d.

2.6. Spherical nanoindentation

To complement the SEM-based statistical analysis with local mechanical properties, spherical nanoindentation was performed on ferrite, pearlite and MnS. For this purpose, a disc-shaped sample was mounted in a Keysight G200 nanoindenter with an integrated continuous stiffness measurement (CSM) unit and a spherical tip with a nominal radius of 10 μm . Indentations in ferrite and pearlite were carried out on the 16MnCrS5 case-hardening steel, while MnS inclusions were probed in a X30MnAl17-1 steel, which contains larger MnS inclusions suitable for confinement of the plastic zone within a single inclusion. Tip calibration, measurement procedures, and data analysis followed the methodology described in [36]. Due to the non-self-similar geometry of the spherical tip, and a previously determined function for the constraint factor, the recorded load and depth curves were converted to equivalent stress–strain curves. The yield strength was determined via the $R_{p0.5}$ offset method based on these curves. Elastic moduli were extracted from CSM data. In total, 7 indents were performed in ferrite, 5 indents in pearlite and 11 indents in MnS. All indents were conducted at a strain rate of 0.001 s^{-1} . Indents in MnS were conducted to a depth of 500 nm for MnS while indents in ferrite and pearlite were conducted to a depth of 1000 nm.

3. Results

3.1. In-situ observation of MnS inclusions under strain

The in-situ experiments allow us to track the mechanisms of damage nucleation and growth, changes in MnS inclusions, and their associated damage sites as a function of strain. This progression is shown using the example of one MnS inclusion in Fig. 4.

The selected inclusion is representative in size and exhibits variation in its local microstructural environment along its length, which is most apparent at the initial stage but highlighted once more at a strain level of 5%. Upon deformation to 3% plastic strain, three distinct damage sites are observed to have nucleated during this initial forming step. There is no clear preference regarding the local environment for these nucleation events: two sites formed within ferritic environment while

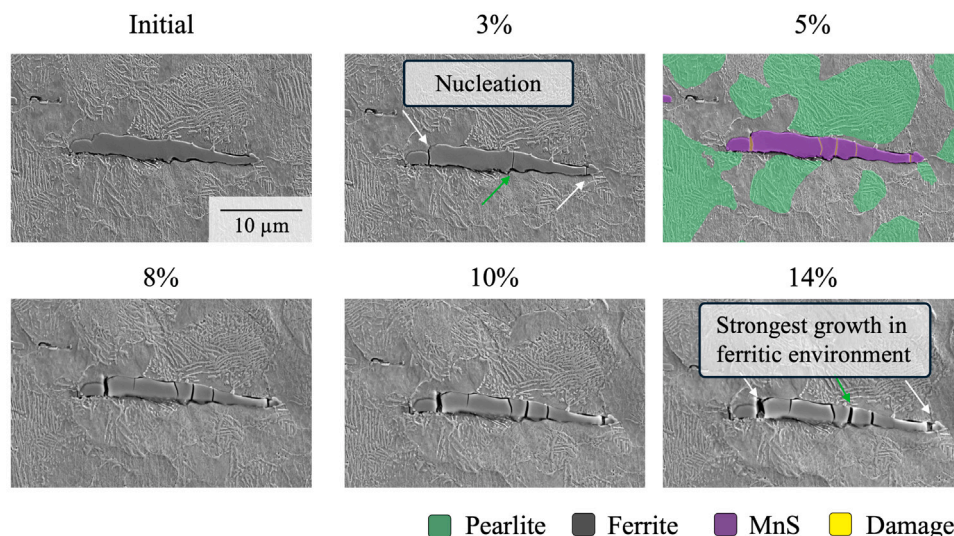


Fig. 4. Sequential micrographs illustrating morphological changes in an MnS inclusion and associated damage sites during incremental straining. White arrows indicate damage sites in a ferritic environment, while green arrows indicate damage in a mixed environment. Phase information is superimposed on the microstructure in the micrograph at a strain level of 5%. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

