Clustered Federated Learning for Population-Based Structural Health Monitoring

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***Abstract*—This article deals with two major challenges in population-based structural health monitoring (PBSHM) for critical infrastructures, with focus on bridges. The first challenge is related to training a collaborative model based on local datasets from different bridges under privacy-preserving constraints. The second challenge is related to the (potential) limited amount of data and/or resources available locally at some bridges. To address these issues, we propose a framework based on clustered federated learning (CFL) for efficient and collaborative training of monitoring models while preserving data privacy. The approach leverages the concept of principal angles (PAs) to cluster the bridges according to their data distributions without domain-based prior information. Cluster-specific models are then trained efficiently according to the available local resources. Moreover, the proposed framework allows the integration of new bridges providing quick and resource-efficient knowledge transfer from the cluster-specific parameters to the infrastructure-specific parameters. Numerical results based on extensive simulations show that the proposed framework performs well, both within supervised and unsupervised settings, yielding more accurate results than traditional schemes.**

***Index Terms*—Clustered federated learning (CFL), data heterogeneity, knowledge transferability, population-based structural health monitoring (PBSHM), principal angles (PAs).**

I. Introduction

STRUCTURAL health monitoring (SHM) of critical infrastructures is an essential practice to safeguard related substantial investments and public resources. In the rapidly evolving landscape of smart cities, bridges serve as vital arteries that facilitate seamless connectivity, drive economic growth, and enhance the quality of urban life. As urban environments become increasingly complex, maintaining bridges' structural integrity and reliability is crucial to ensuring safety and sustainability [1], [2].

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By integrating digital technologies related to advanced sensors and inference algorithms, data-driven SHM approaches have been developed, which enable proactive maintenance and informed decision-making, strengthening the resilience and efficiency of smart city infrastructures [3], [4]. Nonetheless, maintenance and management of bridges keep posing significant challenges in urban environments [5], [6], [7]. Population-based SHM (PBSHM) is a collective approach enabling data sharing across multiple structures, facilitating more comprehensive analysis and predictive maintenance strategies. Moreover, by integrating monitoring processes, authorities can optimize resource allocation, enhance the detection of widespread issues, and improve the overall resilience of bridge networks within intelligent cities.

In the remainder of this section, we briefly review relevant works dealing with SHM and related limitations in Section I-A, while describe the proposed contribution and article organization in Section I-B.

A. Related Work

The availability of informative data remains a significant obstacle for effective design of SHM. Labeled data related to structural damages are often difficult and/or expensive to obtain, making it challenging to develop SHM methods potentially handling all possible damage scenarios [8], [9]. Transfer learning approaches have been explored primarily for generating labeled datasets from finite-element models and interpret unlabeled experimental bridge data [10], [11], [12]. However, data augmentation through hybrid datasets combining numerical and monitoring data requires individual (per bridge) model creation and calibration, leading to extensive computational resources [13].

The current isolated approach to monitoring and assessing each bridge independently leads to inefficiencies and missed opportunities for comprehensive infrastructure management [14], [15]. To overcome these challenges, PBSHM approaches proceed by selecting a pool of bridges and establishing a centralized mechanism for health assessment [16], [17], [18]. The objective of PBSHM is to improve structural health-state inference by using data from multiple structures, facilitating knowledge transfer even when some structures have limited or no damage-state data [19], [20].

Transfer learning has been applied to facilitate cross-structure diagnostics and improve the performance of SHM systems [21], [22], [23], but relevant challenges related to privacy constraints have been overlooked. Model training across different datasets originated from bridges belonging to different stakeholders might not be allowed. Additionally, mismatch learning when transferring information between dissimilar structures can potentially degrade the performance [24], [25], [26], [27].

Structural similarities among bridges in PBSHM have often been assessed using abstract representations, such as irreducible element models or attributed graphs, to compare their topological and material properties [28], [29], [30]. Despite their appealing performance, these methods can be computationally intensive and may only partially capture the dynamic behavior of structures. An alternative approach involves measuring similarity based on patterns identified on real-world data to form groups [31]. Although grouping bridges based on measured data helps mitigate the risk of negative transfer in dissimilar structures, previous works primarily focused on centralized learning (CL), where raw sensor data is transmitted to a central location for analysis. This approach demands excessive communication resources and, more critically, raises concerns about exposing sensitive structural design information [32], [33]. This issue is particularly significant in PBSHM, where data from multiple structures are essential for building robust and effective SHM models via communication-efficient privacy-preserving learning.

Privacy issues in SHM have been considered in [34] and [35] via distributed learning, treating sensor sets on a single bridge as individual clients. Each client locally trains a machine learning model without sharing data, but sensors' limited computational and communication capabilities introduce serious obstacles to their deployment. Moreover, the analysis is restricted to individual bridges, limiting its applicability to PBSHM, which usually involves multiple bridges. Additionally, aspects like scalability, such as integrating new clients into the network, and knowledge transferability across structures remain unexplored.

B. Article Contribution and Organization

This article provides a comprehensive framework based on clustered federated learning (CFL) that ensures high accuracy and enables effective knowledge transferability in PBSHM. The proposed approach minimizes data transmission within a collaborative scenario where models benefit from diverse information gathered across multiple structures while preserving data privacy. More specifically, the framework relies on 1) cluster identification and 2) cluster training. In the former phase, bridge data is analyzed in a privacy-preserving setting to identify clusters based on underlying similarities. In the latter phase, models (one per cluster) are trained independently with each bridge sharing only model parameters with a centralized server.

This work focuses on bridge damage detection, however, the proposed algorithm can be applied in a straightforward way to SHM of other critical infrastructures. From a general perspective, the proposed framework enables a scalable and secure approach to proactive maintenance of critical infrastructures, ultimately strengthening their resilience.

