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A Multiphysics Neural Network Framework for Microdamage Evolution with A Shadow Plasticity Observer

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Abstract: Microdamage evolution in ductile solids is influenced by plastic deformation, stress redistribution and material degradation. A computational framework is presented in which gradient damage mechanics is combined with a neural constitutive predictor. Plastic history is retained through a mechanically inactive auxiliary observer, termed shadow plasticity here. Its state is supplied to a multilayer perceptron without inserting the plastic tensor into the actual elastic deformation. A local damage increment is proposed by the network and converted into a correction of damage resistance. The original constitutive corrector and finite element balance equations are retained. The framework is examined using a single edge notched specimen under nonlinear loading. Complete reference and control histories are compared with an independently verified neural interval covering the first 205 s of a 1000 s loading program. Damage initiation, spatial localization and force response are assessed on explicitly matched supports. Early neural damage error is substantially reduced relative to the original damage only model. The completed controls demonstrate recovery of the reference damage region and structural response. The strongest complete agreement is obtained after the base damage resistances are aligned. Later neural propagation remains unverified. The findings provide a basis for physically structured prediction of microdamage and demonstrate the importance of separating constitutive interaction from material calibration.

Keywords: Microdamage, Multiphysics modeling, Neural networks, Shadow plasticity, Finite element method

Introduction

Microdamage evolution in ductile solids is influenced by plastic deformation and stress redistribution. Its numerical representation requires the interaction between irreversible deformation and material degradation to be considered. Constitutive descriptions of these mechanisms and their application to ductile fracture were reviewed by Besson (2010). A simplified damage model can alter this interaction even when the same external loading is imposed. The resulting changes in damage initiation and localization must therefore be examined at both material and structural levels.

Spatial regularization has been introduced to address the localization sensitivity of continuum damage models. Gradient enhancement was demonstrated for quasi brittle materials by Peerlings et al. (1996). A broader framework for gradient elasticity, viscoplasticity and damage was presented by Forest (2009). An additional field associated with an internal variable was introduced through the micromorphic formulation. Coupled gradient plasticity and damage were subsequently treated at finite strains by Miehe et al. (2016). Their phase field framework provides relevant context for constitutive interaction. It is distinct from the multiplicative damage formulation considered here.

Neural networks have also been investigated for constitutive modeling. Mechanistic homogenization was incorporated into the deep material network of Liu et al. (2019). Thermodynamic laws were encoded in the neural

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architecture proposed by Masi et al. (2021). These developments support the retention of physical structure within a learned model. They do not imply that a small regression error alone establishes physical admissibility.

Material history must also be represented. Path dependent plasticity was learned through recurrent networks by Mozaffar et al. (2019). Constitutive models with evolving internal variables were embedded in a physically recurrent network by Maia et al. (2023). These approaches provide different representations of memory. In the present formulation, history is retained through persistent constitutive states supplied to a multilayer perceptron.

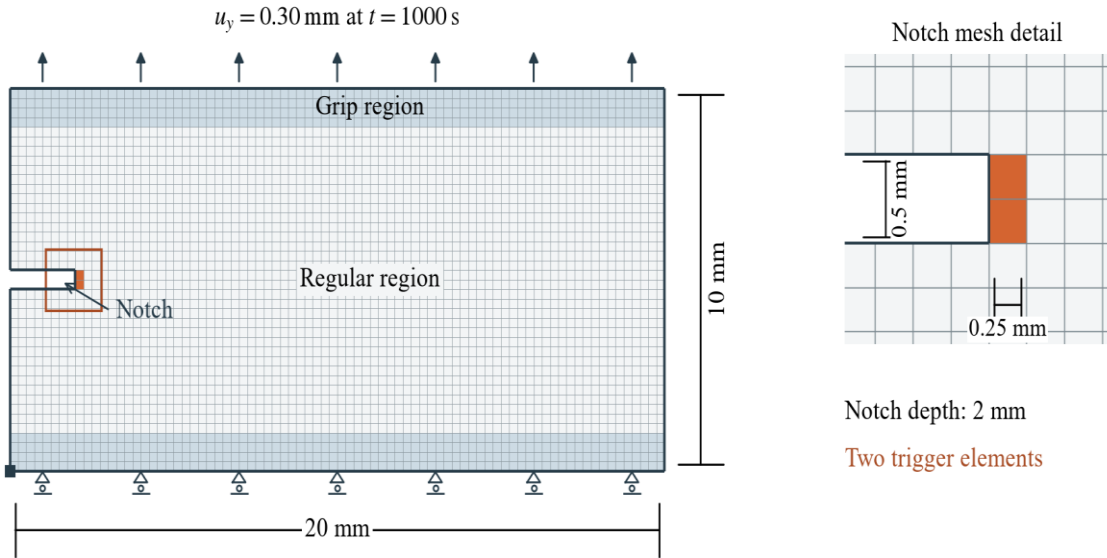
A mechanically inactive plasticity observer is introduced alongside the damage only mechanical branch. This auxiliary calculation is termed shadow plasticity here. Its plastic tensor and accumulated slip are retained as history descriptors. They are not inserted into the student's stress decomposition. A local damage increment is proposed by the neural network. The proposal is converted into a scalar correction of the complete raw damage resistance. The original constitutive corrector remains responsible for the actual damage update. The governing balance equations and resistance floor are retained.

