

An asymmetric pinching damaged hysteresis model for glubam members: Parameter identification and model comparison

Original

An asymmetric pinching damaged hysteresis model for glubam members: Parameter identification and model comparison / Shi, D.; Demartino, C.; Marano, G. C.; Xu, Y.. - In: COMPUTERS & STRUCTURES. - ISSN 0045-7949. - 305:(2024), pp. 1-17. [10.1016/j.compstruc.2024.107574]

Availability:

This version is available at: 11583/2998207 since: 2025-03-10T15:12:55Z

Publisher:

Elsevier

Published

DOI:10.1016/j.compstruc.2024.107574

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(Article begins on next page)

Computers and Structures

An asymmetric pinching damaged hysteresis model for glubam members: parameter identification and model comparison --Manuscript Draft--

Manuscript Number:	CAS-D-24-00504R1
Article Type:	Research Paper
Keywords:	Glue laminated bamboo; Asymmetric Pinching Damaged (APD) hysteretic models; Parameter identification; Parallel genetic algorithm; Bayesian neural network
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Abstract:	<p>Abstract The performance of glue laminated bamboo (glubam) members is governed by the nonlinear response at their joints, where high deformation levels and stress concentrations are developed. Numerous phenomenological models are presently employed to describe the hysteresis behavior of these joints, while these models always have an excessive number of parameters, and the physical interpretation of these parameters is often challenging. Moreover, some hysteresis models cannot capture all hysteresis features such as asymmetry, pinching, and damage. Consequently, this paper introduces a novel phenomenological-based hysteretic model named Asymmetric Pinching Damaged (APD) model, and implemented it in Abaqus by combining connector and spring elements in series or parallel. This model encompasses asymmetry, pinching, and strength degradation for bamboo joint components, with parameters that possess clear physical meanings and are readily comprehensible. This study also presented a parameter identification framework coupling the Parallel Genetic Algorithm (PGA) and Bayesian Neural Network (BNN). By merging the FE modeling and optimizing algorithms with the interactive application of ABAQUS and Python software platforms, the integrated identification framework is capable of performing multi-threaded parallel computation of finite element models considering the BNN-based uncertainty quantification, thus greatly improving the efficiency of parameter identification.</p>
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Highlights

- Asymmetric pinching damaged hysteresis model for glue laminated bamboo (glubam) members
- Parameters identification coupling Bayesian Neural Network (BNN) and PGA
- Comprehensive validation and comparison against other hysteretic models

Dear Editors,

On behalf of my co-authors, we thank you very much for giving us the opportunity to revise our manuscript. We thank the Editor and the Reviewers for their comments and suggestions concerning our manuscript (Ref. No.: CAS-D-24-00504). The authors would like to thank the Reviewers for the extremely careful reading of the manuscript and for providing us with comments and suggestions to improve its quality.

The following responses have been prepared to address the Reviewers' technical comments in a point-by-point fashion. The list of questions raised follows, together with our response to each (in blue).

We tried our best to improve the manuscript, by also making some additional changes to clarify some of the concerns raised. We think that the manuscript has been greatly improved by these revisions and we hope that you will now find it suitable for publication in Computers and Structures.

Once again, thank you very much for your comments and suggestions!

On behalf of the authors,

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An asymmetric pinching damaged hysteresis model for glubam members: parameter identification and model comparison

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Abstract

The performance of glue laminated bamboo (glubam) members is governed by the nonlinear response at their joints, where high deformation levels and stress concentrations are developed. Numerous phenomenological models are presently employed to describe the hysteresis behavior of these joints, while these models always have an excessive number of parameters, and the physical interpretation of these parameters is often challenging. Moreover, some hysteresis models cannot capture all hysteresis features such as asymmetry, pinching, and damage. Consequently, this paper introduces a novel phenomenological-based hysteretic model named Asymmetric Pinching Damaged (APD) model, and implemented it in Abaqus by combining connector and spring elements in series or parallel. This model encompasses asymmetry, pinching, and strength degradation for bamboo joint components, with parameters that possess clear physical meanings and are readily comprehensible. This study also presented a parameter identification framework coupling the Parallel Genetic Algorithm (PGA) and Bayesian Neural Network (BNN). By merging the FE modeling and optimizing algorithms with the interactive application of ABAQUS and Python software platforms, the integrated identification framework is capable of performing multi-threaded parallel computation of finite element models considering the BNN-based uncertainty quantification, thus greatly improving the efficiency of parameter identification.

Keywords: , Glue laminated bamboo, Asymmetric Pinching Damaged (APD) hysteretic models, Parameter identification, Parallel genetic algorithm, Bayesian neural network

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1. Introduction

Structural bamboo is a renewable resource abundantly accessible, exhibiting a lower environmental footprint compared to other construction materials of similar strength. The structural performance of glue laminated bamboo (glulam) constructions is significantly influenced by the nonlinear response observed in the connection zones. These areas, characterized by high levels of deformation and stress concentration, form around fasteners such as nails, dowels, or bolts. Furthermore, these zones are particularly susceptible to significant load reversals throughout the service life of structures, especially under extreme conditions such as earthquakes or strong winds. Therefore, investigating the nonlinear behavior of glulam connections under substantial deformation levels until failure is essential.

The hysteretic behavior of glulam members is governed mainly by the crushing of glulam, the plasticity of fasteners, and friction between components [1, 2, 3]. As a quasi-brittle material, glulam poses a strength/stiffness threshold that irreversibly degrades when surpassed. This degradation leads to a delay in the connection response and drop the stiffness each connector provides [4], reflected in the hysteresis as one of the most recognizable nonlinear features of wood-based structures named as “pinching”. Furthermore, various increasingly prevalent circumstances in structural design can cause significant deviations from the classical symmetrical hysteretic behavior of glulam members, resulting in remarkably asymmetrical responses. The main reasons of asymmetry include the lateral-axial load combinations [5], hybrid connections with stiffer and thicker materials [6, 7, 8, 9], and overturning anchorage systems [10, 11, 12]. Therefore, asymmetry should be carefully handled in the response simulation of bio-based materials.

The complexity of wood-based member behavior has motivated the creation of several hysteretic models. Three main groups exist in the literature: (i) detailed micro-models, where each material is represented individually (e.g., steel and wood) with 3D solid and contact finite elements on a mechanical formulation (e.g., plasticity or continuum damage mechanics). Such models can predict accurate nonlinear response of detailed members/assemblies at expenses of extensive computation efforts [13]; (ii) component macro-models, in which each component (e.g., fasteners, anchors, sheathing/mass timber panels, and frame) is modeled separately using a set of nonlinear coupled or uncoupled springs and/or shell elements, generally based on mechanical and/or phenomenological formulations. These models are typically applied to simulate the dynamic response of planar members or assemblies with an efficient accuracy-to-time ratio (e.g., dowel-type joints [14], Light-frame timber (LFT) walls [15, 16, 12], Cross laminated timber (CLT) walls [17, 18, 19, 20, 21], and Cross laminated timber (CLT) slabs [22]); and (iii) simplified macro-models, where the whole member is simulated with a set of uncoupled/coupled uniaxial Single Degree-Of-Freedom (SDOF) nonlinear springs [23, 24, 25, 26], stated on a phenomenological approach and used for a fast dynamic performance evaluation of the entire structure at expenses of neglect coupling load effects [18]. Among all these options, phenomenological models are most versatile in simulating a broad variety of timber assemblies

35 with symmetric/asymmetric behavior, which is the objective of this article.

36 There are usually two ways to construct phenomenological hysteresis models. One is to program the
37 constitutive rules through user-subroutines to construct user-defined material properties, and the other is
38 to construct new models based on existing basic constitutive material models using series-parallel rules. For
39 the former method, programming of user-subroutines is needed [27, 28, 29]. However, the programming
40 is complex and may also cause convergence problems. Thus, this paper aims at developing a hysteretic
41 model based on existing basic constitutive material models using series-parallel rules. The proposed model
42 in this work explains the mechanism of asymmetric pinching damaged hysteresis behavior, reflecting the
43 asymmetry, pinching, and strength/stiffness degradation behaviors, while being computationally efficient
44 and suitable for implementation in structural-level finite element (FE) analysis.

45 To simulate the complex behaviors of glulam joints mentioned above, the proposed model is expected to
46 show a large number of flexible parameters. Hence, automatic parameter calibration is indispensable. Tra-
47 ditional parameter optimization (identification) methods may fall short in solving this highly non-linear and
48 non-convex optimization problem. To improve the practical value of the proposed model, three innovative
49 methods for parameter identification are investigated and compared in this study: (i) Parallel Genetic Al-
50 gorithms (PGA), (ii) Bayesian Inference (BI) and (iii) coupling method of Bayesian Neural Network (BNN)
51 (Graves [30], Blundell et al. [31]) and PGA (named as BNN-PGA). By scripting programming in Python,
52 the proposed PGA, BI and BNN-PGA method are fully automated to interact with ABAQUS software for
53 carrying out multi-thread parallel finite element analyses during identification process. Parallel computing
54 of FE modeling will serve to make identification faster, and the inference and uncertainty quantification of
55 BNN can further improve the overall optimization efficiency.

56 In the following sections, Section 2 presented the constitutive equations of the proposed hysteretic model.
57 Section 3 calibrated the APD hysteresis model parameters roughly, and outlined the fundamental procedures
58 of three parameter identification frameworks (PGA, BI and BNN-PGA). The calibrated model after param-
59 eter identification was validated and compared against a set of experimental results of glulam components
60 in Section 4, where it was also compared with the response of three other well-known hysteretic models
61 available in the literature (SAWS, Pinching4, and DowelType).

62 2. APD hysteresis model

63 The hysteretic behavior of glulam members is governed mainly by the crushing of glulam and the
64 plasticity of fasteners. Both of them contribute to the final hysteretic behavior of the entire member.
65 Therefore, the APD hysteresis model for entire glulam member was developed by coupling the hysteretic
66 behaviors of these two individual components. The model formulation is presented in detail herewith. This
67 model is designed following the series-parallel rule (Levitin et al. [32], Numanoglu et al. [33], Wang et al.

68 [34]). Series-parallel rules refer to the configuration of components or systems where certain elements are
69 connected in series, while others are connected in parallel. This approach is commonly used in various
70 fields, including electrical engineering, mechanical systems, and structural modeling. In a series connection,
71 components are arranged sequentially so that the same output (e.g., force) flows through each element.
72 In contrast, a parallel connection involves arranging components so that they share the same input (e.g.,
73 displacement), but the output is distributed among them.