The main contributions are summarized as follows.

1) We develop a privacy-preserving framework for PBSHM that leverages structural similarities to cluster bridges and trains models tailored to the specific needs of each cluster.
2) We introduce a one-shot clustering method based on principal angles (PAs) to group structures based on underlying data similarities which does not require any prior knowledge.
3) The proposed algorithm is capable to integrate seamlessly new structures (e.g., bridges added post-training) and assign them to appropriate clusters even with limited data.
4) We present simulation results for supervised scenarios to validate our proposed framework, including comparison with alternative methods based on CL and traditional federated learning (FL) models.
5) We explore the suitability of the proposed framework to unsupervised scenarios, demonstrating its versatility to various settings.

The remainder of the article is organized as follows. Section II introduces the concepts of FL and PAs; Section III describes the dataset used to validate the proposal; Section IV details our proposed approach for clustering and training cluster-specific models; simulation results for both supervised and unsupervised scenarios are presented in Section V; finally, Section VI provides conclusions and outlines future work.

Notation: Bold uppercase letters (e.g., $\boldsymbol{A}$) and bold lowercase letters (e.g., $\boldsymbol{a}$) denote matrices and column vectors, respectively. The transpose operator is denoted $(\cdot)^T$. The induced norm is denoted $||\cdot||$. Calligraphic letters (e.g., $\mathcal{C}$) represent sets, except for $\mathcal{L}$ which is used to denote the loss function. The cardinality of a set $\mathcal{C}$ is represented by $|\mathcal{C}|$. The gradient operator is denoted $\nabla(\cdot)$.

II. Preliminaries

A. FL

FL utilizes a distributed approach to train machine learning models by leveraging data across multiple decentralized clients (bridges in our context) without collecting the data at a central location. Each client receives model parameters from a centralized server and fine-tunes them locally using the available dataset. Fine-tuned parameters are then sent back to the server, where a global model is constructed by aggregating the local model parameters [36]. The decentralized nature of FL enhances privacy by minimizing the exposure of client data and facilitates communication efficiency by allowing data processing on local devices.

A central server is connected with a group of clients ($\mathcal{Q}$) to solve the following optimization problem [37]:

$$\min_{\boldsymbol{\theta}} \underbrace{\frac{1}{|\mathcal{Q}|}\sum_{q\in\mathcal{Q}}\mathcal{L}_q\big(\boldsymbol{\theta};\mathcal{D}_q\big)}_{\mathcal{L}(\boldsymbol{\theta};\mathcal{D}_q)} \tag{1}$$

where $\mathcal{L}_q(\boldsymbol{\theta};\mathcal{D}_q)$ represents the local objective function used by the qth client with its corresponding dataset $\mathcal{D}_q$, and $\boldsymbol{\theta}$

collects the model parameters shared among all clients. The selection of the objective function is task-dependent with cross-entropy and mean squared error (MSE) being commonly used for classification and regression tasks, respectively.

The iterative procedure is implemented with the server distributing the current global model parameters ($\boldsymbol{\theta}_n$) to a randomly selected subset of clients ($\mathcal{Q}_n \subset \mathcal{Q}$) at the nth iteration (namely, *communication round*). The qth client within $\mathcal{Q}_n$ updates the parameters using its local dataset ($\mathcal{D}_q$) with either mini-batch or full-batch gradient descent. In the case of full-batch gradient descent, the update of local parameters is based on

$$\boldsymbol{\phi}_{q,n} \leftarrow \boldsymbol{\theta}_n - \eta \nabla \mathcal{L}_q\big(\boldsymbol{\theta}_n; \mathcal{D}_q\big) \tag{2}$$

where η represents the learning rate and $\boldsymbol{\phi}_{q,n}$ denotes the model parameters of the qth client after the local update. Upon completing local training, clients transmit the locally-updated parameters ($\boldsymbol{\phi}_{q,n}$) back to the server. The server aggregates the updates into a global model as follows:

$$\boldsymbol{\theta}_{n+1} = \sum_{q \in \mathcal{Q}_n} \left(\frac{|\mathcal{D}_q|}{\sum_{j \in \mathcal{Q}_n} |\mathcal{D}_j|} \right) \boldsymbol{\phi}_{q,n}. \tag{3}$$

The process is repeated until convergence (or other stopping criterion).

Despite its growing popularity, FL faces significant challenges due to data heterogeneity across local clients, which can adversely affect the performance of the global model if not properly managed [38]. CFL addresses this issue by grouping clients with similar data distributions into clusters and exploits FL within each cluster [39]. Cluster identification is usually challenging and requires prior knowledge [40]. Fig. 1 provides a pictorial description of the main learning approaches, where edge devices act as clients, collecting data and performing local learning.