The investigation is restricted to a fixed single edge notched specimen. The coupled reference, original damage only baseline, strength aligned control and analytical correction are included in the comparison with neural feedback. Damage initiation, spatial localization and force response are examined together. The strength aligned control separates the existing base resistance calibration difference from the influence of plastic kinematics.

Method

Constitutive Framework

Microdamage evolution was evaluated in a single edge notched specimen under plane strain. The displacement and gradient damage balance equations were solved with a four node user element in Abaqus. The nodal unknowns were two displacement components and the microdamage field χ_d . Spatial coupling remained governed by these equations. A mesh of 3184 physical elements was used. The prescribed displacement reached 0.3 mm over 1000 s. Fields were stored every 5 s. The geometry and loading are shown in Figure 1. The active source parameters are summarized in Table 1. Cubic elasticity was retained with the source crystal orientation. Twelve slip systems and the source damage normal (0, 1, 0) were used.



Bottom: $u_y = 0$; lower left node: $u_x = 0$. Plane strain; 3184 four node elements.

Figure 1. Specimen geometry and prescribed loading conditions

Numerical rate coefficients follow the source mm, N and s convention. No additional reference rate was introduced. Actual plasticity was suppressed in the student through $r_0 = 10^{13}$ MPa. This value was also used in the coupled and observer grip regions. The strength aligned control retained the student mechanics while its base resistances were matched to the reference.

Table 1. Material parameters retained from the source implementation

Parameter	Numerical value	Application
C_{11}, C_{12}, C_{44}	205180, 144940, 92170 MPa	Active cubic elasticity
H, x_H, T_{ult}	-7500, 30000, 0.01 MPa	Damage resistance and penalty
A	320	Gradient coefficient in the adopted unit convention
K_d, n_d	110, 3	Damage rate
K_p, n_p, r_0	551.3, 7.8, 122.5	Coupled plasticity and observer
Student Y_0	300, 120, 10^{13} MPa	Regular material, trigger and grip
Reference Y_0	600, 240, 10^{13} MPa	Coupled, strength aligned and scratch reference branches
θ	10 or 0	Coupled and scratch reference, or actual student branches

The coupled reference and damage only student were distinguished by their mechanical decompositions:

$$F = F_C^e F_C^p F_C^d \quad \text{and} \quad F = F_D^e F_D^d.$$

Plastic history was retained in an auxiliary observer with persistent state variables $\bar{F}^p$ and $\bar{\gamma}$. This auxiliary calculation is termed shadow plasticity here. The source plasticity update was evaluated using the current deformation and the student's previous damage state. The observer tensor was not inserted into the student's mechanical elastic gradient. Stress was calculated from $F_D^e = F(F_D^d)^{-1}$.

Model Variants and Resistance Correction

Strength Aligned Control

The strength aligned control was formed by changing only the base damage resistance in the original student. The regular and trigger values were increased from 300 and 120 MPa to 600 and 240 MPa. The grip value was unchanged. The damage only mechanical decomposition, suppressed plastic flow and original damage corrector were retained. Shadow plasticity was still calculated for observation, but its state was not used to correct resistance or actual stress. No neural predictor was used. This control was included to distinguish resistance calibration from the proposed plastic history correction.