one emerged within a mixed-phase environment. As strain increases, pre-existing damage sites expand further in width and additional new sites continue to nucleate along the inclusion. However, at a final strain of 14%, comparison reveals that the widths of these initial three damage sites did not increase uniformly. Specifically, the damage sites situated within ferritic environments (highlighted with white arrows) grew larger than the site nucleated in a mixed-phase region (highlighted with a green arrow). To confirm these anecdotal observations, we systematically investigated the influence of the local microstructural environment on both nucleation and growth of MnS-associated damage sites using statistical analysis based on data generated by the phase-net and damage-net networks.

3.2. Evaluation of image segmentation performance

To ensure transparency regarding the reliability of our scientific findings, we begin by evaluating the performance of the segmentation networks. The output of the image segmentation process consists of masks in which each pixel is assigned to a specific class or to the matrix. We assess the quality of this classification both qualitatively and quantitatively.

For qualitative assessment, each class is assigned a distinct colour, and the resulting mask is overlaid on the original SEM image. This visual approach allows for intuitive evaluation of segmentation accuracy. A direct comparison between an SEM micrograph and its corresponding segmentation mask is presented in Fig. 5, facilitating a straightforward visual appraisal of both neural networks' performance.

In addition to this qualitative assessment, network performance was quantitatively evaluated using the Dice score [37], a widely-used metric for measuring accuracy in image segmentation tasks [38,39]. Accordingly, Dice scores obtained from 14 phase segmented and 24 damage segmented images are summarised as box plots for each segmentation class in Fig. 6.

The box plots reveal that the medians for all classes segmented by phase-net exceed 0.9, as shown by the lines within each box. Notably, overall Dice scores as well as those for ferrite and pearlite approach 1 with only small variability across images. Although MnS exhibits a higher median Dice score than pearlite, its distribution displays greater spread. One outlier, shown as an open circle at zero results due to misclassification at a small site. In this instance, MnS was predicted but not present in the ground truth. Such pronounced deviations occur

Table 3

Prevalence of environment classes around MnS inclusions.

Class	Occurrence (%)
Fully ferritic	59 ± 2
Fully pearlitic	13 ± 1
Mixed	28 ± 1

because even minor discrepancies greatly affect metrics when site size is small.

A similar pattern is observed in the damage-net results. Here, the Dice scores display a broader variability and occasionally include low or zero values. These low scores typically arise when ground truth damage sites are not identified by the network. Examples of such cases are given in the supplementary materials.

3.3. Damage quantification during in-situ testing

Image segmentation by damage-net enable automated quantification of damage parameters by determining both the number and total area of detected damage sites. These values are normalised to the total MnS area identified by phase-net. By monitoring these parameters with increasing plastic strain, the evolution of damage sites during deformation can be characterised, as shown in Fig. 7. Both the number and total area of detected damage sites increase steadily with rising strain. At the final strain level observed, more than 0.2 sites per μm^2 of MnS are observed (Fig. 7(a)), covering approximately 4% of the area of imaged MnS (Fig. 7(b)).

3.4. Influence of local microstructure on damage initiation and growth

Distribution of microstructural classes around MnS inclusions. To elucidate how the local microstructural environment affects damage prevalence metrics, both area fraction and number of detected damage sites were analysed with respect to their surrounding environment. As previously described, environments were categorised into three distinct classes (fully ferritic, fully pearlitic, mixed) (Section 2.5). Initially, we assessed the overall distribution of environmental classes surrounding MnS inclusions across all strains. The results are presented in Table 3.