74 In this study, series-parallel rules play a crucial role. The overall behavior of a joint can be complex,
75 involving multiple elements that need to interact in specific ways to replicate real-world phenomena like
76 pinching, asymmetry, energy dissipation, stiffness degradation, and strength deterioration. By applying
77 series-parallel rules in hysteretic behavior modeling, a more flexible and resilient joint model, capable of
78 handling various loading conditions, can be developed. This approach is particularly valuable when dealing
79 with materials or structures that exhibit non-linear and path-dependent behaviors, such as those observed in
80 glubam joints or other composite materials. Noting that this model is an improvement version of the model
81 proposed in Xu et al. [35], Shi et al. [36, 37]. The basic materials and some assumptions are similar, but the
82 asymmetry and damage effect are more comprehensively considered in the current model. In addition, the
83 model behavior is further validated based on experimental results. Such improvements allows the model to
84 represent the complex behaviors of bio-based materials better.

85 *2.1. Basic material model*

86 This section will introduce the constitutive rule of basic material model used in APD hysteresis model
87 including elasto-plastic rule (herein EP material model), STOP rule (herein S material model) and LOCK
88 rule (herein L material model). The EP material model requires the specification of four parameters: (i)
89 elastic stiffness, (ii) yield strength, (iii) post-yield stiffness, and (iv) hardening rule. As depicted in Figure
90 A.17, this study employs both isotropic and kinematic hardening rules for the EP material model, named
91 as EP-ISO and EP-KIN, respectively. STOP materials can be visualized as a slider in a slot with fixed
92 boundaries. The deformation is constrained by these boundaries, allowing frictionless relative movement
93 within the slots' limits. When the distance to one end of the slot is finite and the other is effectively infinite,
94 the STOP material acts as a one-sided constraint. Consequently, STOP materials are categorized into
95 Tension-STOP (TS) and Compression-STOP (CS) types, restricted on the tension and compression sides,
96 respectively (shown in Figure A.16). As illustrated in Figure A.18, the LOCK material model operates
97 based on a threshold value defined by either deformation or internal force. The material behaves according
98 to its initial properties until this threshold is met. Once the threshold is reached, the material becomes
99 "locked" and behaves as a rigid body. In this study, the LOCK material is characterized by linear-elastic
100 behavior with the threshold defined by internal force. For further details on the EP, STOP and LOCK
101 material models, see Shi et al. [36, 37].

102 *2.2. Constitutive rule of fastener plasticity*

103 The behavior of the fastener is modeled by connecting EP-KIN and L material in series (see Figure
104 A.19a). The threshold value of the L material is set to the yield strength f_{sy} of the EP-KIN material.
105 Figure A.19 illustrates the simulated monotonic and hysteresis behavior of the fastener model. The model
106 captures variations in elastic stiffness before and after yielding, reflecting the embedding process of fasteners
107 with reduced post-yielding stiffness compared with the initial stiffness (see Figure A.19b). Experimental
108 results indicate that the initial loading stiffness $K_{initial-loading}$ is always smaller than the unloading stiffness
109 $K_{unloading}$ (see A.19c). To model this phenomenon, a lock element is incorporated into the fastener model.
110 The force contributed by the fastener under monotonic loading can be calculated refer to Shi et al. [36].

111 *2.3. Constitutive rule of glubam crushing*

112 A series combination of \pm EP-ISO and \pm STOP materials is used to model the crushing of glubam and
113 the permanent deformation of the hole, as shown in Figure 1. This model is divided into tension-sided
114 and compression-sided crushing, depicted in Figures 1 a and b, respectively. Specifically, three groups of
115 +EP-ISO and TS materials were connected in parallel to simulate the tension-sided yield of the glubam,
116 representing contact between the fasteners and the glubam hole during the tension-sided reloading/reverse
117 loading stage. Similarly, three groups of -EP-ISO and CS materials are connected in parallel to model the
118 compression-sided yield of the glubam, representing contact during the compression-sided reloading/reverse
119 loading stage.

120 For TS material, the distance between the slider and the right end of the slot (upper limit) is set to the
121 gap width G_{i+} ($i = 1, 2, 3$), while the distance to the left end (lower limit) is set to a large value, making
122 it unattainable (e.g., 30 mm). The simulated monotonic and hysteresis behavior of tension-sided glubam
123 crushing are illustrated in Figures 1 c and e. For CS material, the distance between the slider and the left
124 end of the slot (upper limit) is set to the gap width G_{i-} ($i = 1, 2, 3$), with the right end distance similarly
125 selected as an unattainable value. The behavior of compression-sided glubam crushing is shown in Figures
126 1 d and f. Therefore, the TS and CS materials retain details about the irrecoverable deformation of glubam
127 and the contact status between the fastener and glubam on the tension and compression sides, respectively.

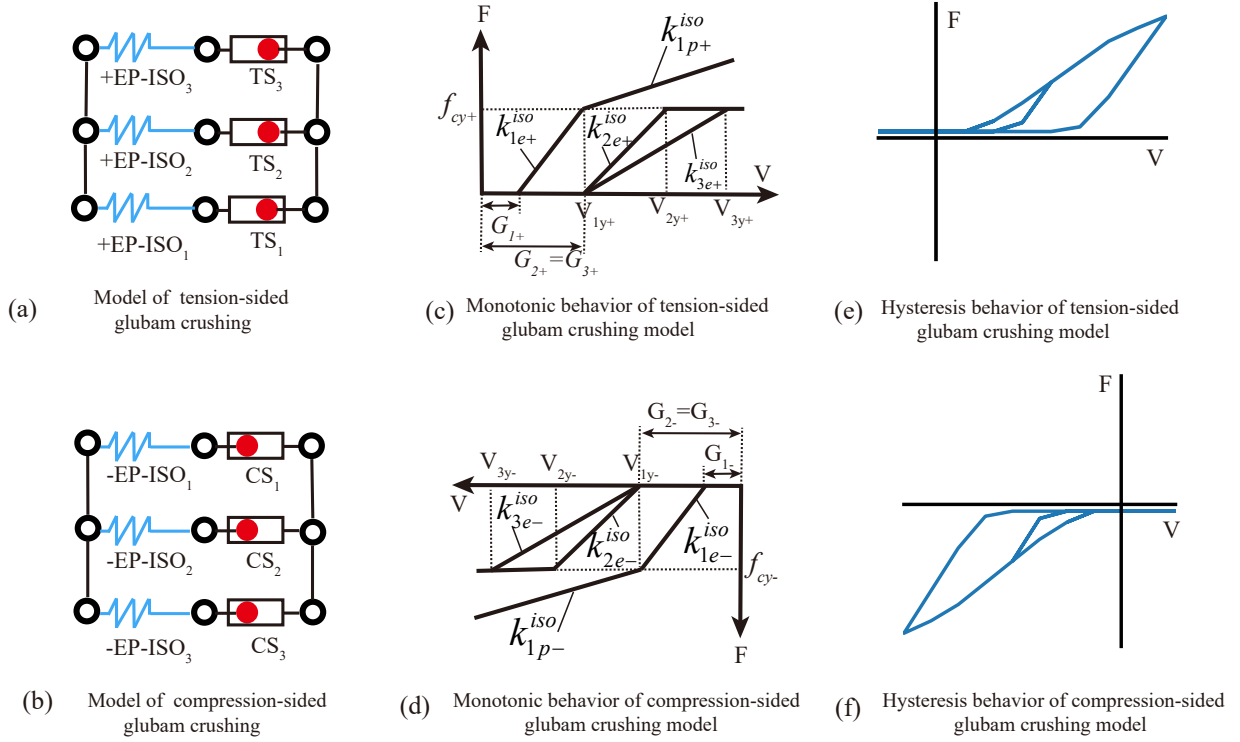


Figure 1: Constitutive rule of glubam crushing model: configuration of glubam crushing model (a and b), monotonic behavior of glubam crushing model (c and d) and hysteresis behavior of glubam crushing model (e and f). (modified based on Shi et al. [37])

128 Two assumptions formulate the basis of the glubam crushing model, namely (i) the yield strengths for
 129 $\pm EP-ISO_1$, $\pm EP-ISO_2$ and $\pm EP-ISO_3$ are equal, (ii) $\pm EP-ISO_2$ and $\pm EP-ISO_3$ are elasto-perfect
 130 plastic. These assumptions allow for a gradual elasto-plastic transition in the force-slip curve and enable the
 131 loading and unloading stiffness to be set as unequal. Based on the aforementioned model and assumptions,
 132 the resistance force generated by the glubam crushing action can be calculated using the following equations.
 133 Compared with Shi et al. [36], these equations reflects the asymmetry of tension and compression sides.

$$F_{c\pm}(V) = \Sigma F_{i\pm}(V) \quad (i = 1, 2, 3) \quad (1)$$

$$F_{i\pm}(V) = 0 \quad (|V| < G_{i\pm}) \quad (2)$$

$$F_{i\pm}(V) = k_{ie\pm}^{iso}(V - G_{i\pm}) \quad (G_i < |V| < V_{iy\pm}) \quad (3)$$

$$F_{i\pm}(V) = k_{ip\pm}^{iso}(V - V_{iy\pm}) + f_{cy\pm} \quad (|V| > V_{iy\pm}) \quad (4)$$

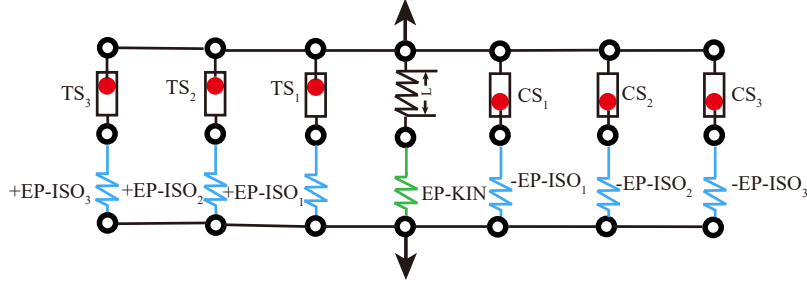


Figure 2: Proposed asymmetric pinching damaged (APD) hysteresis model for joints (modified based on Shi et al. [37])

134 where $F_{i\pm}$ is the force generated by the i th combination of \pm EP-ISO and \pm STOP materials in glulam
 135 crushing model, $G_{i\pm}$ is the gap of the $STOP_{i\pm}$ material, $V_{iy\pm}$ is the yield displacement of the i th combination
 136 of EP-ISO and STOP materials in glulam crushing model, $k_{ie\pm}^{iso}$ is the elastic stiffness of the $\pm EP - ISO_i$
 137 material, $k_{ip\pm}^{iso}$ is the post-yield stiffness of the $\pm EP - ISO_i$ material ($k_{2p\pm}^{iso} = k_{3p\pm}^{iso} = 0$), and $f_{cy\pm}$ is the
 138 yield strength of the $\pm EP - ISO_i$ material.