Analytical Correction Control

In the analytical correction control, damage only mechanics and the original student base resistances were retained. The persistent shadow observer was advanced using the current deformation and previous student damage state. A separate local damage problem was then solved numerically using the updated observer plastic tensor, previous accumulated slip and reference resistance parameters. The proposed increment was converted into a scalar correction of the complete raw student resistance. The resistance floor was retained, and actual damage was computed by the original corrector. No network was used. Analytical therefore denotes a direct constitutive calculation, not a closed form solution.

Neural Correction Model

In the neural correction model, the active local proposal solve was replaced by a multilayer perceptron. Training targets were local damage increments generated on the analytical trajectory, not coupled finite element damage fields. Traction descriptors, student state and persistent shadow history were supplied as inputs. The proposal was limited by the source activation envelope and converted through the same inverse mapping into a raw resistance correction. The floor and original damage corrector were retained. Actual stress was still computed from the damage only branch with its original base resistances. No analytical proposal fallback or direct overwrite of actual damage was permitted.

A multilayer perceptron with two 64 neuron hidden layers and hyperbolic tangent activation was used. Ten mechanics derived inputs represented traction, damage, time increment, observer history and resistance. Positive source active proposals were fitted with Adam using a standardized logit target. Normalization statistics were

calculated from training data only. A bounded sigmoid output was used. Training and development validation were separated by time blocks. Trials and accepted records from each increment were kept in one partition.

The proposed increment δ_p was restricted by the original increment bound and a source activation envelope. The envelope causes the proposal to approach zero as the initial observer overstress approaches zero. The required resistance was then calculated as

$$Y_{\text{req}} = t_D(\delta_p) - K_d \left(\frac{\delta_p}{\Delta t} \right)^{1/n_d}, a = Y_{\text{req}} - Y_D^{\text{raw}}(\delta_p).$$

Here t_D denotes the actual student damage traction. The source numerical rate coefficient $K_d = 110$ and exponent $n_d = 3$ were retained in the adopted mm, N and s convention. The scalar action a was held fixed during the original damage corrector. The complete raw resistance was corrected before its physical lower bound was applied. Infeasible inverse proposals were projected onto that bound. Inactive states were handled by the source activation rule. The analytical control solved the scratch damage problem directly. In the neural model, that active proposal solve was replaced by the network without an analytical fallback. Actual damage remained governed by the original corrector.

For the neural run, the complete element residual was differentiated numerically. Forward perturbations were applied to all twelve nodal unknowns. The corresponding displacement increments were perturbed consistently from identical incoming constitutive states. All blocks of the unsymmetric Jacobian were retained. The original controls used their existing approximate tangent.

Comparison Procedure

The coupled reference, original damage only model, strength aligned damage only control and analytical correction control were retained for comparison with the neural model. The regular and notch trigger reference resistances were twice the corresponding original damage only values. Grip resistance was unchanged. That calibration difference cannot be attributed to the plastic deformation decomposition.

Local damage and microdamage were compared over all elements and saved times. The complete control histories covered 0 to 1000 s. The independently verified neural fields covered 0 to 205 s. Field comparisons involving the neural model used the same 42 saved times for every model. The retained neural force history ended at 196.875 s. Force comparisons used exact common timestamps without interpolation. Damage regions were assessed at thresholds of 0.01, 0.05, 0.1 and 0.2. Region overlap, extent, area and first saved threshold crossings were evaluated alongside force and displacement. Shared edge connectivity was used to distinguish the damage region attached to the notch from remote activation. A threshold damage band was interpreted as an indication of fracture localization rather than a resolved traction free crack surface. The fixed specimen study was not an independent experimental or generalization test.

Results and Discussion

Early Neural Correction

The verified neural comparison covered 42 saved field times from 0 to 205 s. Every model was evaluated over the same 3184 elements. The mean field error in Table 2 is the average of the 42 spatial RMSE values. The neutral observer without resistance feedback reproduced the original damage only fields and force history exactly. It was therefore omitted from overlapping curves.