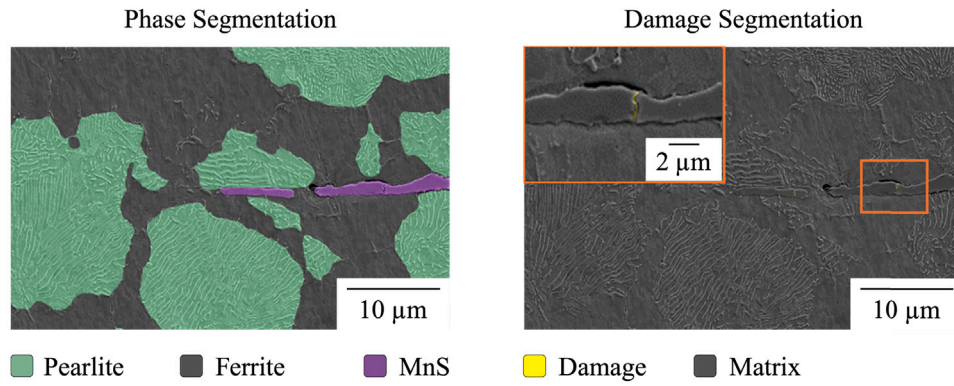


Fig. 5. Secondary electron micrograph of an etched 16MnCrS5 specimen with superimposed segmentation masks: (a) phase segmentation, where green denotes pearlite, purple indicates MnS, and grey corresponds to ferrite; (b) damage segmentation, where yellow highlights areas classified as damage and grey represents all other areas. The inset displays a higher magnification of the rectangular region marked in orange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

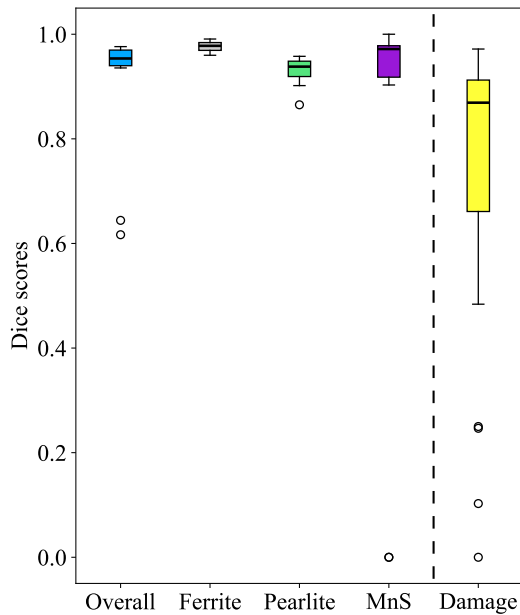


Fig. 6. Box plots showing Dice scores for network performance evaluation across segmentation classes: ferrite (grey), pearlite (green), MnS inclusions (purple), overall performance for phase-net (blue), and performance for damage-net segmenting damaged regions (yellow). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

This analysis shows that MnS inclusions are most frequently found within ferritic regions rather than mixed ones. Purely pearlitic surroundings are comparatively rare. Small deviations across different strain levels, as indicated by the standard deviation, are likely due to small changes of the imaged area resulting from applied strain.

Environment dependence of damage nucleation. In order to unravel whether damage site nucleation preferentially occurs within specific environments, we first started by analysing damage site number fraction per class (Fig. 8a).

The data reveal that damage site nucleation is most frequent within ferritic environments compared with mixed or purely pearlitic ones and show little variation with increasing strain. On average, approximately 60% of damage sites occur within purely ferritic surroundings, about 30% within mixed environments and roughly 15% within exclusively pearlitic environments. Furthermore, these results show that, although

new damage sites are initiated at all strain levels (cf. Figs. 4 and 7), these damage sites nucleate within all environmental classes with consistent probability at any given level of applied strain. To quantitatively assess preferred nucleation sites accounting for environmental occurrence rates (Table 3), we calculated the conditional probability that a site initiates within a particular environment $p(D|E)$ using Bayes' theorem [40]

$$p(D|E) = \frac{p(E|D)p(D)}{p(E)} \quad (1)$$

where $p(E|D)$ denotes the probability for observing a certain environment at a damage site, $p(D)$ is overall probability for damage formation, and $p(E)$ is the occurrence rate for each environmental class. $p(D|E)$ was computed per class across all strains and is visualised in Fig. 8b.