139 2.4. Constitutive rule of joint model

140 The glulam joints are represented by a series of two-dimensional axial connector elements, CONN2D2,
 141 available in ABAQUS. Each element is assigned with basic material behaviors, including elasto-plastic (EP
 142 material model), STOP (S material model), and LOCK (L material model) behaviors. In this joint model,
 143 all nodes are positioned at the same location, and the mechanical behaviors are assigned exclusively to the
 144 tension and compression degree of freedoms (DOFs) of the connector elements. As mentioned earlier in this
 145 section, the contributions of the steel bolt and glulam bearing are modeled individually, and the overall
 146 behavior of the joint is a parallel superposition of the actions contributed by the fastener and glulam. The
 147 schematic of the overall joint model is shown in Figure 2. The proposed model effectively represents three
 148 typical features observed in the hysteresis behavior of glulam joints: pinching, asymmetry, and strength
 149 degradation.

150 2.4.1. Pinching

151 As loading increases, the bamboo fibers are crushed by the fastener. Due to the irreversible nature of
 152 fiber crushing, the affected glulam area cannot provide an immediate response in subsequent loading cycles.
 153 This slack leads to a delay in the connection response and reduces the stiffness each connector provides
 154 [4]. This effect is reflected in the hysteresis as 'pinching,' one of the most recognizable nonlinear features
 155 of wood-based structures. To model this pinching phenomenon, TS and CS materials were used to capture
 156 the irrecoverable deformation of glulam.

157 *2.4.2. Asymmetry*

158 As discussed before, various circumstances increasingly prevalent in structural design can cause significant
 159 deviations from the symmetrical hysteretic behavior of glulam members (e.g., [36]), resulting in notably
 160 asymmetrical responses. Three common scenarios exemplify such asymmetry: (i) assemblies subjected to
 161 lateral-axial load combinations (e.g., shear walls of lower stories), resulting in an asymmetrical displacement
 162 response [5]; (ii) hybrid connections integrating glulam members with stiffer and thicker materials (e.g.,
 163 concrete, steel plates, and multilayered gypsum boards), leading to fastener fixation on one side of the
 164 shear plane accompanied by strong frictional forces, known as the "rope effect" (particularly evident in
 165 concrete). This phenomenon generates a pronouncedly asymmetrical force response [9, 6, 7, 8]; and (iii)
 166 overturning anchorage systems (e.g., hold downs, steel angle brackets, and Anchor Tie-down Systems (ATS)),
 167 which exhibit an asymmetric tensile/compressive behavior (termed taxonomic asymmetry), characterized by
 168 hysteresis only in tension and a stiff quasi-linear response in compression [10, 11, 12]. In the proposed joint
 169 model, the tension-sided and compression-sided crushing model were combined in parallel, thus modeling
 170 each side of hysteretic responses separately. When overlaying these two contributions, the asymmetrical
 171 responses presented in the hysteresis responses can be modeled.

172 *2.4.3. Damage (Strength degradation)*

173 To model the strength degradation presented in the hysteresis behavior, a damage criterion was intro-
 174 duced into the $+EP - ISO_1$ and $-EP - ISO_1$ material to model the force descending stage of tension side
 175 and compression side, respectively. As shown in Figure 3 a and b, two threshold values (F_{d+} and F_{d-})
 176 and two damage indexes (I_{d+} and I_{d-}) was introduced to define the damage initiation and end points. The
 177 resulted hysteresis behavior after incorporating damage criterion were illustrated in Figure 3 c and d. With
 178 this damage behavior, the resistance force generated by the combination of $\pm EP - ISO_1$ and $\pm STOP_1$
 179 materials can be calculated using the following equations:

$$F_{1\pm}(V) = 0 \quad (|V| < G_{1\pm}) \quad (5)$$

$$F_{1\pm}(V) = k_{1e\pm}^{iso}(V - G_{1\pm}) \quad (G_{1\pm} < |V| < V_{1y\pm}) \quad (6)$$

$$F_{1\pm}(V) = k_{1p\pm}^{iso}(V - V_{1y\pm}) + f_{cy\pm} \quad (V_{1y\pm} < |V| < V_{d\pm}) \quad (7)$$

$$F_{1\pm}(V) = k_{d\pm}(V - V_{d\pm}) + I_{d\pm} * F_{d\pm} \quad |V| > V_d \quad (8)$$

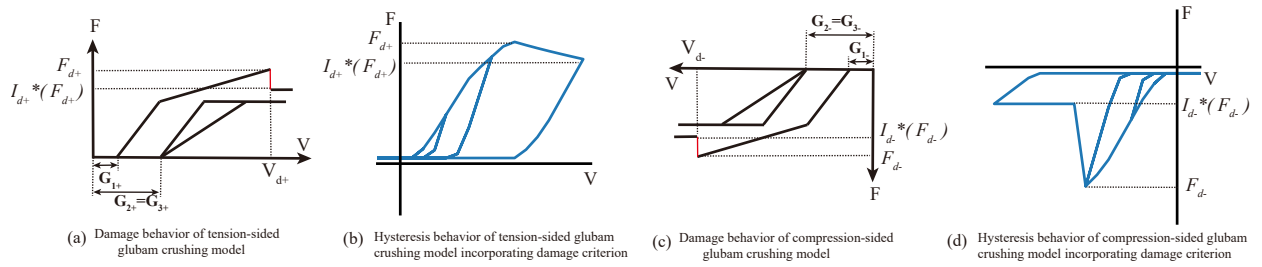


Figure 3: Damage behavior of glubam crushing model. (modified based on Shi et al. [37])

3. Automatic identification of APD hysteresis model parameters

To simulate the complex behaviors of glubam joints, the proposed model incorporates numerous flexible parameters, making automatic parameter calibration essential. To enhance the model's practical value, this study investigates and compares three methods for parameter identification: (i) PGA, (ii) BI, and (iii) BNN-PGA. The first two methods have already been proposed and validated in existing studies (Shi et al. [37, 38]), and therefore, they will only be briefly described in this section. However, the parameter tuning, comparison of PGA and GA, and the estimated parameter distributions in BI-based identification, are the original works completed in this study and will be discussed in detail.

3.1. Parameter tuning and comparison of PGA and GA

The rough determination of parameters involves extraction of the characteristic points and parameters of the hysteresis curves from the tested results (i.e. the stiffness, K , and the yield slip, V_y). The yield point is determined according to BS EN 12512:2001 [39]. A more advanced method to calibrate the yield point is proposed in [40, 37], which is more suitable for a bi-linear load-deformation response. After determining these key points, following similar procedures and principles in [36, 40], the model parameters controlling the hysteresis curves can be calibrated manually. Noting that the parameters for positive and negative sides should be identified separately to reflect the asymmetry.

Based on the rough parameter obtained above, a more precise procedure is further developed for parameter identification. Genetic algorithms (GA) is a well-known optimization algorithm based on fitness function evaluation, recombination, mutation and individual selection of the next generation [41, 42]. GA are widely used in many fields, but often require too much time and repetitive evaluation. The most time-consuming operation within GA is the evaluation of the fitness function [43, 44]. Hence, an effective and efficient PGA algorithm is developed in [36] based on a master-slave configuration based parallel programming structure. Some procedures need to be carried out serial (recombination, mutation and selection operators) are only executed in the master thread, while the other CPU cores are parallel adopted for fitness evaluation of the

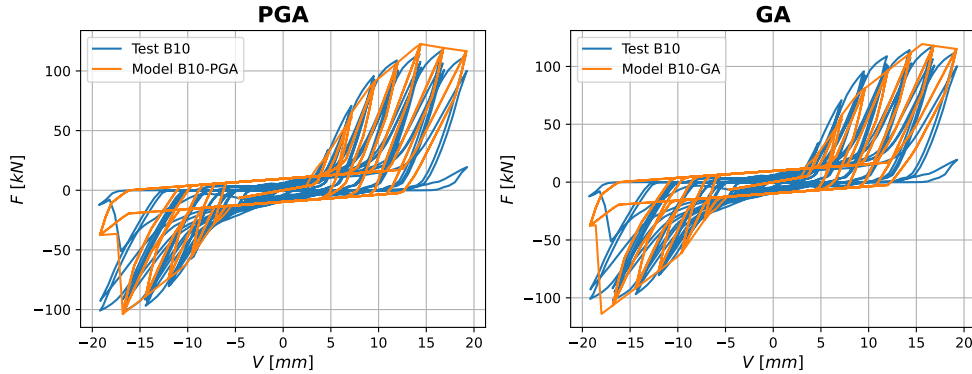


Figure 4: Comparison of identification accuracy for PGA and traditional GA.

204 design population, which does not require inter-cores communication. The parallel execution of the solution
 205 algorithm is schematically depicted in Figure B.20 [45]. More details are introduced in [36].

206 To mitigate convergence issues associated with PGA in complex optimization problems, a careful tuning
 207 of parameter setting of the PGA, such as mutation rate, crossover rate, population size and generation num-
 208 ber has been carried out to improve convergence. Preliminary tuning identified that the optimal convergence
 209 is achieved with a crossover probability of 0.8, a mutation probability of 0.08, a population size of 30, and
 210 a total generation of 50. After the rough determination of model parameters, an amplification factor of 10
 211 and a reduction factor of 0.2 for the estimated values of all parameters are chosen as the upper and lower
 212 bounds of the search space. Rough estimation of model parameters and constraining the search space can
 213 similarly enhance the convergence of the optimization process. In each generation, 30 slave threads evaluate
 214 30 individuals simultaneously, with one processor core assigned to each thread. The random initialization
 215 of the GA population can lead to variability in the solutions across different runs. However, through exten-
 216 sive trials, we determined that using the specified parameter settings reliably leads to convergence towards
 217 a near-optimal solution while maintaining high identification efficiency. This configuration also minimizes
 218 redundant iterative computations, as increasing the number of generations beyond a certain point provides
 219 only marginal improvements in accuracy. The PGA was terminated based on a maximum number of genera-
 220 tions. These criteria were chosen to ensure a balance between computational efficiency and solution quality.
 221 The computational tasks were executed using two Intel(R) Xeon(R) Silver 4310 CPUs, with 24 cores and
 222 48 logical processors in each, which enabled efficient execution of the parallel genetic algorithm.