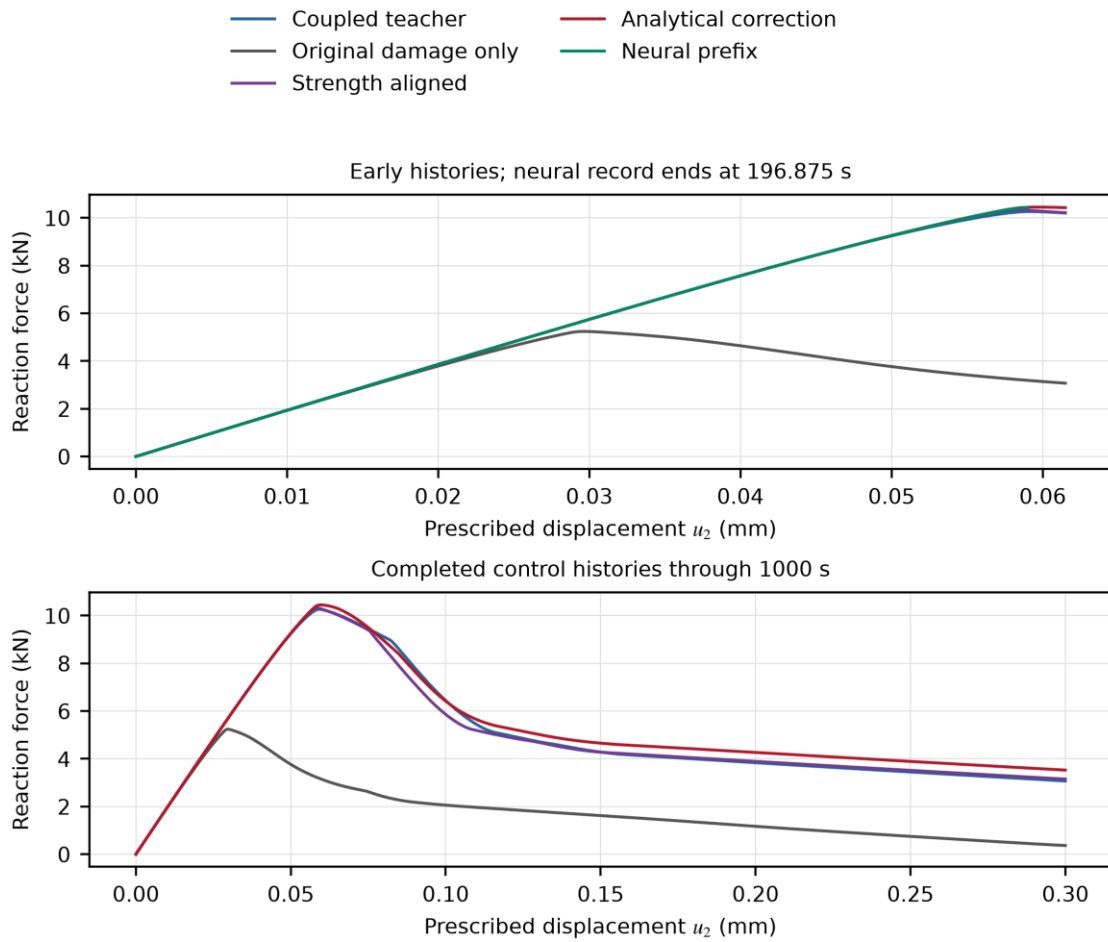
Table 2. Field agreement over the verified neural interval

Model	Mean RMSE of d	Mean RMSE of χ_d	Region RMSE of d	Force RMSE (N)
Original damage only	3.108×10^{-3}	2.826×10^{-3}	3.398×10^{-2}	2853.0
Strength aligned	2.162×10^{-5}	2.008×10^{-5}	4.599×10^{-4}	24.3
Analytical correction	2.068×10^{-5}	1.836×10^{-5}	5.190×10^{-4}	34.8
Neural correction	2.864×10^{-5}	2.436×10^{-5}	7.275×10^{-4}	33.2

The region errors in Table 2 were pooled over the same reference mask $d_c \geq 0.01$. There were 264 element and time pairs across 24 nonempty frames. Force errors used 49 identical native timestamps from 0 to 195 s. The available neural force record extended to 196.875 s, separately from its field record through 205 s. No force value was extrapolated to the field endpoint.