The results indicate that for all environmental classes, the likelihood of newly formed damage sites increases consistently with rising strain (except at 8% for the mixed and pearlitic environments). However, no consistent preference emerges regarding which environment favours nucleation across all strains. For example, at 3%, 5%, and 10% strains, pearlitic environments display the highest probability of damage nucleation, while at 8% and 14% strains ferritic regions seems more favourable.

Environment dependence of damage growth. To investigate how microstructural environment influences subsequent growth behaviour, we correlated damage area fractions with environmental class using our established method (Section 2.5). Mean area fractions, normalised by total imaged MnS area, are displayed for each class and strain level in Fig. 8c.

An increasing trend with strain is evident for all environmental classes containing ferrite. Only within purely pearlitic surroundings between strains of 5% and 8% no clear trend emerges. Furthermore, there is a marked dependence of damage area on environmental class. These differences become more pronounced at higher strains, with ferritic regions exhibiting larger average damage areas than mixed or purely pearlitic regions. However, trends observed in area or number fractions may be affected by uneven distributions of environments around MnS inclusions, thus they do not directly translate to intrinsic growth rates.

Further insight was gained by analysing mean damage site size as a function of local pearlite fraction (rather than discrete classification), shown in (Fig. 8d). This approach reduces sensitivity to class imbalance effects. Here two key findings emerge: (1) At maximum strain of 14%, higher local pearlite fraction corresponds to smaller mean void sizes. (2) When tracking changes in mean void size across strains for each bin (Fig. 8d), greater pearlite content yields less variation between strains compared to lower fractions.

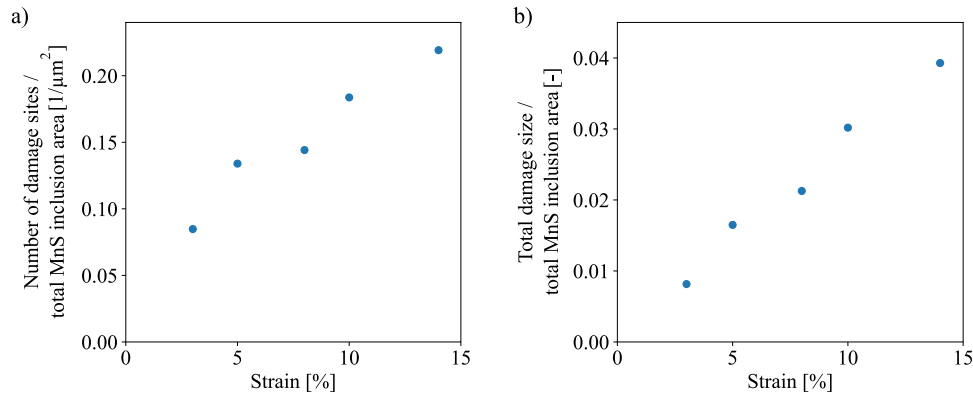


Fig. 7. Evolution of key damage parameters during in-situ tensile testing as functions of strain: panel (a) displays the number count, while panel (b) shows total damage area, both normalised by total MnS inclusion area identified via image segmentation.