223 The proposed PGA was compared with the traditional GA regarding identification accuracy and effi-
 224 ciency, as shown in Figure 4 and Table 1. The searching space defined by the traditional GA is consistent
 225 with that of the PGA. The Relative Root Mean Square Errors (RRMSE) (see Eq.9) was used herein to eval-
 226 uate the identification accuracy. From Table 1, it can be seen that the PGA and the traditional GA exhibit
 227 comparable identification accuracy. Meanwhile, the PGA significantly enhances identification efficiency.

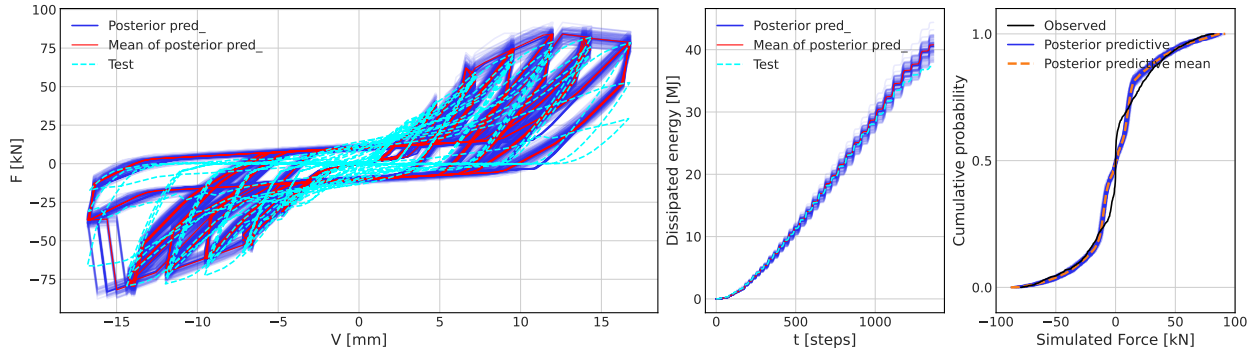
Table 1: Comparison of the traditional GA and PGA.

Method	PGA	Traditional GA
Accuracy	$RRMSE=8.32\%$	$RRMSE=8.95\%$
Computation cost	Around 25 min	Around 11 h
Evaluation times	1500	1500
Overall Efficiency	High	Low

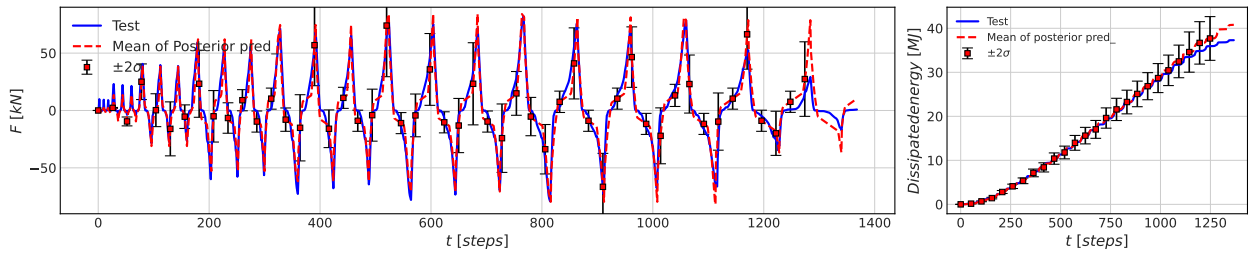
228 *3.2. BI-based identification and estimated parameter distributions*

229 Following the procedures proposed in [38], we employ Sequential Monte Carlo (SMC) as a method to
 230 address this issue by sampling the joint posterior distribution. By tempering the posterior, this algorithm can
 231 partially avoid getting trapped in local optima and achieve better convergence. This approach is particularly
 232 useful in dealing with multimodal and non-convex problems.

233 To mitigate convergence issues associated with BI in complex optimization problems, informative priors
 234 were incorporated to constrain the parameter space and smooth the posterior landscape, making it easier
 235 for the SMC algorithm to converge. Selecting proposal distributions that are closer to the target posterior
 236 distribution can significantly enhance convergence. In this study, truncnormal distribution with mean values
 237 equal to the roughly determined parameters values discussed in section 3.1 was chosen as the prior distribu-
 238 tion. An amplification factor of 3.0 and a reduction factor of 0.1 for mean values of all the parameters are
 239 selected as the upper bound and lower bound of the truncnormal distribution. 0.5 times the mean values
 240 are selected as the standard deviations of the prior distributions. To quantify the estimated uncertainty, the
 241 bounds of the response were calculated based on the posterior distribution of the APD model parameters.
 242 100 sets of model parameters were generated from posterior distribution and their corresponding standard
 243 deviation σ was calculated. The generated parameter sets were inputted into the APD model to obtain
 244 corresponding output responses under cyclic loading conditions, as illustrated in Figure 5.



(a) Posterior prediction of hysteretic curve, energy dissipation and cumulative probability of simulated force values.



(b) Time history and standard deviation of the predicted force and energy dissipation

Figure 5: Comparison of the test result and 100 posterior sample under cyclic loading.

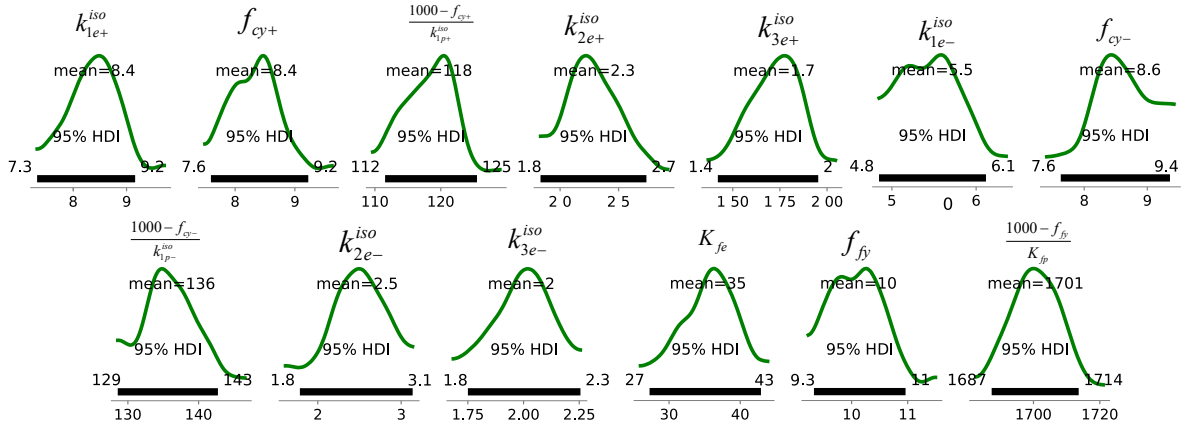


Figure 6: Mean values of the posterior SMC samples and the detailed marginal posterior PDF of each parameter

245 After synthesizing the response data for 100 groups, the statistical measures, specifically the mean and
 246 standard deviation (σ), were calculated. Figure 5 b compares the mean values of these 100 samples with
 247 the prior data, with error bars representing $\pm 2\sigma$. Generally, the output bounds encompassed the test data,
 248 indicating that the estimated parameters closely represent the true parameter values. As shown in Figure 5
 249 a, the comparison of hysteresis curves and energy dissipation history demonstrates that the posterior data

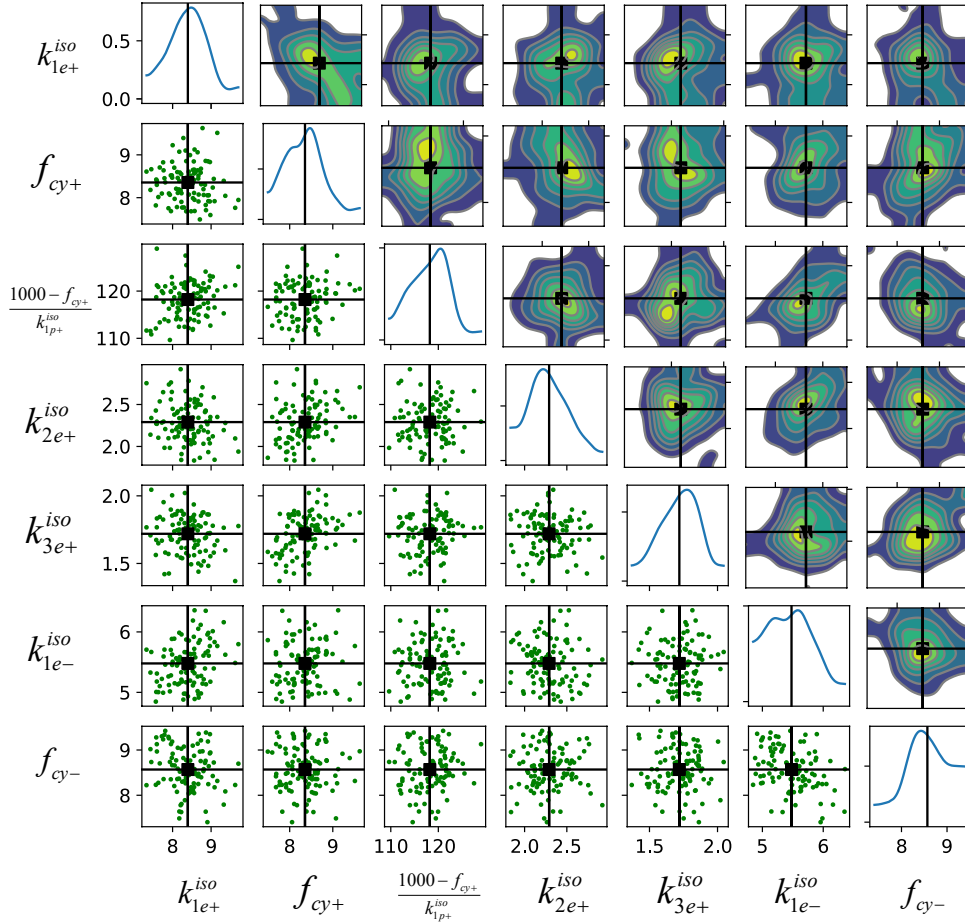


Figure 7: Pair plot using posterior samples of 7 representative inferred parameters obtained using SMC.

effectively captures the key features of the test data.

The mean values of the posterior SMC sample parameters and the detailed marginal posterior probability density functions of selected parameters are shown in Figure 6. Figure 7 displays the pair plot for seven representative inferred parameters, constructed from posterior samples derived via SMC. On the diagonal, the plots depict the kernel density estimates for the marginal PDFs of each parameter. Below the diagonal, the plots illustrate the posterior samples within the parameter pair space, and the contour plots of the kernel density estimates are presented above the diagonal.

