
Machine learning driven recovery modelling for Critical Infrastructure networks: Integrating topological and data-driven approaches

Y.I Syed & Y. Mahmood

Earth Sciences New Zealand

ABSTRACT

Critical infrastructure networks constitute the foundation of societal functionality and their rapid recovery following disruptive events is central to resilience planning. Traditional topology-based recovery models provide valuable insight into network structure and component criticality but are limited in their ability to represent heterogeneous and nonlinear recovery dynamics at the component level. This study proposes a hybrid recovery modelling framework that integrates topology-based analysis with machine learning prediction to improve recovery time estimation. Component-level recovery times derived from a topology-based recovery model are employed as training dataset for multiple machine learning algorithms, including Linear Regression, Support Vector Machines, Random Forest, Neural Networks, and XGBoost.

Results demonstrate that substation-level learning substantially outperforms direct system-level prediction. Tree-based models, particularly XGBoost and Random Forest, achieve the highest accuracy. The findings confirm that modelling recovery dynamics at the component level preserves nonlinear behaviour that is obscured by prior aggregation. The proposed hybrid topology-machine learning framework enhances predictive accuracy while maintaining interpretability, offering a robust and operationally meaningful decision-support tool for critical infrastructure recovery planning.

1 INTRODUCTION

Critical infrastructure (CI) networks, which support essential services like energy, water, transportation, telecommunications, healthcare, and finance, are increasingly exposed to a wide range of hazards such as natural disasters (Syed, 2021). Rapid and effective restoration of these infrastructures after disruptions is crucial to minimize economic losses and ensure public safety (Kong et al., 2023). However, recovery planning for large-scale infrastructure systems is a complex challenge due to interdependencies among components, heterogeneous damage patterns, and limited restoration resources (Rinaldi et al., 2001). Traditional recovery approaches, relying on manual processes and static models, often fail to capture the

dynamic and nonlinear nature of recovery. Recovery requires timely damage assessments, prioritization of repair actions, allocation of resources, and sequencing of restoration activities (Zhao et al., 2025).

Authors have demonstrated the importance of network topology in guiding recovery prioritization using graph-theoretic metrics in a previous work (Syed et al., 2021). However, topology-based models mainly provide relative importance rankings and often overlook variability in recovery time and nonlinear recovery dynamics at the component level. Recent advances in machine learning (ML) offer a complementary approach to address these limitations by learning complex relationships from data, enabling more accurate predictions of recovery times at the component level (Alkhaleel, 2024; Derras & Makhoul, 2023). Motivated by this progression, the present study systematically compares multiple ML algorithms for recovery time prediction and examines how their outputs differ from, and complement, topology-based recovery insights. Building directly on the authors' prior topology-based framework, the study develops and evaluates a hybrid topology-ML decision support framework that enhances system-level recovery estimates by incorporating ML based recovery time predictions at the substation level, while maintaining interpretability and operational relevance.

2 RELATED WORK

Network science has been widely used to model and analyse the resilience and recovery of CI networks, with topology-based models prioritizing components based on structural importance measures such as degree, betweenness centrality, and network efficiency (Ji et al., 2024; Wang et al., 2021). While these models are interpretable and computationally efficient, they often rely on static assumptions regarding recovery duration and do not account for variability in recovery times or heterogeneous damage behaviour across components. Optimization and simulation-based methods have been used to incorporate operational constraints and generate detailed restoration schedules, but they are often computationally complex and sensitive to the accuracy of recovery time estimates, which can limit their scalability for large networks or real-time applications (Shuai et al., 2022; Yang et al., 2018; Zhou et al., 2024).

Recently, several studies have used ML techniques for infrastructure recovery modelling, enabling more adaptive, data-driven representations of recovery dynamics. One of the pioneer works by Buxton et al. (2010) emphasised the significance of interdependency modelling among CI networks to guarantee their effective operation. The authors proposed a Bayesian belief networks (BBNs) methodology using interdependency-mapped conditional probability tables to model interdependent networks. Syed et al. (2019) addressed the challenge of high-dimensional data in CI network modelling by applying clustering algorithms for dimensionality reduction. Their methodology involves generating simulation datasets, clustering network components based on topological characteristics and developing models using the reduced feature set. This approach was demonstrated on an interdependent power-transport model, resulting in improved accuracy and computational efficiency. Zhou et al. (2024) developed a recovery framework that leverages deep graph learning to enhance network resilience against cascading failures. The framework utilises structural graph embedding and deep reinforcement learning to extract real-time network topology information to update maintenance priorities dynamically.

However, these approaches often require large datasets, specialized architectures, and substantial computational resources, which may limit their practical deployment for rapid decision-making in real-world recovery contexts. Furthermore, while these models can capture complex interdependencies and post-disruption behaviours, few have integrated these techniques with network topology, which is essential for providing the interpretability and transparency required for operational decision support. This study seeks to address these limitations by combining the strengths of both topology-based and ML approaches, offering a more comprehensive, scalable, and interpretable solution for infrastructure recovery planning.