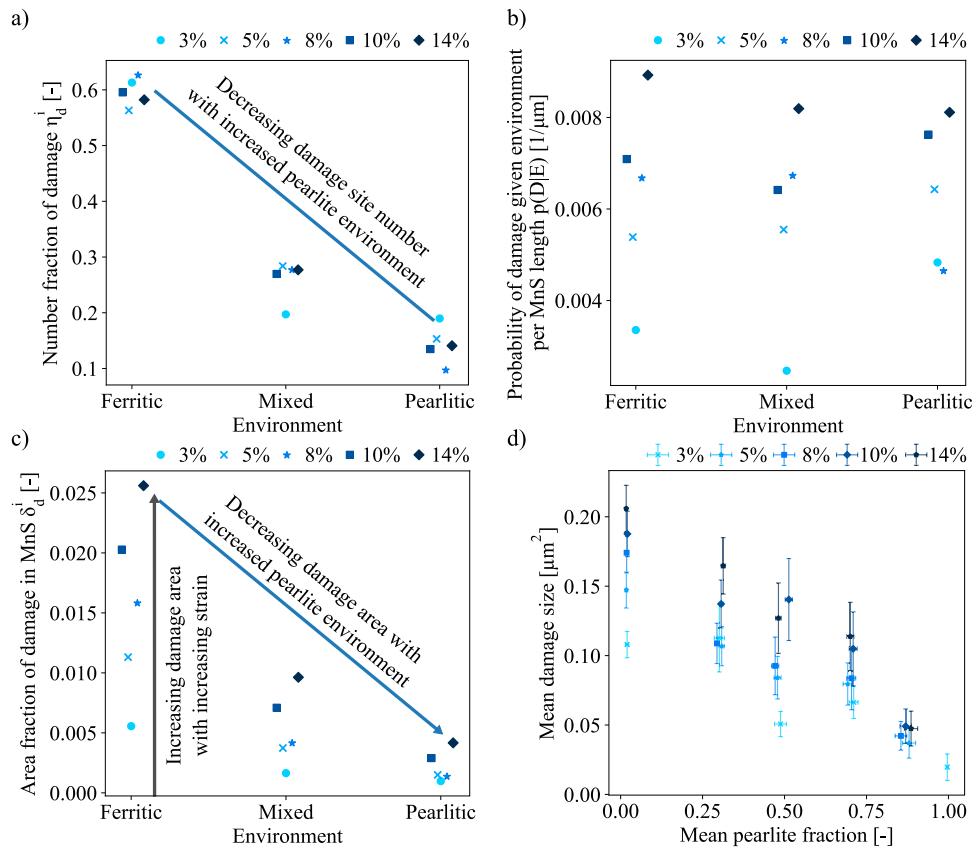


Fig. 8. Damage prevalence and damage site metrics as a function of local microstructural environment and strain level. (a) Number fraction of damage sites, (b) probability of damage site initiation, (c) mean area fraction of damage sites, (d) mean size of individual damage sites. Different colours correspond to different strain levels.

3.5. Spherical indentation

Equivalent indentation stress-strain curves obtained from spherical indentation experiments, along with the corresponding constraint factor versus strain are shown in Fig. 9 for ferrite, pearlite, and MnS.

Although an initial elastic regime is evident, its slope in the equivalent indentation stress-strain curve is not suitable for accurate determination of elastic modulus (E). This is because the depth in this initial regime is only a few nm and the elastic-plastic transition introduces inaccuracies in tip calibration as well as in the conversion from load-depth to stress-strain. We therefore report elastic moduli from continuous stiffness measurements (CSM), which provide higher fidelity values (Table 4). The average moduli determined fall within

the ranges reported in literature for ferrite and pearlite [41,42] and for MnS [20].

Although the elastic region in Fig. 9 is not suitable for determining the elastic modulus, it can be used to identify the onset of plasticity and thus define the yield strength. Here, yield strength was defined as the equivalent indentation stress at 0.5% plastic strain using an offset based on the initial elastic slope of the stress-strain curve. The mean values for each phase are reported in Table 4. The curves show similar yield strengths for ferrite and MnS and a slightly higher value for pearlite. Although factors, such as indentation size effects, interlamellar spacing and chemistry are expected to influence the yield strength, our reported values are consistent with literature ranges for pearlite [43] as well as for MnS and ferrite [23]. Differences in plastic behaviour are apparent