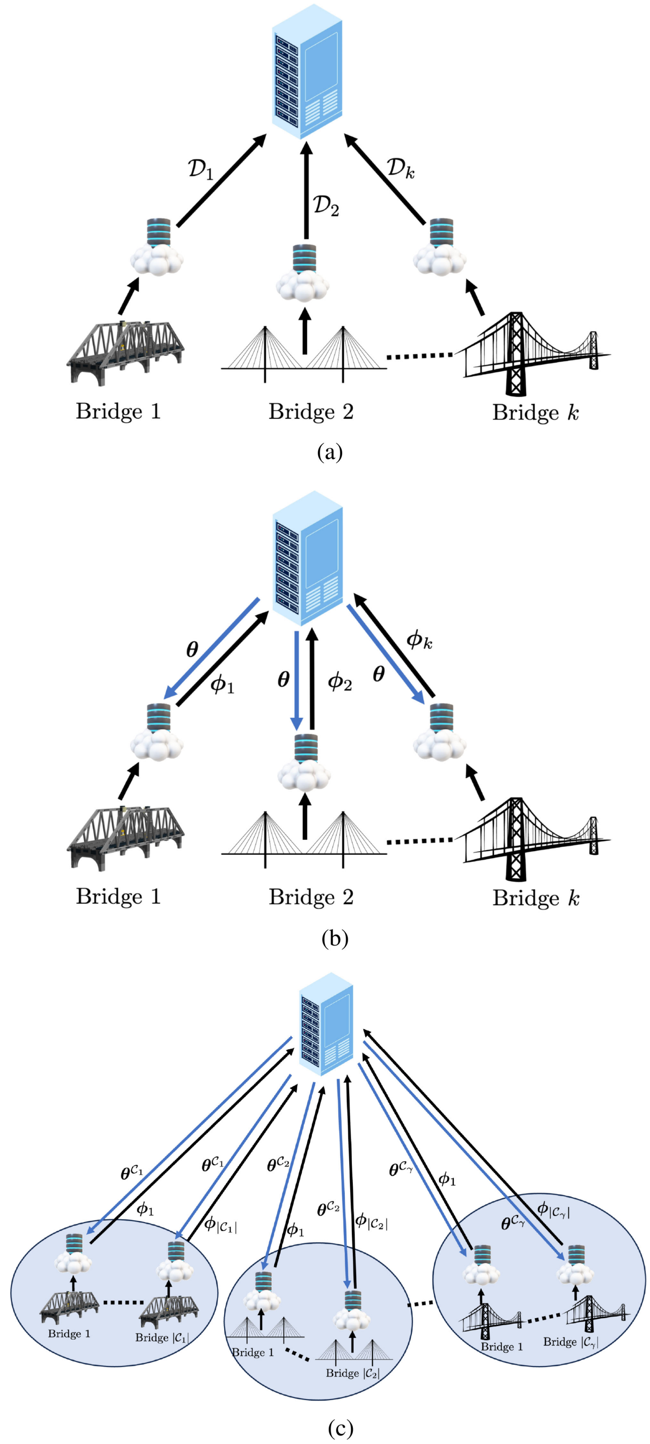


Fig. 1. Learning paradigms. (a) CL. (b) FL. (c) CFL.

B. PAs

Principal component analysis (PCA) is a traditional statistical method in signal processing, data analysis, and pattern recognition, which simplifies the analysis of large datasets by reducing their dimensionality [40], [41].

For a data matrix $\boldsymbol{X}$ of size $s \times f$, where s represents the number of samples and f represents the number of feature variables,[1] the covariance matrix ($\boldsymbol{C}$) is computed as

$$\boldsymbol{C} = \frac{1}{s-1} \boldsymbol{X}^T \boldsymbol{X}. \tag{4}$$

The core concept of PCA involves performing eigenvalue decomposition (EVD) of the covariance matrix ($\boldsymbol{C}$) identifying the principal components that capture the variance in the data via eigenvectors ($\boldsymbol{v}_i$) and corresponding eigenvalues (λ_i). The covariance matrix ($\boldsymbol{C}$) is decomposed as

$$\boldsymbol{C} = \boldsymbol{V} \boldsymbol{\Lambda} \boldsymbol{V}^T \tag{5}$$

where the matrix $\boldsymbol{V} = (\boldsymbol{v}_1, \ldots, \boldsymbol{v}_f)$ collects the eigenvectors and $\boldsymbol{\Lambda} = \mathrm{diag}(\lambda_1, \ldots, \lambda_f)$ is a diagonal matrix with the eigenvalues on the main diagonal. PCA identifies a subspace via the eigenvectors associated to the largest eigenvalues [42].

The PAs ($0 \leq \theta_1 \leq \cdots \leq \theta_q \leq [\pi/2]$) between two subspaces $\mathcal{U}$ and $\mathcal{Y}$, having, respectively dimensions p and q (with $1 \leq q \leq p$), are defined recursively as [43]

$$\begin{aligned} \cos(\theta_k) = \boldsymbol{u}_k^T \boldsymbol{y}_k = \max_{\boldsymbol{u} \in \mathcal{U}} \max_{\boldsymbol{y} \in \mathcal{Y}} \boldsymbol{u}^T \boldsymbol{y} \\ \text{s.t.} \quad \|\boldsymbol{u}\| = \|\boldsymbol{y}\| = 1 \\ \text{s.t.} \quad \boldsymbol{u}^T \boldsymbol{u}_i = 0\,,\ \boldsymbol{y}^T \boldsymbol{y}_i = 0 \quad \forall i = 1, \ldots, k-1 \end{aligned} \tag{6}$$

[1] It is assumed that each column has null sample mean.

TABLE I
BRIDGE PROPERTIES

Bridge Name	Length (m)	SMA (m^4)	MUL (kg/m)
B_{09}	09	0.1139	16875
B_{11}	11	0.2080	20625
B_{19}	19	0.6660	15741
B_{23}	23	1.1133	17419
B_{27}	27	1.7055	19372
B_{31}	31	2.4651	21650
B_{35}	35	3.4162	21752
B_{39}	39	4.5132	23352
B_{25}	25	1.3901	18358
B_{37}	37	3.9425	22552

with $\{\boldsymbol{u}_1, \ldots, \boldsymbol{u}_q\}$ and $\{\boldsymbol{y}_1, \ldots, \boldsymbol{y}_q\}$ named *principal vectors*.

The PA is a useful metric to assess the level of (mis)alignment between subspaces, providing insight into data distribution similarities [44]. The more significant the difference in data heterogeneity between two clients, the more orthogonal their subspaces, making it a valuable criterion for clustering and optimizing FL performance [40].