Mean damage error was reduced by 99.1% relative to the original damage only model. Both field errors were lower at 39 saved times and equal at the three remaining times. The damage region error was also substantially reduced. The improvement was therefore not explained solely by the large undamaged background. The analytical and strength aligned controls nevertheless retained lower mean field errors than the neural correction. Distinct superiority over these stronger controls was not established.

The force response is shown in Figure 2. Early neural feedback recovered the increasing reference response, whereas premature softening was obtained in the original damage only model. The complete control responses are shown separately in the lower panel. A neural curve is not extended into that later interval.



No force extrapolation. Neural fields extend separately to 205 s.

Figure 2. Force responses over separately verified loading intervals

Figure 3 shows the declared 90 and 195 s events. The excessive spread of early damage in the original model was suppressed by the corrected models. The figure uses one common scale from 0 to 0.09 across every model and all 42 early frames. Later control figures use a separate common scale from 0 to 0.4. The fields were not normalized independently. The reference regions at $d_c \geq 0.1$ and $d_c \geq 0.2$ were empty throughout the neural interval. These early results therefore establish damage initiation and localization agreement, not developed neural crack propagation.

At 195 s, the neural region with $d \geq 0.01$ contained 32 elements compared with 30 in the reference. Its intersection over union was 0.9375, compared with 0.0872 for the original model. Some overextension remained at the 205 s endpoint: 46 neural elements were active compared with 38 reference elements. The overlap decreased

to 0.8261 and the notch-connected extent exceeded the reference by 0.75 mm. The selected 195 s figure is therefore accompanied by the complete interval metrics rather than treated as a perfect endpoint prediction.