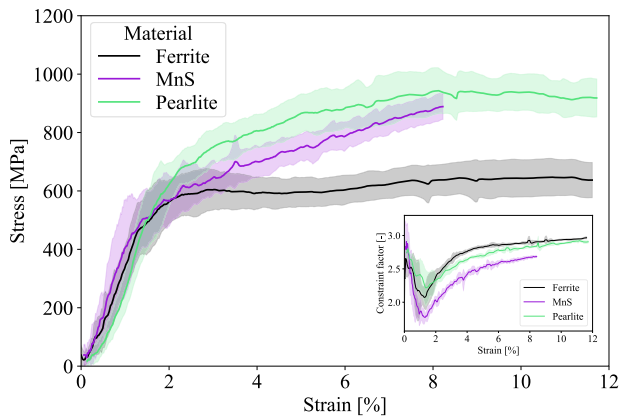


Fig. 9. Equivalent stress–strain curves from spherical indentation for ferrite, pearlite, and MnS. The inset shows the constraint factor as a function of strain. Solid lines represent the mean value across multiple indents, shaded band indicate ± 1 standard deviation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4

Average elastic modulus and yield strength $R_{p0.5}$ (mean + standard deviation) for ferrite, pearlite, and MnS. Elastic modulus determined via CSM during spherical indentation.

Phase	Ferrite	Pearlite	MnS
E (GPa)	193 ± 3	201 ± 2	111 ± 1
$R_{p0.5}$ (MPa)	580 ± 80	720 ± 90	580 ± 60

in the strain hardening behaviour among phases: ferrite shows modest strain hardening, pearlite shows stronger initial hardening followed by a plateau, whereas MnS displays a linear hardening behaviour at a near-constant rate throughout the measured range.

4. Discussion

4.1. Deep learning-based segmentation of phases and damage

The automated segmentation approach employing nnU-Net architecture demonstrated varying performance across different microstructural classes. While phase segmentation achieved consistently high Dice scores, damage segmentation exhibited greater variability. This disparity can be attributed to three primary factors.

Firstly, damage only constitutes 6.9×10^{-5} of the total imaged area. This severe class imbalance results in few positive training examples for the damage network. Additionally, individual damage sites are also small, with a high boundary-to-interior pixel ratio, making them especially susceptible to segmentation errors, as this characteristic is challenging for the nnU-Net's design philosophy, which relies on learning multi-scale representations [28].

Secondly, the Dice coefficient exhibits heightened sensitivity to segmentation errors when applied to rare, small objects. A single missed damage site, even if it comprises only a few pixels, results in a Dice score of zero for that image. In contrast, misclassifying a comparable number of pixels at phase boundaries between ferrite and pearlite has negligible impact on phase segmentation scores due to the large total area of correctly classified phase pixels. This metric behaviour creates statistical instability: with few damage sites per image, the Dice score lacks sufficient sampling to stabilise, effectively computing statistics on small counts where individual errors dominate the result. Consequently, the observed variability in damage segmentation Dice scores

partially reflects limitations of the metric itself rather than systematic network failure.

Lastly, distinguishing between actual damage and artefacts is particularly difficult near MnS interfaces. These artefacts can arise due to locally increased etching, scratches from metallographic preparation or even changes in surface topology during the in-situ experiment due to dislocation activity. Although unfavourable towards accurate damage segmentation, these classes of artefacts are commonly expected for high-throughput methods, in particular for methods that take large areas into account.

Despite these limitations, automated segmentation enabled analysis on a scale that is infeasible by manual annotation. Processing thousands of micrographs across multiple strain levels and environmental conditions required consistent labelling criteria that human annotators struggle to maintain over extended periods. This consistency, however, is particularly valuable for comparative studies where subtle differences in damage evolution must be quantified. While the segmentation accuracy for damage sites shows greater variability than for phase segmentation, the achieved performance is sufficient for drawing reliable conclusions about damage evolution trends and environmental effects as visualised by the consistent trends shown in Fig. 8. Thus, despite these methodological considerations, clear trends emerge from our data regarding how local microstructural environment affects both damage nucleation and growth. Future work could consist of dedicated networks, with architectures tailored to small damage sites, or a two-step approach, consisting of detection and a subsequent segmentation.