III. Data Description

To validate the proposed methodology, a dataset was generated through numerical simulations based on a vehicle-bridge interaction (VBI) model. It includes the simulations of 10 different simply-supported bridges with a modulus of elasticity equal to 3.5×10^{10} N/m^2 and different properties (length, second moment of area (SMA), and mass per unit length (MUL)) as provided in Table I. Each bridge was modeled using a finite element method grounded in Euler-Bernoulli beam theory, with the number of elements proportional to the length of the bridge.

The VBI-2D tool simulated the interaction between road traffic and bridges. It is an open-source MATLAB software which allows for customizing various parameters (e.g., vehicle models, road irregularities, bridge properties). The coupled vehicle-bridge response was computed via direct integration of the system's equations of motion. The simulations involved single vehicles traversing the bridges at constant speeds, with various road, vehicle, and bridge configurations to capture the dynamic structural responses. Vibration signals were measured at five equidistant locations along each bridge with various vehicle properties, environmental conditions [45], [46], [47], [48], [49].

More specifically, three scenarios (one healthy and two damaged) are considered.

1) *Healthy:* No damage in the bridge.
2) *DC1:* Damage located at the midpoint of the first half of each bridge.
3) *DC2:* Damage located at the midpoint of the entire bridge.

The damage was modelled as a 20% or 30% stiffness loss at each location. For the scenario with 20% (resp. 30%) stiffness loss, 500 (resp. 100) events were generated.

IV. Proposed Algorithm

The proposed approach relies on three key steps.

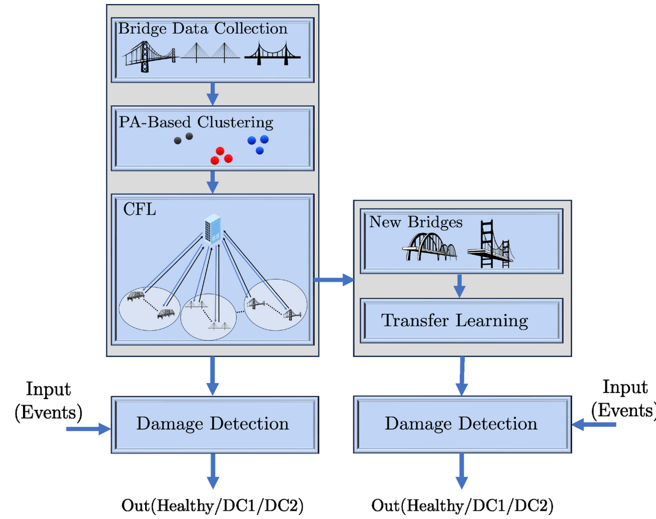


Fig. 2. Proposed model.

1) Unsupervised privacy-preserving clustering to identify groups among the datasets of available bridges exploiting the concept of PAs.
2) CFL-based model training exploiting efficiently FL in each cluster.
3) Robust accommodation of new bridges exploiting transfer learning.

The workflow of the proposed algorithm is illustrated in Fig. 2 and the details are provided in the rest of this section.

A. PA-Based Clustering

The clustering algorithm exploits the concept of minimum PAs between subspaces derived from bridge local data, i.e. bridges in the same cluster exhibit similar subspace (and physical) characteristics. Accurate cluster identification opens the opportunity to train optimally-customized models [50], as opposed to using a single model for different bridges usually resulting in modest performance.

Local data at each bridge is processed via fast Fourier transform (FFT) and PCA. More specifically, PCA is applied to the magnitudes of the FFT components and the main eigenvectors (associated with the strongest eigenvalues) are shared with the central server, which computes the minimum PAs across all the pair of bridges.[2] K-means is then applied to the computed minimum PAs and the elbow method is adopted for selecting the proper number of clusters.

The use of PAs ensures a data-driven clustering approach, capturing inherent similarities in vibration characteristics. Engineers and bridge owners can interpret the clustering results by analyzing how bridges are grouped based on their structural response patterns from sensor data. Once clustered, operators can use cluster-specific models to compare a bridge's behavior with its peers, aiding in detecting anomalies or potential structural degradation.

The proposed clustering approach does not require any prior knowledge about the bridges and is privacy-preserving since

[2]The PAs are computed as in [43], using the SciPy library.

only anonymous compressed information from the raw data is shared.

B. CFL

The central server randomly initializes one model per cluster, with model size depending on the maximum duration of the events in the datasets associated with the specific cluster. Each cluster operates independently with bridges acting as clients receiving initial model parameters from the server. The bridges update the model locally by conducting one or more training epochs with their local data and transmit the updated parameters back to the central server.

The central server aggregates the parameters from the bridges within the same cluster and redistributes the cluster-specific model parameters back to the corresponding bridges for the next communication round. Additionally, the bridges share their local validation accuracy (or loss) to enable the server monitoring performance improvements across communication rounds.

C. Transfer Learning

The proposed framework can easily accommodate new bridges into the clustered model. Upon joining the network, a new bridge extracts the principal vectors from its local dataset according to the procedure in Section IV-A and sends them to the central server. The server identifies the appropriate cluster for the new bridge and shares the existing model parameters of that cluster. Upon receiving the parameters, the new bridge fine-tunes the cluster-specific model, thus effectively leveraging the pretrained parameters.

D. Communication Overhead

We refer to communication overhead as the amount of data exchanged during the training process. Assuming that the same precision is used for measurements and model parameters, we consider the number of (real-valued) symbols as a reliable estimate of the communication overhead.