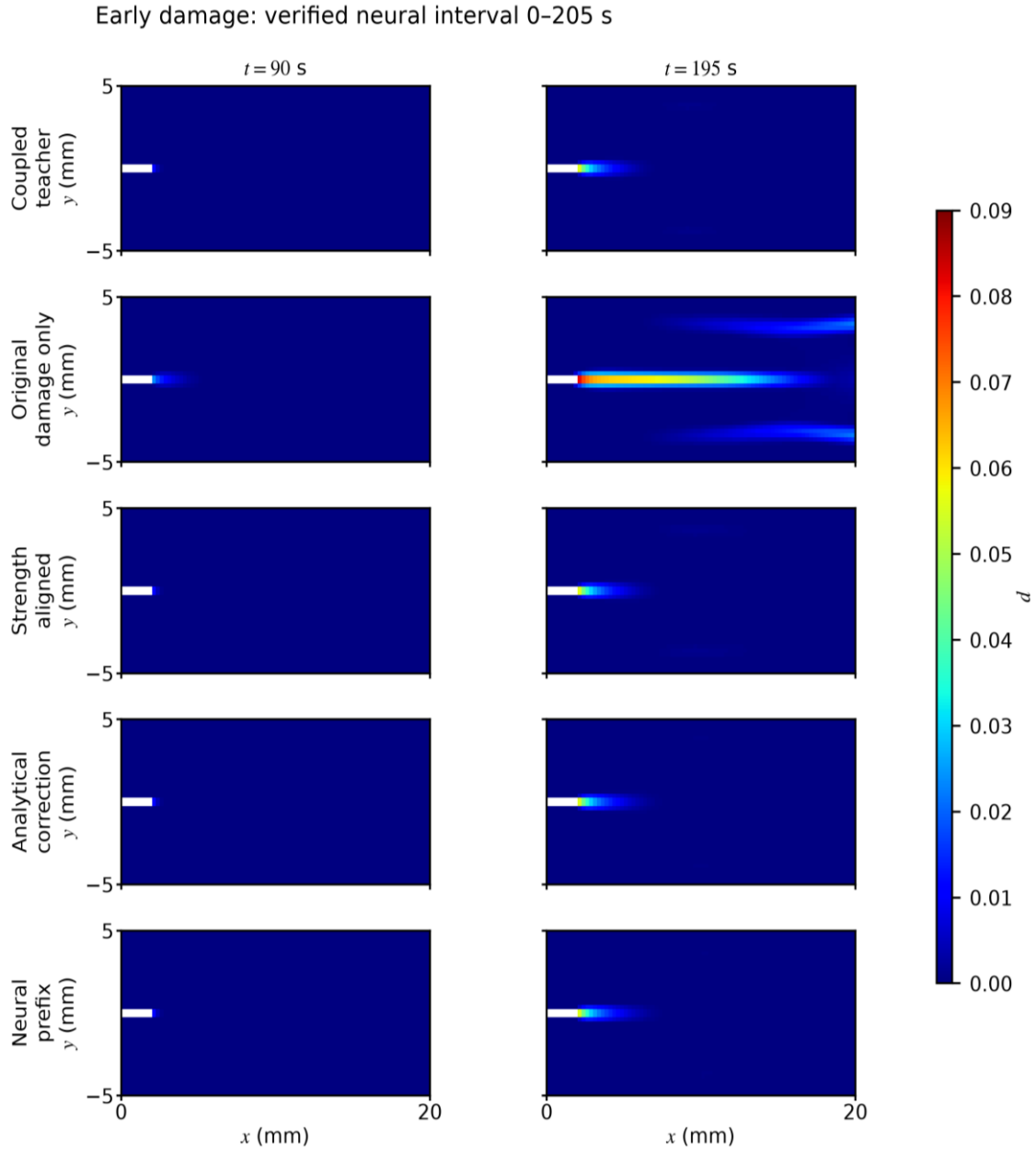


Figure 3. Early damage fields over matched neural increments

Complete Damage Localization in the Controls

The complete control comparison covered 201 saved times from 0 to 1000 s. The results in Table 3 are not directly comparable with the shorter averages in Table 2. The original damage only response was improved by both strength alignment and analytical correction. Both damage fields had lower error at 198 saved times and equal error at three times.

The strongest complete agreement was obtained with the strength aligned control. Its peak and terminal forces differed from the reference by 0.58% and 2.63%. The analytical correction also recovered the force level and damage band, but its terminal force remained 14.88% higher. Similar damage contours alone were therefore insufficient to establish identical structural response.

Table 3. Field and force agreement over complete histories

Model	Mean RMSE of d	Mean RMSE of χ_d	Peak force (kN)	Final force (kN)
Coupled reference	Reference	Reference	10.265	3.071
Original damage only	0.00925	0.00772	5.241	0.367
Strength aligned	0.00159	0.00141	10.324	3.151
Analytical correction	0.00341	0.00313	10.449	3.527

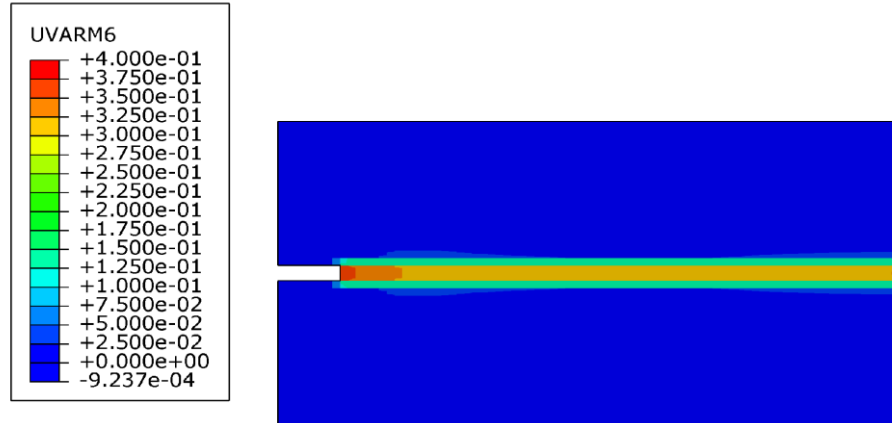
Native Abaqus damage contours are shown in Figure 4 for the coupled reference and analytical correction at 1000 s. The plotted variable UVARM6 is local damage d . The common rainbow scale and undeformed geometry were retained. Native within element extrapolation was used with averaging disabled. Small negative display extrema can arise from that extrapolation; they are not negative accepted local damage. Numerical errors were calculated from unextrapolated integration point means.