4.2. Influence of local environment on damage nucleation and growth

It is widely recognised that damage prevalence in multiphase steels is primarily influenced by the strain incompatibility between a compliant and/or soft phase, which can accommodate comparatively large amounts of strain, and a stiff and/or hard phase which can accommodate comparatively less strain [44]. In the case of 16MnCrS5 damage occurs predominately in and around the MnS inclusions [23,45], either via MnS fracture under the present loading or via interface decohesion under transverse loading [19]. Among the three constituent phases, ferrite accommodates the largest plastic strain [27]. It is therefore reasonable to expect ferritic surroundings to be associated with higher damage prevalence. What remains to be unravelled is whether the environment primarily affects damage nucleation, growth, or both.

Based on the statistical results presented in Fig. 8b and d along with the in-situ observations shown in Fig. 4, we separate the roles of damage nucleation and growth as a function of the local environment.

Damage nucleation. The statistical analysis of damage nucleation presented in Fig. 8b shows no consistent preference for nucleation in a particular environment across strains. The apparent fluctuations that appear to favour pearlite or ferrite at different strains are likely consistent with sampling variability rather than a physical effect since there is no mechanistic reason for the preferred environment to oscillate with strain. This is also reflected in Fig. 4, where multiple nucleation events occur over a range of global strains without a consistent environmental bias.

This lack of a clear trend suggests that mechanisms beyond the surrounding environment have a larger impact on nucleation behaviour. Likely contributions include crystallographic grain orientation near inclusions and local stress concentrations arising from abrupt changes in inclusion thickness or morphology.

Damage growth. In contrast to nucleation, analysis of mean void size as a function of microstructural environment reveals a clear trend towards greater damage site growth in ferritic environments. As illustrated by Fig. 4, among the three initial damage sites (white arrows), those embedded in purely ferritic neighbourhoods expand most with increasing strain. Our statistical analysis based on image segmentation (Fig. 8d) confirms this stronger growth of damage sites in ferritic environments.

Consistent with this observation, the resulting smaller mean void size in the vicinity of pearlite is particularly pronounced where the pearlite fraction is highest. For example, the mean void size approximately doubles when moving from a 90% pearlitic environment to a 70% environment. Moreover, the strain dependence becomes more pronounced where ferrite predominates. Given that nucleation is, at most, only weakly dependent on environment class, observed differences across pearlite fractions must arise predominantly from variations in growth behaviour. Thus, these results suggest that growth is governed by the local microstructural environments, with faster growth occurring where ferrite predominates and slower growth where pearlite content is high.

Our analysis likely underestimates the full growth-suppressing effect of highly pearlitic environments because its based on two-dimensional (2D) micrographs and cannot capture the three-dimensional (3D) phase connectivity. As such, subsurface ferritic ligaments not intersected by the section plane may contribute to increasing apparent void growth even where the 2D section appears pearlitic. The high likelihood of this phenomenon is further supported by the frequent occurrence of ferritic environments given in Table 3.

Damage in MnS in multiphase environments. Combining the in-situ observations and statistical analysis with the phase-specific mechanical response from spherical indentation, we propose the following mechanism for damage in MnS when the tensile axis is parallel to the inclusion axis.

Rock-salt crystals such as MnS exhibit negligible tensile plasticity prior to fracture at room temperature (as shown for MgO, CaO [46, 47]). Fracture, thus, occurs once the local tensile stress reaches the fracture strength at or shortly after the elastic limit. In the initial elastic regime, the inclusion–matrix system can be approximated as iso-strain (Voigt bound) along the loading direction. However, because the elastic modulus of MnS is approximately half that of ferrite and pearlite (Table 4), the average elastic stress in MnS remain below its fracture strength at the matrix elastic limit. Fracture of MnS is therefore not expected at this stage. Once the phases surrounding MnS yield, local stress concentrations, amplified at intersections with slip bands observed in Fig. 4, quickly increase the tensile stress in MnS towards its fracture strength, triggering crack initiation.