3.3. BNN-PGA coupling parameter identification

The proposed PGA method offers significantly improved computational efficiency over the traditional serial GA. However, like other heuristic algorithms, PGA still necessitates computing a large number of cases. This is especially challenging for hysteretic models with high computational demands, where the optimization efficiency remains sub-optimal. To address this issue, this section introduces an innovative

262 method that combines the strengths of BNN (Graves [30], Blundell et al. [31]) with PGA. BNNs effectively
263 merge Bayesian statistics with neural networks, offering a probabilistic interpretation of the model prediction
264 process and enabling the quantification of prediction uncertainties, which is a feature absent in traditional
265 neural networks. By incorporating the uncertainty quantification from BNN predictions, it is possible to
266 forego the creation of a large-scale training dataset, which considerably reduces the computational load
267 and enhances the practical value of the proposed method. Consequently, BNNs are increasingly applied in
268 fields such as reliability analysis and structural response prediction (Perez-Ramirez et al. [46], Dang et al.
269 [47], Wang et al. [48]).

270 Within the basic principles of BNN, Monte Carlo Dropout is a notable technique (Gal and Ghahramani
271 [49, 50]). It involves applying dropout not just during training, but also during inference, to simulate the
272 sampling from a posterior distribution. This method allows for multiple stochastic forward passes through
273 the network, with dropout serving to create a resampled weight combination each time, thus enabling the
274 estimation of the uncertainty in the network predictions. Compared with other implementation manner
275 of BNN such as Bayes by Backprop, Stochastic Gradient Langevin Dynamics, and Kronecker-Factorised
276 Laplace, Monte Carlo Dropout is simpler to be integrated into various neural network architectures without
277 necessitating significant modifications to their structure or optimization processes. Thus, it has been selected
278 as the BNN implementation method for this study.

279 3.3.1. Framework of BNN-PGA

280 The overall framework of the coupling BNN-PGA is shown in Figure 8. It can be separated into four
281 different parts:

282 (1) Part 1: Generation of parameter combinations

283 This part adheres strictly to the principles of the traditional GA. The initial populations for the first
284 generation are randomly generated within predefined upper and lower limits. For subsequent generations,
285 processes such as crossover, recombination, and potential mutation are employed to develop new populations
286 from the selected samples of the preceding generation.

287 (2) Part 2: BNN training

288 Frequently, the parameter identification process using PGA is iterated multiple times to assess the impact
289 of key configurations, reduce fluctuations, and enhance the accuracy of the final results. This iterative process
290 effectively serves as data preparation for BNN training, eliminating the need to generate a large dataset for
291 BNN only. The parameter combinations and their corresponding fitness values are recorded, and are used
292 as the inputs and outputs for the BNN, respectively. Once the BNN model is well-trained, it is integrated
293 into the PGA-based optimization process. The inference results for each parameter combination, including
294 mean value and standard deviation, are used as the basis for fitness calculation and parameter selection in
295 subsequent steps.

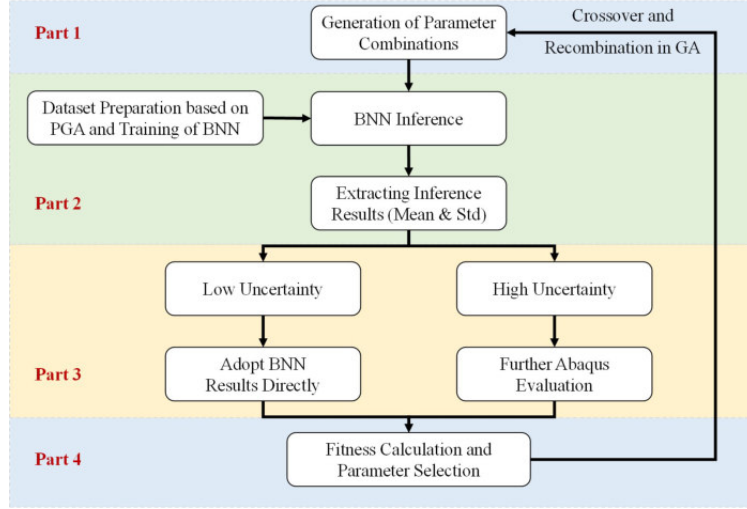


Figure 8: Framework of the proposed BNN-PGA method

296 (3) Part 3: Uncertainty quantification

297 The uncertainty of the inference results is quantitatively assessed by the ratio of the predicted stan-
 298 dard deviation to the mean value. High uncertainty results prompt further evaluation of the corresponding
 299 parameter combinations using the ABAQUS model in a parallel manner. Conversely, for results with low un-
 300 certainty, the mean fitness value from the BNN inference is directly utilized. Notably, in critical generations
 301 such as the last generation, all parameters are evaluated using ABAQUS to enhance reliability.

302 (4) Part 4: Fitness value calculation and parameter selection

303 Following part 3, fitness values for all populations in the current generation are obtained either through
 304 the mean square error between the ABAQUS simulation results and experimental data or via BNN inference.
 305 The optimal parameter combination is then selected to form the basis of the next generation.

306 3.3.2. Key settings and BNN model evaluation

307 In this study, the optimization process using BNN-PGA employs a Multi-Layer Perceptron (MLP)
 308 (Rosenblatt [51], Haykin [52]), also known as a fully connected neural network, as the foundational net-
 309 work architecture. This structure is implemented using PyTorch and is chosen for its efficiency in both
 310 training and inference stages. It is adept at establishing the required mapping relationship between the 20-
 311 dimensional vector inputs (key parameters in the proposed numerical model) and the 1-dimensional scalar
 312 output (prediction MSE corresponding to this parameter combination). Given that each input dimension
 313 operates independently, there is no need for selecting recurrent architectures such as Long Short-Term
 314 Memory networks (LSTM) or Gated Recurrent Units (GRU), nor for iterative architectures like Temporal
 315 Convolutional Networks (Hochreiter and Schmidhuber [53], Cho et al. [54], Xu et al. [55, 56], Gu et al.
 316 [57]). Moreover, more complex networks such as the Transformer, and its modifications like Reformer and

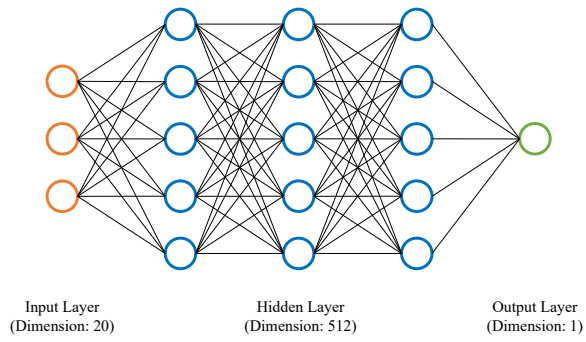
Table 2: Key hyperparameters in BNN

Name	Value	Description
Dataset size	6,500	The total number of samples for BNN
Dataset separation	-	Training: 70%; Validation: 20%; Testing: 10%
Number of layer	3	The number of hidden layers in BNN
Dropout ratio	0.5	Dropout ratio in Monte Carlo dropout processes
Sample time	5	The number of repetitive dropout processes adopted for uncertainty quantification
Hidden unit	512	The dimension of hidden unit in BNN
Initial learning rate	0.0002	The initial learning rate adopted in BNN training

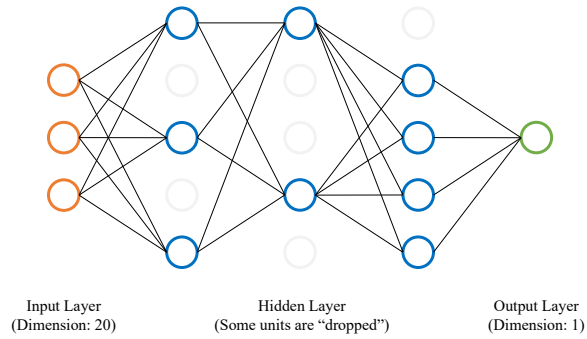
317 Informer, as well as TimesNet, are not considered due to the limited size of the available training dataset
318 and the goal of maintaining high efficiency (Vaswani et al. [58], Kitaev et al. [59], Zhou et al. [60], Wu
319 et al. [61]). The foundational theories of MLP, thoroughly discussed in the provided references, will not be
320 reiterated here.

321 During the training and validation phases, different architectural settings, particularly the number of
322 hidden layers and the neuron count in each layer, are meticulously compared. Some key hyperparameters
323 of the adopted BNN are provided in Table 2. The typology of the active BNN model and BNN model after
324 Monte Carlo dropout are provided in Figure 9. During the training process of the neural network, the training
325 and validation loss are continuously monitored. If the validation loss does not decrease for several epochs
326 (e.g., 50), the neural network training can be terminated and the model with the minimum validation loss
327 is regarded as the “well-trained” model. The following methods are adopted for controlling the overfitting:
328 (1) Searching for optimal hyperparameters based on cross-validation; (2) Monitoring the validation loss
329 continuously; (3) Exponential learning rate decay; and (4) Proper dropout during the training and inference
330 processes. Noting that, the overfitting cannot be completely eliminated during the inherent property of the
331 neural networks and highly non-convex of the optimization problem itself. However, the aforementioned
332 measures are valuable in controlling the effect of overfitting and can support the obtaining the acceptable
333 results presented in Table 3.

334 In this study, the BNN training utilizes a dataset of 6,500 samples, generated from PGA parameter
335 identification cycles. The training process for the BNN model is efficient, taking less than 10 minutes.
336 The performance of the optimally trained BNN model is detailed in Figure 10. The results indicate that
337 approximately 70% of the samples exhibit a relative deviation of less than 20%. However, 7.6% of the samples
338 show a relative error exceeding 40%. A trade off between dataset construction burden and absolute model
339 accuracy is the main reason of adopting such a BNN model as the final model without further accuracy
340 improvement.