The communication overhead for CL (O_{CL}) is

$$O_{\text{CL}} = \sum_{k=1}^{K} \text{size}(\mathcal{D}_k) \tag{7}$$

where $\text{size}(\mathcal{D}_k)$ denotes the size of the local data at the kth bridge and K is the total number of bridges.

The communication overhead for FL (O_{FL}) is

$$O_{\text{FL}} = 2\text{PTK} \tag{8}$$

where P represents the total number of the model parameters and T denotes the total number of communication rounds.[3]

The communication overhead for CFL (O_{CFL}) is defined as

$$O_{\text{CFL}} = \sum_{c=1}^{C} O_c \tag{9}$$

where C is the number of clusters and O_c represents the communication overhead for the cth cluster which is computed similarly to (8). The similarity of the bridges within the same cluster allows for using models with smaller number of parameters in some clusters, thus resulting in reduced overall communication overhead.

V. Simulation Results

We conducted extensive experiments in both supervised and unsupervised scenarios for PBSHM to assess the performance of the proposed CFL-based framework. We utilized Scikit-Learn and SciPy libraries and employed PyTorch during the training and testing phases of ML models. In our study, 8 bridges participated in the CFL process, while the remaining 2 bridges were excluded from the training phase and reserved to evaluate the algorithm's transferability. We employed the Adam optimizer and cross-entropy loss for training, using a batch size of 32. In the supervised scenario, the dataset was split into 80% for training/validation and 20% for testing; in the unsupervised scenario, 70% (healthy) data for training/validation and 30% for testing. The learning rate was set between 10^{-4} and 10^{-3} and optimized with random grid search. The number of communication rounds for training was independently set for each cluster.

For clustering, each participating bridge processed 30% of its local data with sampling frequency of 200 Hz computing the 100 FFT components. Different tests suggested that 3 principal vectors from PCA are sufficient to ensure effective clustering while preventing data reconstruction from a potential eavesdropping attack.

For the supervised scenario,[4] a consistent structure was selected for each cluster model featuring 3 convolutional layers with a stride of 1, filter size of 5 × 5, and ReLU activation function. The channel counts for the layers is 5 to 64, 64 to 32, and 32 to 6, respectively. The output is flattened and directed into a fully-connected layer that classifies the data into 3 categories: 1) Healthy; 2) DC1; and 3) DC2. However, the input size is selected depending on the duration of the events in the training set, thus resulting in a different size for the model in each cluster.

For the unsupervised scenario, we select autoencoders (AEs) with convolutional and deconvolutional layers as cluster models. Each encoder features 3 convolutional layers with a kernel size of 3 × 3 and a stride of 2, complemented by a ReLU activation function. The channel counts for the encoder layers of the models for Cluster 1 and Cluster 2 are 16 to 32, 32 to 64. The output is flattened and directed into a fully connected layer, creating the latent space representation of size 16. The encoder for Cluster 3 is slightly different, with channel count being 32 to 64, 64 to 128. Then, again, the output is flattened and directed into a fully connected layer, creating the latent space representation of size 32. The decoder used the transposed convolutional layers to reconstruct the original input shape. Again, the input size is selected depending on the duration of the events.

[3] In this work, the value of P is computed using PyTorch (https://pypi.org/project/torch-summary/).

[4] Unless differently specified, the models are trained with data from the scenario with 20% stiffness loss.

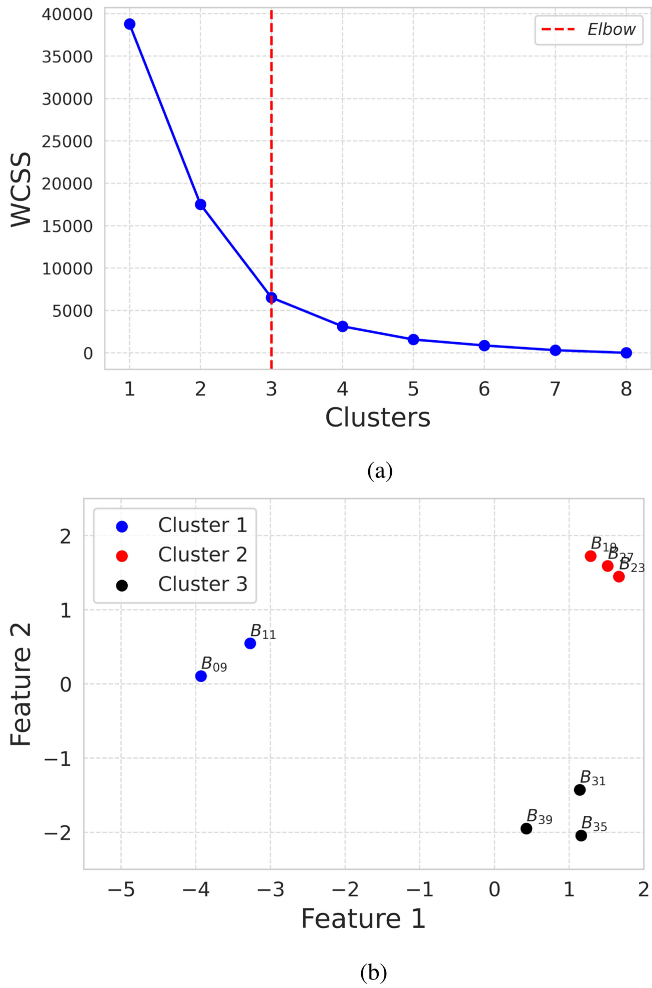


Fig. 3. Clustering analysis. (a) Elbow method. (b) 2 Feature space.