This mechanistic picture explains why damage nucleation shows little dependence on environment class: ferrite and pearlite have comparable indentation-equivalent yield strengths (Table 4), so the onset of plasticity is controlled more by crystallographic orientation and local morphology than by phase identity alone. By contrast, subsequent damage growth depends strongly on the surrounding phase. Because pearlite exhibits higher work-hardening than ferrite (Fig. 9), post-yield macroscopic strain partitions preferentially into ferrite, leading to greater separation of MnS fragments following fracture, and larger void areas in ferritic environments Fig. 8d. Mixed environments show intermediate growth consistent with their local ferrite fraction. We therefore conclude that nucleation is dominated by local morphological features and slip-band interactions, whereas growth is governed by strain partitioning arising from the mechanical contrast between the surrounding phases. Based on these insights, our findings can guide the design of multiphase microstructures in a way that allows for more precise control of damage evolution and, as a consequence, higher component performance.

Consequently, while the identity of neighbouring phases has little influence on nucleation, ferritic local environments around MnS inclusions increase overall damage prevalence by accelerating post-nucleation growth. To elucidate 3D environmental effects, serial sectioning [48] or tomography experiments [49] could provide valuable additional insights. Combined with grain orientation mapping, such data could clarify how internal grain boundaries, misorientations between inclusions and matrix, and surface topography influence stress concentration and crack nucleation in MnS.

5. Conclusion

In this study, we quantified how phase distribution and local mechanical properties in 16MnCrS5 influence the prevalence and evolution of MnS-induced damage by combining machine-learning image segmentation with spherical nanoindentation. Our results demonstrate that neighbouring phases set the local strain partitioning around MnS inclusions, thereby affecting damage prevalence during deformation. The main conclusions are:

- Damage nucleation is largely insensitive to whether the local environment is ferritic or pearlitic within the examined strain range, consistent with the comparable indentation-equivalent yield strengths of both phases.
- Once nucleated, damage grows fastest in ferritic environments and is strongly inhibited in highly pearlitic surroundings due to pearlite's higher strain-hardening.
- Mixed environments exhibit intermediate growth proportional to their local ferrite fraction.

CRediT authorship contribution statement

Maximilian A. Wollenweber: Writing – original draft, Methodology, Investigation, Formal analysis. **Tom Reclik:** Writing – original draft, Software, Methodology, Investigation, Formal analysis. **Clara Reinhart:** Writing – review & editing, Software, Investigation, Formal analysis. **Verena Maier-Kiener:** Writing – review & editing, Investigation. **Talal Al-Samman:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Ulrich Kerzel:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Sandra Korte-Kerzel:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used the LLMs RWTHGPT and Claude (claude.ai) in order to improve language and readability. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

The authors express their gratitude to the Deutsche Forschungsgemeinschaft (DFG), Germany for financial support in context of the Collaborative Research Centre CRC/Transregio 188/2 “Damage Controlled Forming Processes”, project B02 and project T02, project no. 278868966. Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under the National Research Data Infrastructure, Germany – NFDI 38/1 – project number 460247524.

The data used in this publication was managed using the research data management platform Coscine (<http://doi.org/10.17616/R31NJNJZ>) with storage space of the Research Data Storage (RDS) (DFG: INST222/1261-1) and DataStorage.nrw (DFG: INST222/1530-1) granted by the DFG and Ministry of Culture and Science of the State of North Rhine-Westphalia, Germany. This article is partly based upon work from COST Action CA21121 MecaNano, supported by COST (European Cooperation in Science and Technology–www.cost.eu)

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.msea.2026.150251>.

Data availability

Data will be made available on request.

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