(a) Active BNN



(b) BNN after Monte Carlo dropout (the "dropped" neurons are selected randomly)

Figure 9: The typology of the BNN model before and after Monte Carlo dropout

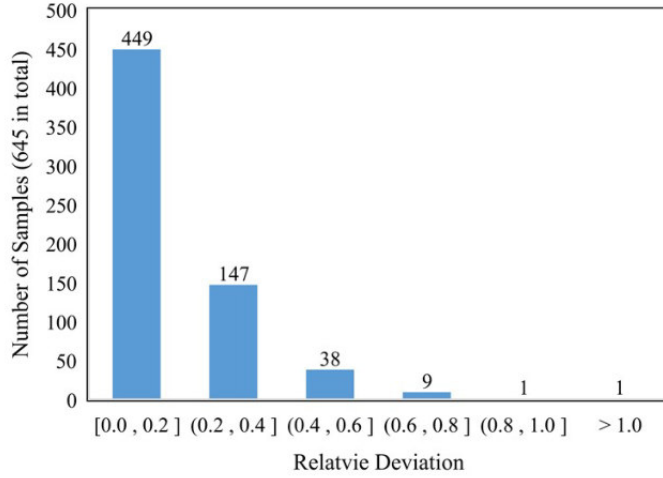


Figure 10: Distribution of relative distribution on the testing dataset

Table 3: BNN-PGA optimization results and comparison

Type	Threshold (Std / Mean Value)	Time (s)	Time reduction (%)	Best fitness value (MSE) in the last generation
Pure PGA (ABAQUS simulation only)	-	45382	-	86.7
	0.5	47248	-4.1	78.2
BNN-PGA	1.0	28665	36.8	100.7
	1.5	10680	76.5	164.9
BNN only	-	5257	88.4	197.7

3.3.3. BNN-PGA optimization performance

In the implementation of BNN-PGA, if the ratio between the standard deviation and mean value of the predicted fitness values are less than a certain threshold (discussed in Table 3), the BNN inference results will be directly adopted. In addition, for the last one in every 10 generations and the final evaluation generation, all parameter combinations will be evaluated through ABAQUS simulation to improve the reliability of optimization. The functions adopted for fitness evaluation is mean square error (MSE). The results of BNN-PGA optimization and comparison with pure PGA method is provided in Table 3. “Std” and “Mean Value” represent the standard deviation and mean value calculated based on the results of multiple BNN predictions, and the ratio between them are adopted for measuring the prediction uncertainty. It can be seen that, even with limited BNN model accuracy, the proposed BNN-PGA method still reaches similar performance with the pure PGA parameter identification. This achievement highly relies on the uncertainty quantification, for the optimization process based on the mean predicted MSE only fails in reaching similar accuracy. In terms of efficiency, the overall parameter time can be reduced by 36.8% with a threshold of 1.0.

Despite its similar accuracy and higher efficiency, the BNN-PGA method has significant room for improvement, particularly since the accuracy of the BNN model can continually improve as more samples are

356 accumulated. Additionally, this method is particularly well-suited for large-scale designs or simulations. In
 357 large-scale simulations, the accumulation of available samples accelerates, leading to a more reliable BNN
 358 model, which in turn could improve the overall time reduction ratio. Furthermore, the inference time for
 359 BNN does not vary significantly with an increasing simulation scale, whereas PGA simulations based on
 360 ABAQUS (or other finite element software) generally take more time. Consequently, the advantages of the
 361 BNN-PGA method become more pronounced as the scale of the simulation increases.

362 4. Validation of APD hysteresis model

363 4.1. Experimental benchmark tests for model validation

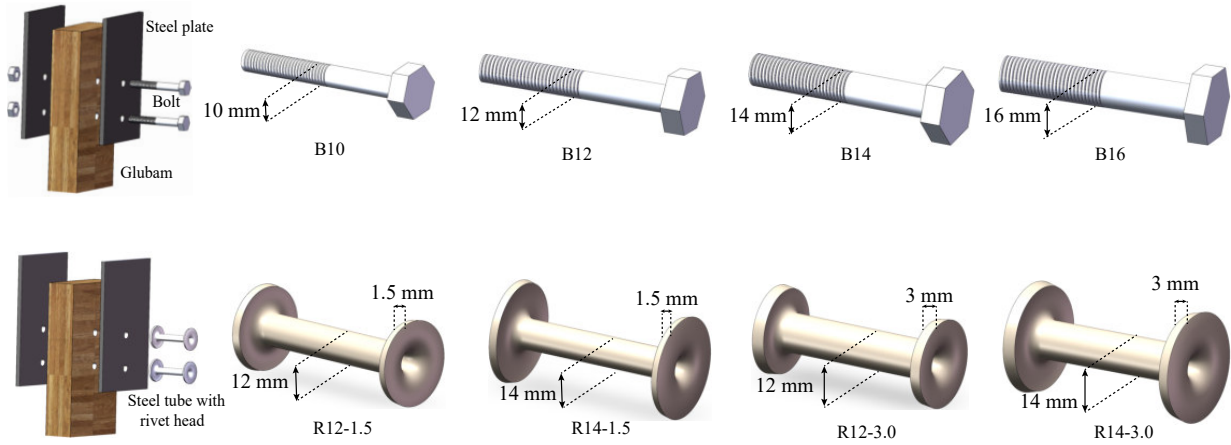


Figure 11: Configuration of glulam joints. (modified based on [37, 62])

364 The experimental benchmarks for APD hysteresis model validation comprised eight groups of cyclic test
 365 results of glulam connections including two joints types: (i) bolted connections and (ii) riveted connections
 366 with hollow steel tube. Adopting experimental data from two types of joints with different features helps
 367 improve the reliability of validation. Detailed configurations about the studied joints are illustrated in
 368 Figure 11. For riveted connections with hollow steel tube, the thickness and outer-diameter of steel wall
 369 were accounted as the variables resulting in 4 configurations: R12-1.5, R14-1.5, R12-3.0 and R14-3.0. For
 370 bolted connections, the diameter of bolt was accounted as the variables resulting in 4 configurations: B10,
 371 B12, B14 and B16. The tested hysteresis behaviors were illustrated in Figure 12 These data are obtained
 372 from the experiments finished by the authors previously [37, 62].

373 4.2. APD hysteresis model response

374 The optimal parameter combinations of APD model for the 8 experimental benchmark tests are obtained
 375 following the framework proposed in Section 3. The model parameters were first roughly determined in

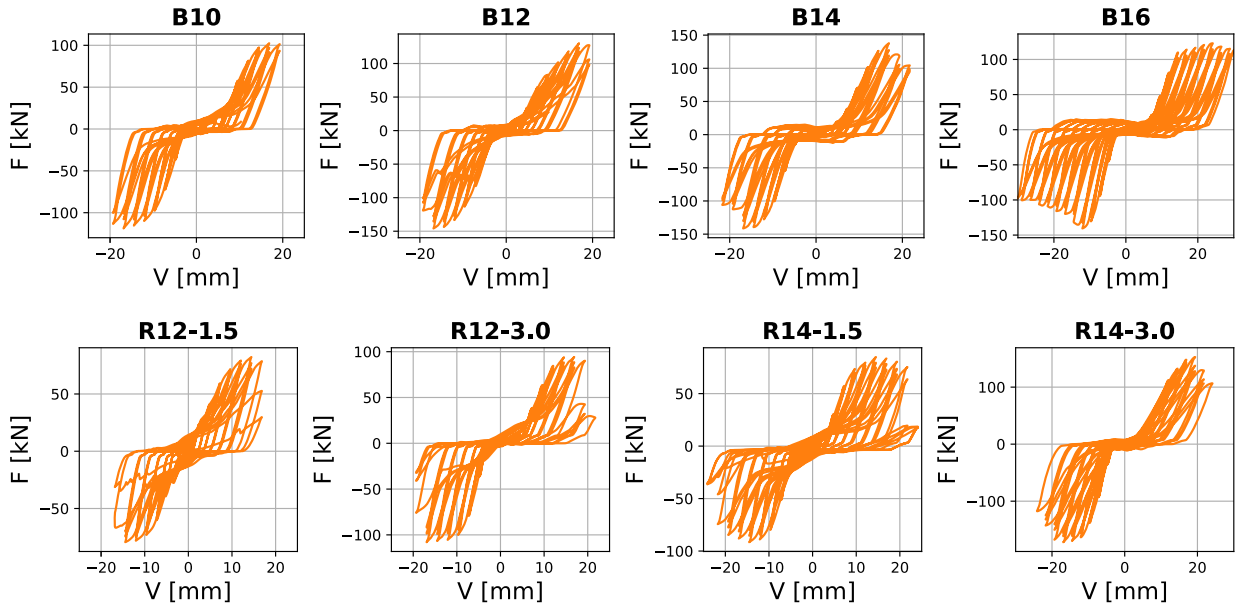


Figure 12: Cyclic test results of two types of glulam connections. (modified based on [37, 62])

376 Section 3.1, and then an amplification factor 10 and a reduction factor 0.1 for roughly determined parameter
 377 values are selected as the upper bound and lower bound of the searching space of parallel genetic algorithms.
 378 The population size and generation number are chosen as 50 and 50, thus a total of 2500 evaluations are
 379 performed. 25 slave threads are arranged to evaluate 25 individuals simultaneously in each generation and
 380 1 processor is distributed to execute each thread. The optimal predicted hysteretic behavior and energy
 381 dissipation-time history for the 8 benchmark tests are illustrated in Figure 13. It can be observed the
 382 proposed model can fit the pinching, damage and asymmetric behavior very well, and the energy dissipation
 383 also achieve a good fit between the tested and predicted values.