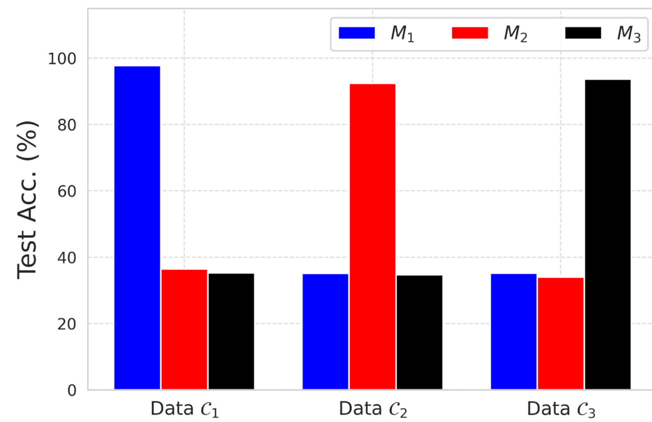


Fig. 4. Cluster models performance.

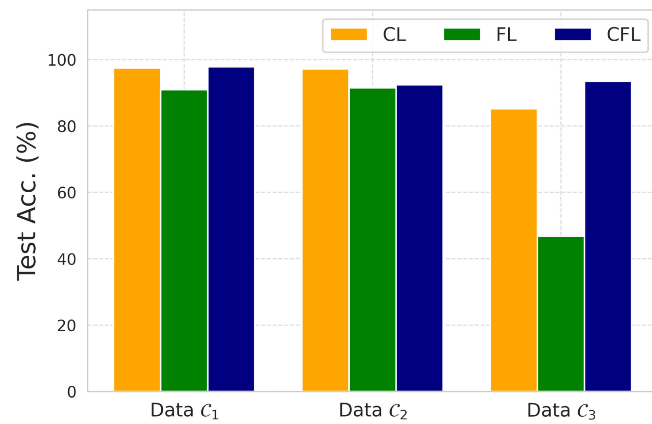


Fig. 5. Accuracy comparison.

A. Clustering Analysis

Fig. 3(a) describes how the optimal number of clusters was selected based on the metric within-cluster sum of squares (WCSSs) with the elbow pointing at 3 clusters. We apply PCA to the angle matrix and project it into a 2-D feature space to further analyse the embeddings derived from PAs used for clustering the bridges. Fig. 3(b) displays the results of the PCA into a 2-D feature space, where 3 distinct clusters are clearly identified. The 3 clusters effectively group the bridges with similar structural cross-section geometries, thus supporting the claim that the clustering algorithm works without prior information. Additionally, it is worth noticing that the clusters appears related to the natural frequencies of the bridges: e.g., bridges B_{09} and B_{11} have much closer natural frequencies compared to B_{27}.

B. Supervised Scenario

Fig. 4 demonstrates the effectiveness of the proposed CFL approach by testing the model of the cth cluster (M_c) on data from the dth cluster ($\mathcal{C}_d$). More specifically, it is apparent that each cluster maintains high accuracy (achieving approximately 95%) by sharing only model parameters and keeping the models specific to each cluster. High level of performance is attained without the need for fine-tuning of the models to individual bridges within each cluster before testing, suggesting that the cluster is robust enough to generalize across all bridges in the specific cluster. In contrast, the performance of a model on data from different clusters is notably lower, highlighting the variability in data characteristics across different bridges.

Fig. 5 compares the performance of the proposed CFL approach with traditional approaches, such as CL and FL. Apparently, the proposed methodology consistently outperforms the conventional FL scheme across all cluster bridges. Differently, when compared to CL, the proposed approach does not exhibit a clear advantage in terms of performance (sometimes better, sometimes slightly lower). However, it is worth remembering that CL requires transferring all data to a central server, leading to significant communication/computational resources and high risk in terms of privacy.

Fig. 6 showcases the effectiveness of the proposed methodology in reducing communication overhead, illustrating that traditional schemes, such as CL and FL incur greater communication costs than the proposed CFL scheme. Also, the communication overhead related to each individual cluster is shown to highlight the different behavior across clusters.[5] In contrast, traditional schemes lack clustering information,

[5]This different behavior can be attributed to differences in model architectures, number of communication rounds needed to stabilize the loss, and event sizes of the bridges involved in the training procedure.

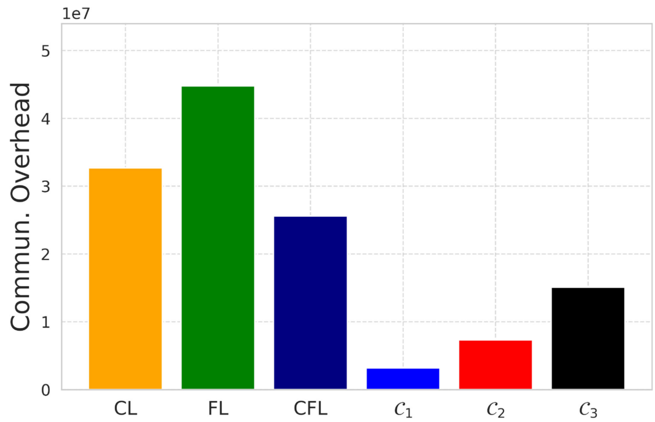


Fig. 6. Communication overhead.

TABLE II
ACCURACY WITH 30% STIFFNESS LOSS

Epochs	Accuracy (%)		
	$\mathcal{C}_1$	$\mathcal{C}_2$	$\mathcal{C}_3$
1	64.22	62.36	48.07
5	83.21	76.53	72.19
10	87.5	82.17	80.1

resulting in the transmission of all possible information to the central server.