Figure 5 compares the completed controls at 300 and 1000 s. At 300 s, the reference region with $d \geq 0.1$ contained four elements and occupied 0.25 mm². At 1000 s, it contained 288 elements and occupied 18 mm². The same element sets were recovered by the strength aligned and analytical controls at both times. This is agreement in the threshold region, rather than equality of every damage amplitude.

Propagation was also assessed over the complete history. Shared edge connectivity was used to isolate the damage component attached to the notch. At $d \geq 0.1$, mean front position error was 1.44 mm for the original model, 0.54 mm after strength alignment and 0.64 mm with analytical correction. These values used 147, 147 and 146 times with defined paired fronts, respectively. Empty fronts were not assigned zero error. Remote activation occurred in the reference during part of the history. A global maximum damage coordinate was therefore not interpreted alone as the crack front. The advancing connected band provides an indication of fracture localization, not a resolved traction free surface.

Interpretation and scope

(a) Coupled reference



(b) Analytical correction control, 1000 s

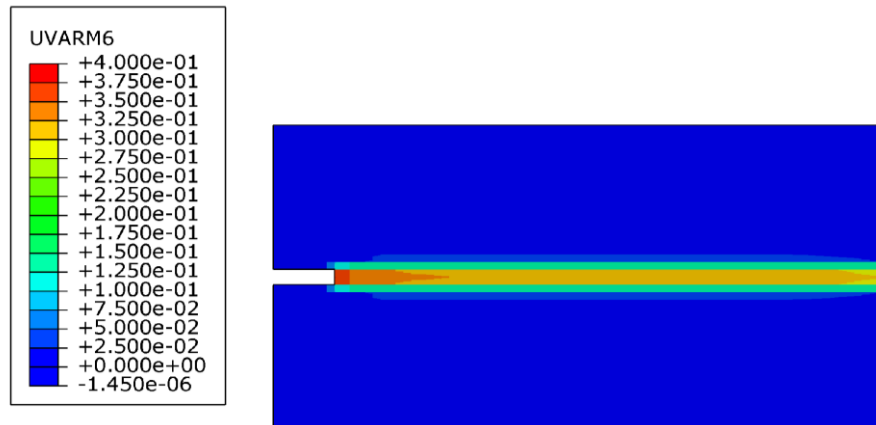


Figure 4. Native contours from the completed control simulations

The observer retained useful history but did not reproduce the coupled plastic state exactly. At 205 s, maximum element mean accumulated slip was 0.00122 in the neural observer and 0.00159 in the coupled reference. These values arose on different finite element trajectories. The comparison does not isolate observer error from the changed mechanical path.

The reported neural analysis terminated during a constitutive trial after the accepted 205 s state. That later trial was excluded. The retained interval passed finite output, irreversibility and corrector compatibility checks. One gate remained ambiguous at stored precision but compatible with the source rule. Full internal tensor histories were not independently exported. The early comparison is consequently a bounded result, not evidence of full neural completion or later propagation. Numerical safeguards in a subsequent implementation do not extend the scope of these reported data.

The positive finding is reliable early damage correction within the retained physical model, together with complete localization evidence from the controls. The base resistance difference was also shown to be important. The study does not establish an independent advantage of the observer or neural correction over appropriate strength alignment. Broader loading, mesh and experimental validation remain necessary.