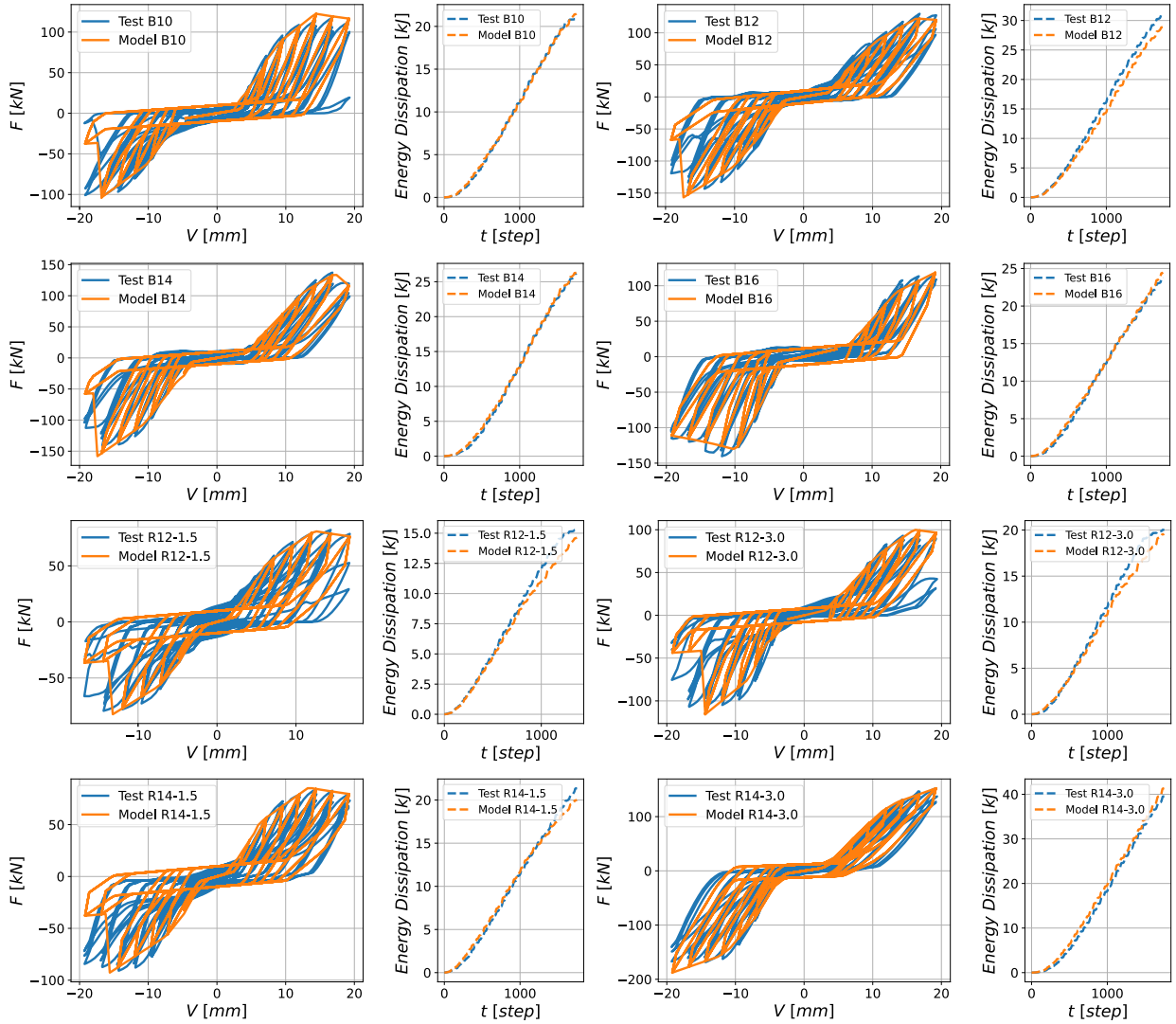


Figure 13: Comparison of the hysteretic responses from the tests and the optimal APD model prediction.

384 4.3. Comparison with other hysteretic models

385 The predicted responses by the APD hysteresis model are also compared with three well-known hysteretic
 386 models available in the literature. These models are: (i) the SAWS model (or more called MSTEW) of
 387 Stewart [63] and later modified by Folz & Filiatrault [64]; (ii) the Pinching4 model of Lowes et al. [65]; and
 388 (iii) the DowelType model of Dong et al. [66]. These three models are available in the OpenSees software,
 389 where the first two are commonly used to simulate timber connections, and the latter is recently incorporated
 390 into this software.

391 Figure 14 and 15 compare the force–displacement hysteresis of the four models for the 8 benchmark tests.
 392 To quantitatively compare the prediction accuracy of different models, the predicted response is compared

Table 4: *RRMSE* (see Eq.9) between tested response and predicted response.

Model	Configuration							
	B10	B12	B14	B16	R12-1.5	R14-1.5	R12-3.0	R14-3.0
APD	8.32%	13.38%	7.56%	9.75%	12.42%	10.21%	18.32%	13.15%
Saws	17.64%	25.31%	21.44%	32.21%	16.15%	15.43%	23.25%	28.61%
Pinching 4	12.64%	16.32%	13.45%	12.58%	16.12%	18.33%	14.41%	23.56%
DowelType	7.65%	14.72%	9.53%	8.34%	6.63%	8.32%	10.28%	10.31%

393 with the tested responses using the Relative Root Mean Square Errors (RRMSE), as shown in Table 4. The
 394 RRMSE provides a measurement of the error between two signals, \mathbf{a} (tested value) and \mathbf{b} (predicted value),
 395 and is defined as:

$$RRMSE(\mathbf{a}, \mathbf{b}) = \frac{\sqrt{\left[\frac{1}{N_s} \sum_{i=1}^{N_s} (a_i - b_i)^2\right]}}{\sqrt{\left[\frac{1}{N_s} \sum_{i=1}^{N_s} (a_i)^2\right]}} \times 100 (\%) \quad (9)$$

396 where N_s denotes the total number of data samples in the signals.

397 Comparison shows that the APD model and DowelType gives the best fit among the four models in
 398 all cases, followed by the Pinching 4 model, while the SAWS model performed the worst fitting accuracy.
 399 According to the fitting results, It is verified the proposed APD model is capable of capturing all hysteresis
 400 features observed from the test including asymmetry, pinching, and damage behavior. The APD model
 401 proposed in this paper is able to consider the elastic, yielding, pinching, and failure behaviors of materials
 402 under cyclic loading, including the asymmetric hysteretic response observed under tension and compression.
 403 Consequently, this model is also applicable to materials other than glubam, provided they exhibit significant
 404 irreversible damage, as indicated by a pinching effect in the hysteresis curve during loading. The pinching
 405 effect in hysteresis behavior is commonly observed in materials and structural elements that experience
 406 degradation in stiffness and strength under cyclic loading, especially when there is damage or slip between
 407 components. This behavior is characterized by a narrowing or "pinching" of the hysteresis loops around
 408 the origin in a force-displacement or stress-strain relationships. For example, masonry structures, especially
 409 those without significant reinforcement or with poor mortar joints, can display pinching effects due to
 410 crack propagation and slippage at the mortar-brick interface under lateral cyclic loads. Wood and timber
 411 elements, particularly those with connections like nails, bolts, or dowels, can show pinching behavior due
 412 to the slippage of fasteners or crushing of wood fibers near the joints when subjected to cyclic loads. The
 413 APD model is also applicable to these materials.

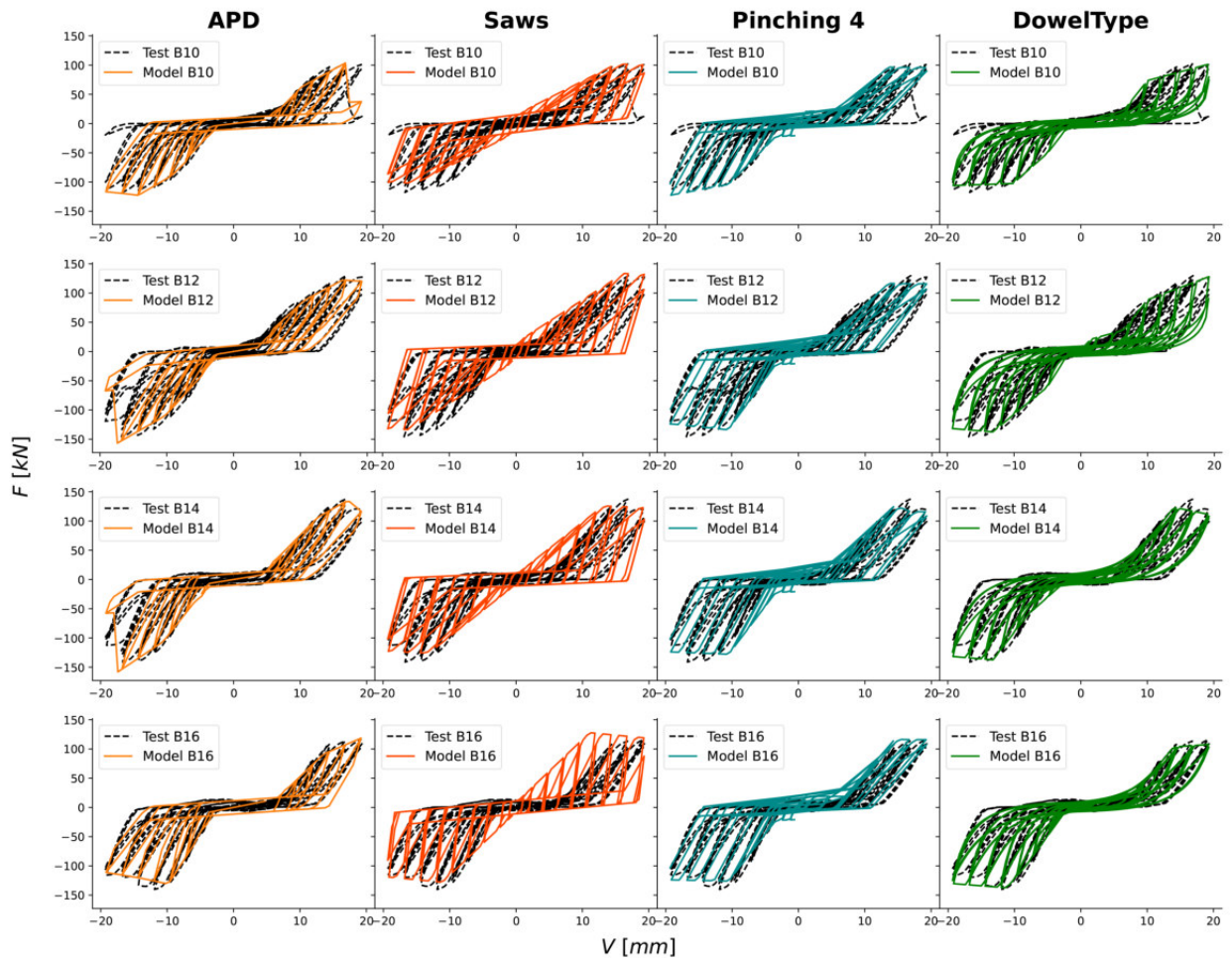


Figure 14: Comparison of force–displacement hysteresis between the experimental and prediction results of four models (APD, Saws, Pinching 4 and DowelType) (bolted connections).