In Table II, we present the performance of the proposed framework when the damage condition of the bridge changes from 20% reduction in stiffness to 30% reduction. This increase in damage severity can negatively impact detection performance, necessitating an update of the detection model to maintain high accuracy. We consider fine-tuning of the cluster model parameters, enabling rapid adaptation to new damage conditions. Notably, with only 10 epochs and limited event data, the proposed framework consistently achieves an accuracy exceeding 80% for each cluster demonstrating to be effective even with evolving damage conditions.

Fig. 7 illustrates the integration of 2 new bridges (B_{25} and B_{37}) into the existing CFL system, each having data with size approximately 30% of the size of the data from existing bridges. The addition of the new bridges expands the angle matrix from 8 $\times$ 8 to 10 $\times$ 10. After PCA, each new bridge (indicated by a cross ($\times$) in Fig. 7) seamlessly joins the system. More specifically, B_{25} and B_{37} align with Cluster 2 and Cluster 3, respectively. The examples illustrate the adaptability and efficiency of the clustering algorithm in integrating new bridges. After identifying their respective clusters, the new bridges swiftly adapt the previously trained clustered parameters for personalized damage detection.

Fig. 8 provides insights into selecting the appropriate model parameters for transferring knowledge from the cluster-specific models to new bridges (B_{25} and B_{37}). The results confirm that B_{25} and B_{37} integrate well into Cluster 2 and Cluster 3, respectively. The results are related to the performance after local fine-tuning over 20 epochs to achieve an average accuracy 95% with limited data. Conversely, when new bridges use parameters from clusters to which they do not belong, loss in performance is experienced.

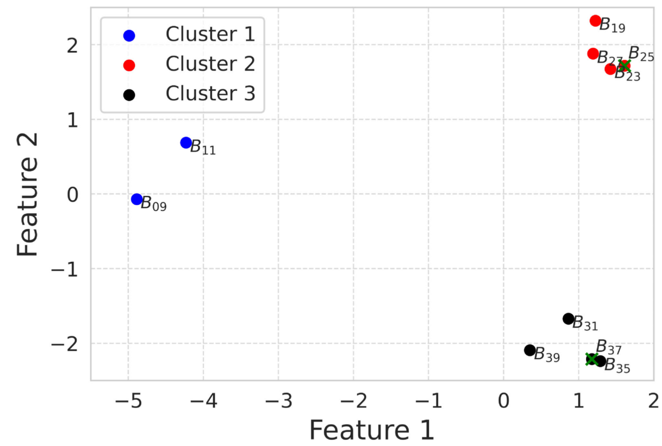


Fig. 7. New bridges integration.

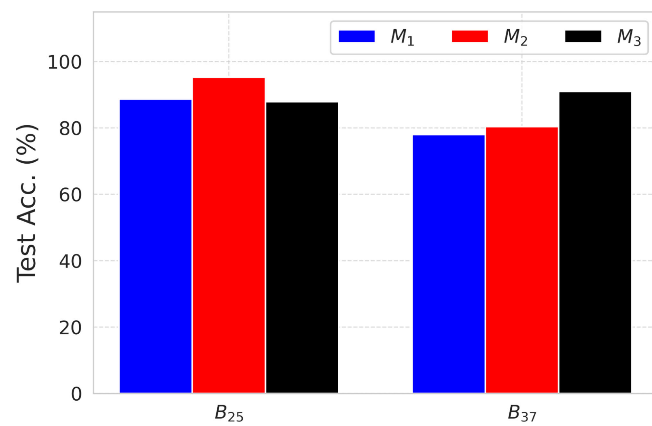
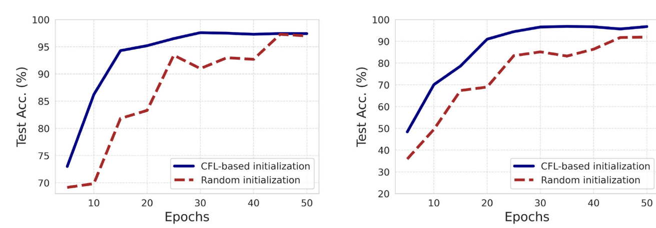


Fig. 8. Test accuracy of new integrated bridges.



(a) (b)

Fig. 9. Test accuracy of newly integrated bridges. (a) B_{25}. (b) B_{37}.

Fig. 9 illustrates the efficacy of employing the pretrained cluster-specific model for a new bridge compared to developing a new model with random initialization. The accuracy curves, derived from testing on 150 events, clearly shows that the model using cluster-specific parameters learns faster and maintains a substantial performance advantage over the model with random initialization, until the performance gap between the two approaches narrows close after 45 epochs and the accuracy reaches convergence.

C. Unsupervised Scenario

In the case of unsupervised damage detection, we assume that each bridge fine-tunes the model from the corresponding cluster to create a personalized model. Cluster models are