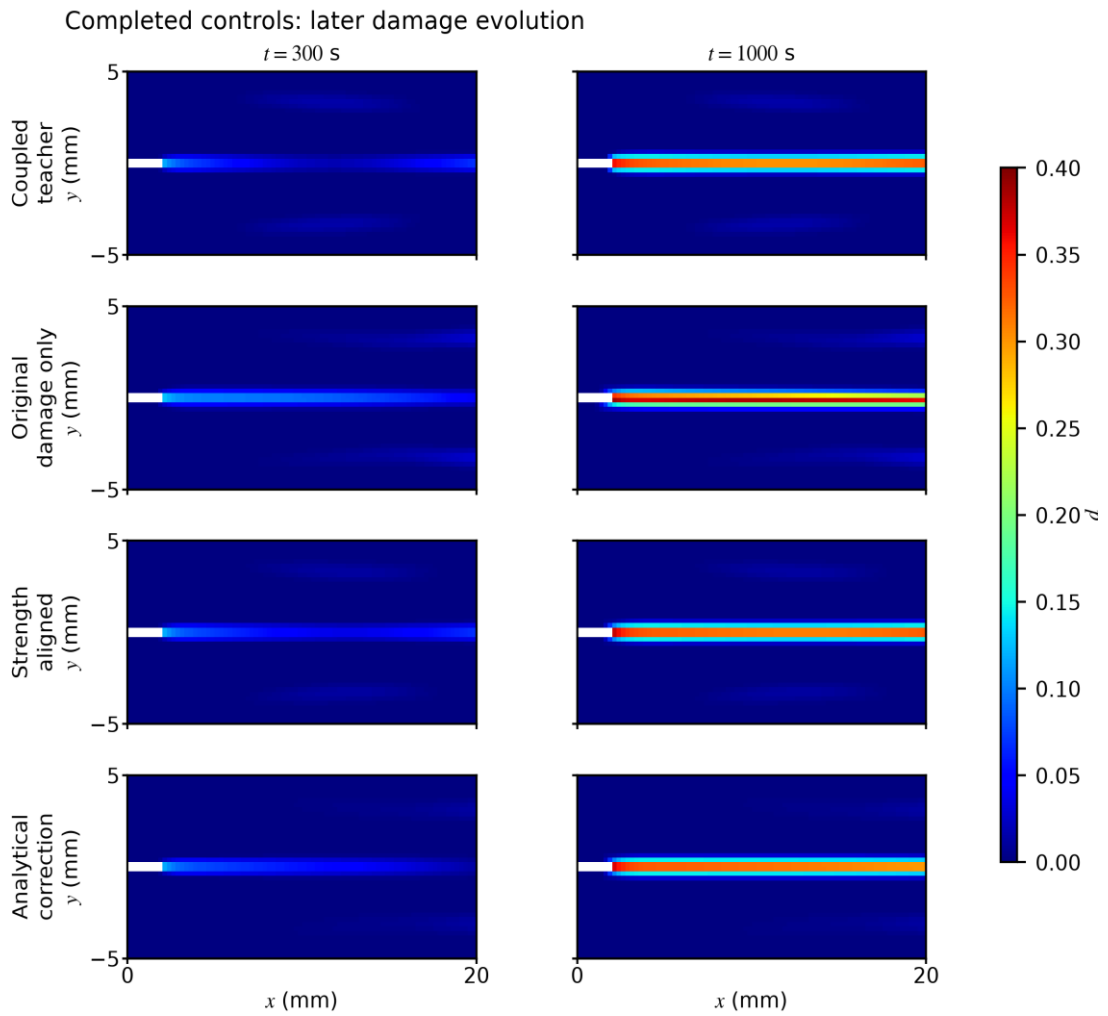


Figure 5. Damage propagation indicated by completed control histories

Conclusion

A neural increment proposal was embedded within the original constitutive damage corrector. Plastic history was retained by a mechanically inactive observer. Actual stress continued to be calculated from the damage only mechanical branch. The governing finite element equations were not replaced by a learned field map. Reliable damage localization and structural response were obtained in the completed control simulations. The reference threshold region was recovered at the declared later comparison times. The strength aligned damage only control

provided the closest complete agreement. The calibration difference must therefore be separated from any claimed benefit of plastic history or neural correction.

Early neural field agreement was substantially improved relative to the original damage only model. The neural findings are restricted to the independently verified early interval. Full neural completion and later crack propagation are not established by those results. The next requirement is a complete neural trajectory with the same field, connectivity and force checks. Additional loading paths and mesh resolution studies are required before broader predictive claims can be made

Scientific Ethics Declaration

* The authors declare that the scientific, ethical and legal responsibility of this article published in EPSTEM Journal belongs to the authors.

* This study was based on numerical simulations and did not involve human participants or animal experiments.

Conflict of Interest

* The authors declare that they have no conflicts of interest.

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