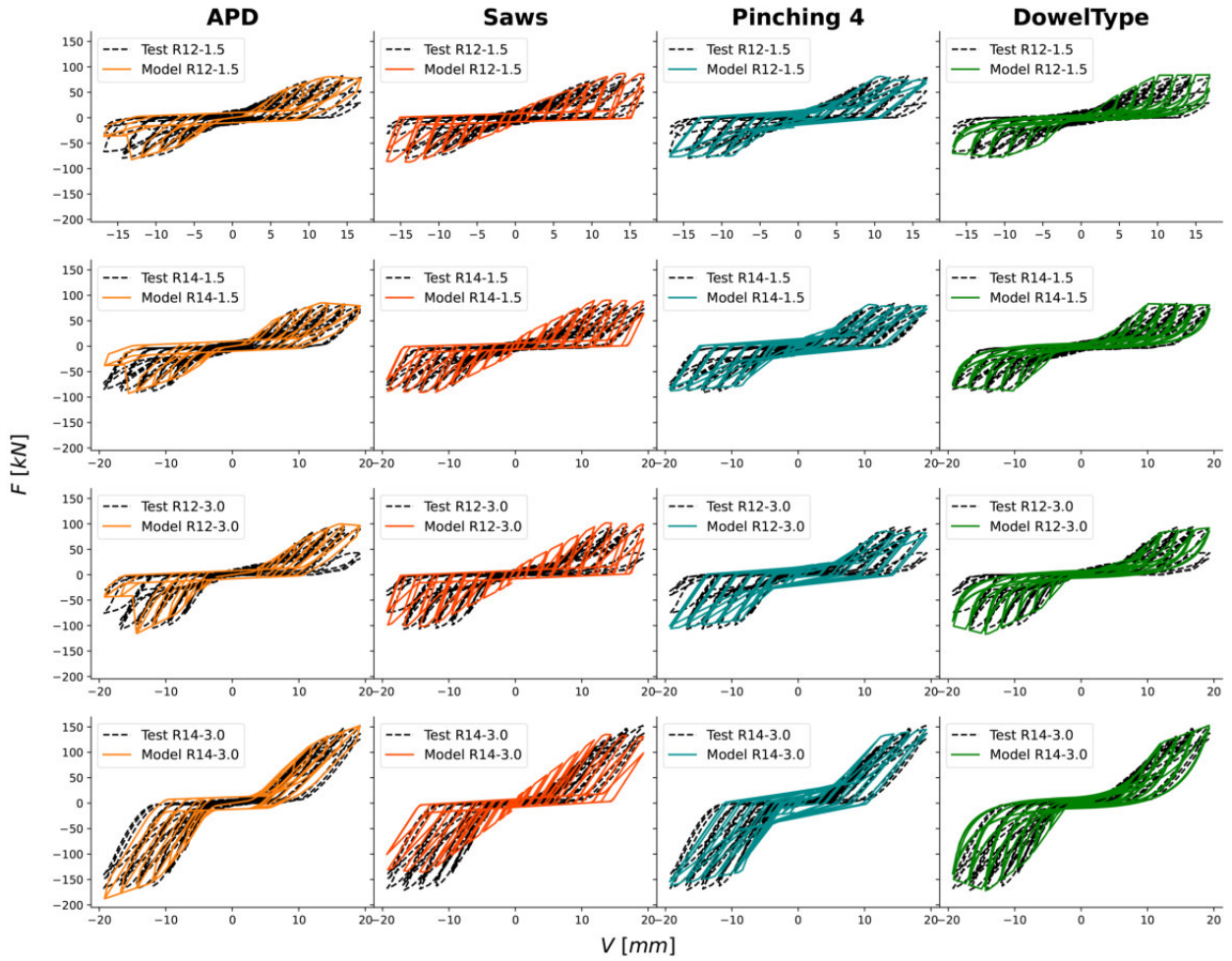


Figure 15: Comparison of force–displacement hysteresis between the experimental and prediction results of four models (APD, Saws, Pinching 4 and DowelType) (riveted connections).

414 5. Conclusions

415 This study develops a APD hysteresis model based on previous study for glulam members, comple-
 416 mented by identification frameworks designed for seamless integration with commercial finite element soft-
 417 ware ABAQUS. The calibrated model, following parameter identification, was compared and validated
 418 against a series of experimental glulam benchmark tests and three established hysteretic models (SAWS,
 419 Pinching4, and DowelType). The study yields the following conclusions:

- 420 (1) The proposed APD hysteresis model accurately captures the complex behaviors of glulam members,
 421 including asymmetry, pinching effects, and strength/stiffness degradation.
- 422 (2) Three parameter identification methods, PGA, BI, and BNN-PGA, are introduced, enhancing the
 423 capabilities of parallel numerical computation and parameter identification coupling BNN and finite element

424 models. These methods enable the automatic and precise identification of parameters in complex hysteretic
425 models.

426 (3) Compared to three other well-known hysteretic models (SAWS, Pinching4, and DowelType), the APD
427 and DowelType models consistently outperform the others in all test cases, underscoring its advantages in
428 simulating the behaviors of glulam members.

429 **Acknowledgments**

430 This study was carried out within the “Artificial Intelligence for ENVIRONMENTAL impact minimization
431 of SEISMIC Retrofitting of Structures (AI-ENVISERS)” project – funded by European Union – Next Gen-
432 eration EU within the PRIN 2022 PNRR program (D.D.1409 del 14/09/2022 Ministero dell’Università e
433 della Ricerca). This manuscript reflects only the authors’ views and opinions and the Ministry cannot be
434 considered responsible for them.

435 **Declaration of Competing Interest**

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

438 **Data availability**

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

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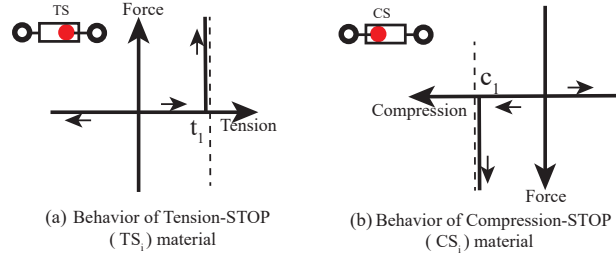


Figure A.16: Behavior of STOP (S) material model: Tension-STOP (TS) material model (a) and Compression-STOP (CS) material model (b). (modified based on Shi et al. [36, 38])

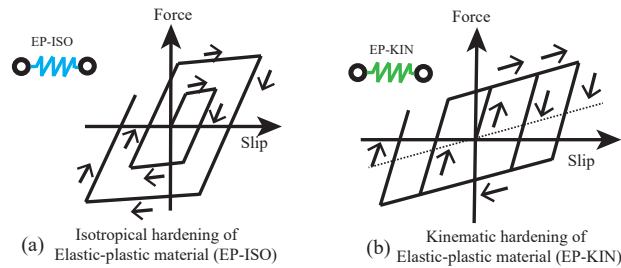


Figure A.17: Behavior of Elasto-plastic (EP) material model: Isotropic hardening Elasto-plastic (EP-ISO) material model (a) and Kinematic hardening Elasto-plastic (EP-KIN) material model (b). (modified based on Shi et al. [36, 38])

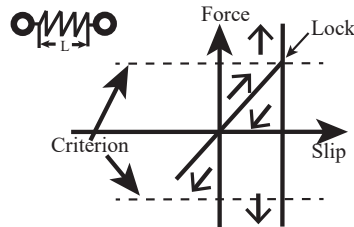


Figure A.18: Behavior of LOCK (L) material model. (modified based on Shi et al. [36, 38])

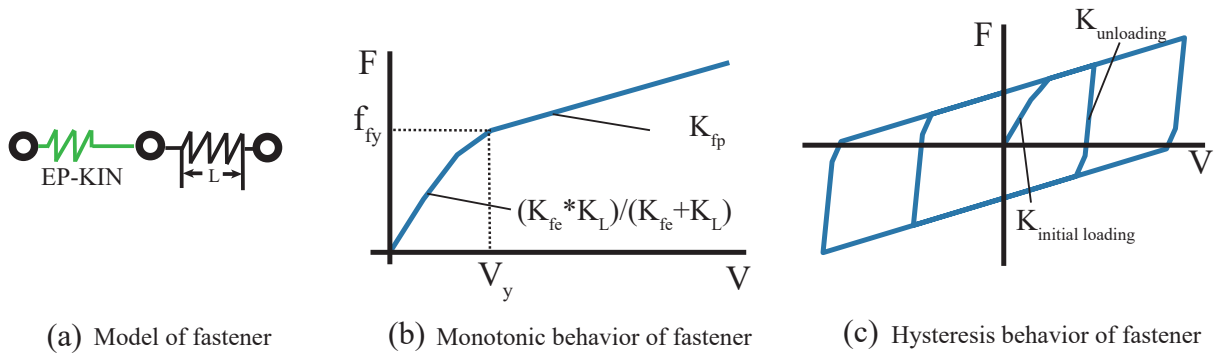


Figure A.19: Constitutive rule of fastener model: configuration of fastener model (a), monotonic behavior of fastener (b) and hysteresis behavior of fastener (c). (modified based on Shi et al. [36, 38])

577 **Appendix B. Flowchart for PGA**

578

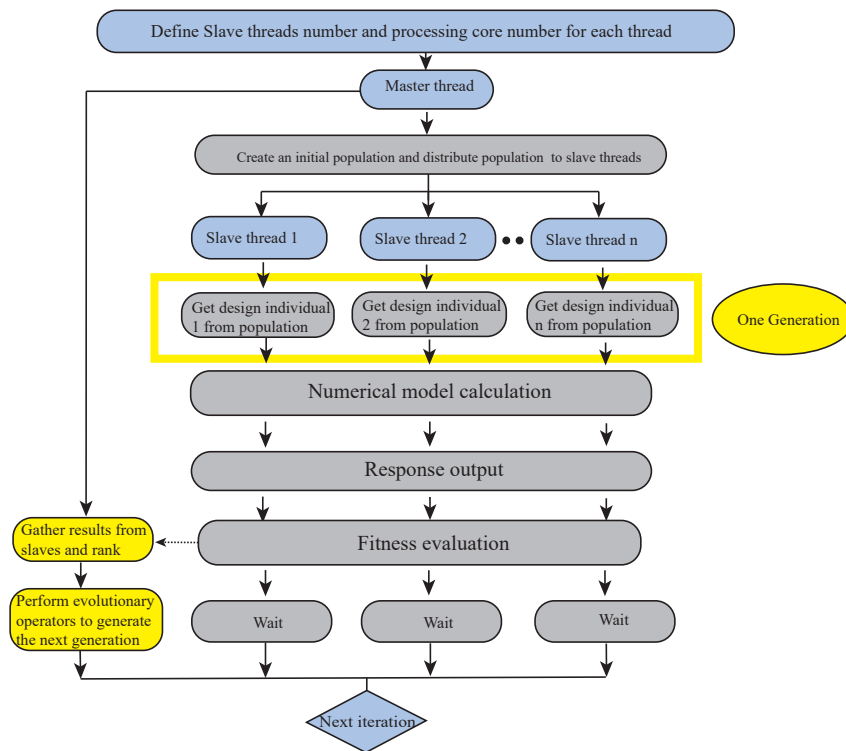


Figure B.20: Flowchart for parallel algorithm. (modified based on Shi et al. [36])

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