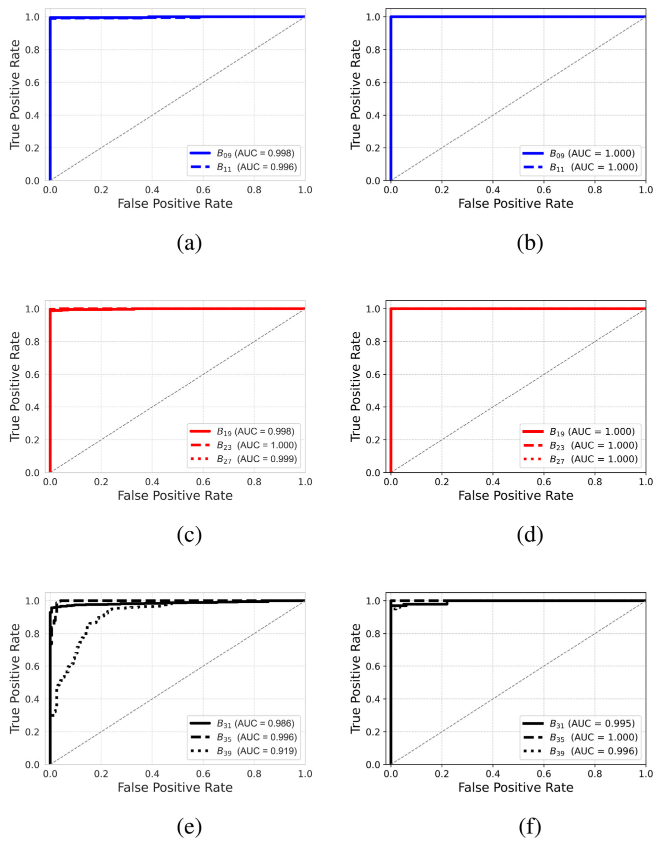


Fig. 10. ROCs of different bridges experiencing both types of damages DC1 and DC2. (a) Cluster 1 (20%). (b) Cluster 1 (30%). (c) Cluster 2 (20%). (d) Cluster 2 (30%). (e) Cluster 3 (20%). (f) Cluster 3 (30%).

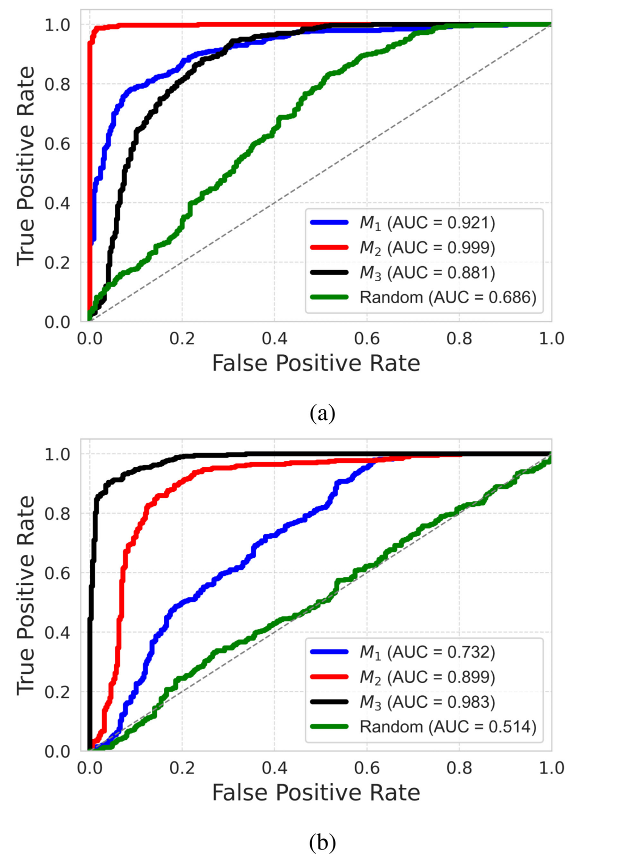


Fig. 11. ROCs of new bridges experiencing both types of damages DC1 and DC2. (a) B_{25}. (b) B_{37}.

trained over 2000 communication rounds and local fine-tuning is performed over 300 epochs. We use the MSE as loss function and the Adam optimizer.

Reconstruction losses were collected from 200 healthy events (50 from training to establish the baseline) and 200 damaged events. The Tukey outlier removal method and an exponentially weighted moving average (EWMA) equation are implemented to enhance detection. Results are evaluated in terms of receiver operating characteristics (ROCs), with *Healthy* status (resp. presence of a *Damage*) being labeled “0” (resp. “1”).

Fig. 10 shows the ROCs of all bridges, grouped by clusters, under damaged conditions with stiffness losses of 20% and 30%. The area under the curve (AUC) is consistently above 0.9 and exceeds 0.99 in some cases. Bridges in Cluster 3 perform slightly worse, particularly with 20% stiffness loss, than those in Cluster 1 and 2. This behavior can be linked to the structural cross-section geometries of the bridges in the cluster, but a formal analysis falls beyond the scope of this article. Furthermore, it is apparent that as the stiffness loss increases, the proposed algorithm more effectively distinguishes damaged cases from healthy ones, thereby improving overall performance. Finally, It is worth noticing that clustering (being based solely on healthy data) is performed with the same procedure as in the supervised scenario.

Fig. 11 shows the ROCs of the new bridges (B_{25} and B_{37}) when experiencing damaged conditions and after being integrated in the system exploiting the cluster models or a random initialization. Again, the performance confirms the advantage of using the proposed method and also the effectiveness of being placed in the proper cluster.

VI. Conclusion and Future Works

In this article, we proposed a CFL-based framework for effective PBSHM in a privacy-preserving environment with validation on bridge monitoring. We developed an unsupervised classifier to cluster bridges with similar underlying properties. The proposed clustering algorithm exploits the PAs across data subspaces and does not require prior knowledge of the bridges. Cluster-specific models are trained and tested on various types of damage across different bridge structures. Additionally, we introduced a mechanism to seamlessly integrate new bridges with limited training data into the architecture. Our approach was validated via numerical simulations in both supervised and unsupervised scenarios. The results showed that the proposed CFL-based approach outperforms traditional learning methods in terms of accuracy and communication efficiency.

A key limitation of the proposed method is the potential increase in communication overhead (with respect to a CL framework) when model convergence requires a higher number of communication rounds between the bridges and the central server. Quantization [51] and low-rank model adaptation [52] techniques could be explored in future works to address this issue. Other relevant issues to be investigated are related to handling more efficiently heterogeneous computational resources across bridges, understand potential different performance of different clusters, and protect the overall architecture from the risk of parameter poisoning.

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