3 METHODOLOGY

3.1 Overview of the Modelling Framework

The proposed methodology adopts a hybrid topology–ML approach for modelling post-disruption recovery of CI networks. A topology-based recovery model is first used to generate component-level recovery times under a range of simulated damage scenarios using RiskScape (Paulik et al., 2022). These recovery times are then used as training targets for ML models operating at the substation level. Finally, predicted substation recovery times are aggregated to reconstruct system-level recovery trajectories. This formulation enables accurate recovery time prediction while preserving component-level interpretability and operational relevance.

The study evaluates a range of ML algorithms with varying levels of complexity and interpretability, including Linear Regression, Support Vector Machines, Random Forest, Artificial Neural Networks, and Extreme Gradient Boosting (XGBoost). These models were selected to enable a systematic comparison between linear, kernel-based, ensemble-based, and deep learning approaches for recovery time prediction.

3.2 Dataset Description

The dataset is organized into four comma-separated value (CSV) files, each containing 500 damage simulations. The first three files contain damage states for substations, cables, and poles, respectively, with each column corresponding to one damage simulation and each row representing a substation. Damage levels are encoded using an ordinal scale ranging from 0 (no damage) to 5 (complete failure). The fourth file contains recovery time outputs produced by a topology-based recovery model, where each column corresponds to a recovery time contribution of an individual substation. Recovery time is estimated based on network design consisting of multiple routes between a source and destination, repair strategies for a variety of component types, and priorities in repair for critical facilities.

3.3 Training and Testing Strategy

To prevent information leakage between training and testing data, a simulation-based split strategy is adopted. The first 100 damage simulations (20% of the dataset) are used for model training, and the remaining 400 simulations (80%) are reserved for testing. All substations within a given simulation are consistently assigned to either the training or testing set. A simulation-based train–test split was adopted instead of random cross-validation to reflect realistic operational conditions, in which recovery models must generalise to previously unseen damage scenarios rather than resampled variations of the same scenario. This approach provides a realistic assessment of generalization performance for recovery planning applications.

3.4 Feature and Target Construction

Recovery time prediction is formulated at the substation level. Each data sample corresponds to a specific substation under a given damage simulation. For simulation i and substation j , the input feature vector is defined as:

$$x_{i,j} = [S_{i,j}, C_{i,j}, P_{i,j}]$$

Where $S_{i,j}$, $C_{i,j}$, and $P_{i,j}$ denote the damage levels of the substation, cables and poles respectively. The target variable is the corresponding substation-level recovery time:

$$y_{i,j} = RT_{i,j}$$

Where $RT_{i,j}$ is obtained from the topology-based recovery model. This formulation results in a total of $500 \times 9 = 4500$ substation-level samples.

System-level recovery time was reconstructed from substation-level predictions by aggregating predicted recovery times across all substations for each damage simulation. For a given test simulation i , the reconstructed system recovery time is computed as:

$$\widehat{RT}_i^{system} = \sum_{j=1}^{N_s} \widehat{RT}_{i,j}$$

Where $\widehat{RT}_{i,j}$ denotes the predicted recovery time of substation j under simulation i , and N_s is the total number of substations. This aggregation enables direct comparison between reconstructed system-level recovery trajectories and the topology-derived system recovery times, while preserving the underlying component-level predictions.

3.5 Performance Evaluation Metrics

Model performance is evaluated using the coefficient of determination R^2 and the root mean squared error (RMSE). Metrics are computed at both the substation level and the reconstructed system level to assess predictive accuracy and error propagation from component-level predictions to system-level recovery estimates.

4 RESULTS AND DISCUSSION

This section presents a detailed evaluation of the predictive performance of ML models considered in this study. The assessment is structured to provide both qualitative and quantitative insight into model behaviour. First, a visual examination of model predictions is conducted to identify overall trends, dispersion patterns, and potential biases across the range of recovery times. This is followed by a quantitative analysis using standard performance metrics, which enables objective comparison between models and supports a deeper interpretation of their relative strengths and limitations.

4.1 Visual Evaluation of Model Predictions

Figure 3 (a–e) presents scatter plots of actual versus predicted system-level recovery time (RT) obtained from the evaluated ML models. Actual recovery times here refer to the recovery times that were estimated using the topology-network based approach. The system-level recovery time is calculated as the aggregate of substation-level recovery times for each damage simulation and represents the total duration required to restore the electricity network to full operational status following a disruptive event. This metric captures the cumulative effect of component-level damage and restoration processes on overall system performance.

In each subplot, the predicted system RT is plotted against the topology-derived system RT, which serves as the reference or baseline value. The dashed 1:1 line represents perfect agreement between predicted and actual values and is used as a visual benchmark for assessing prediction accuracy. Points lying close to this line indicate accurate model predictions, while deviations above or below the line suggest tendencies toward overestimation or underestimation, respectively. Because the recovery times are derived from discrete damage simulations, visible clustering occurs along the horizontal axis. This clustering reflects repeated system-level recovery times resulting from similar damage configurations across simulations. Nevertheless, the dispersion of predicted values around the 1:1 line provides clear qualitative insight into model accuracy, systematic bias, and robustness, particularly at higher recovery times, which are most relevant for severe disruption scenarios. These scenarios are of greatest practical importance for resilience assessment, emergency response planning, and long-term recovery strategy development. The extent to which models maintain accuracy and avoid excessive dispersion in this upper range of recovery times offers a strong indication of their robustness and suitability for real-world recovery planning applications.

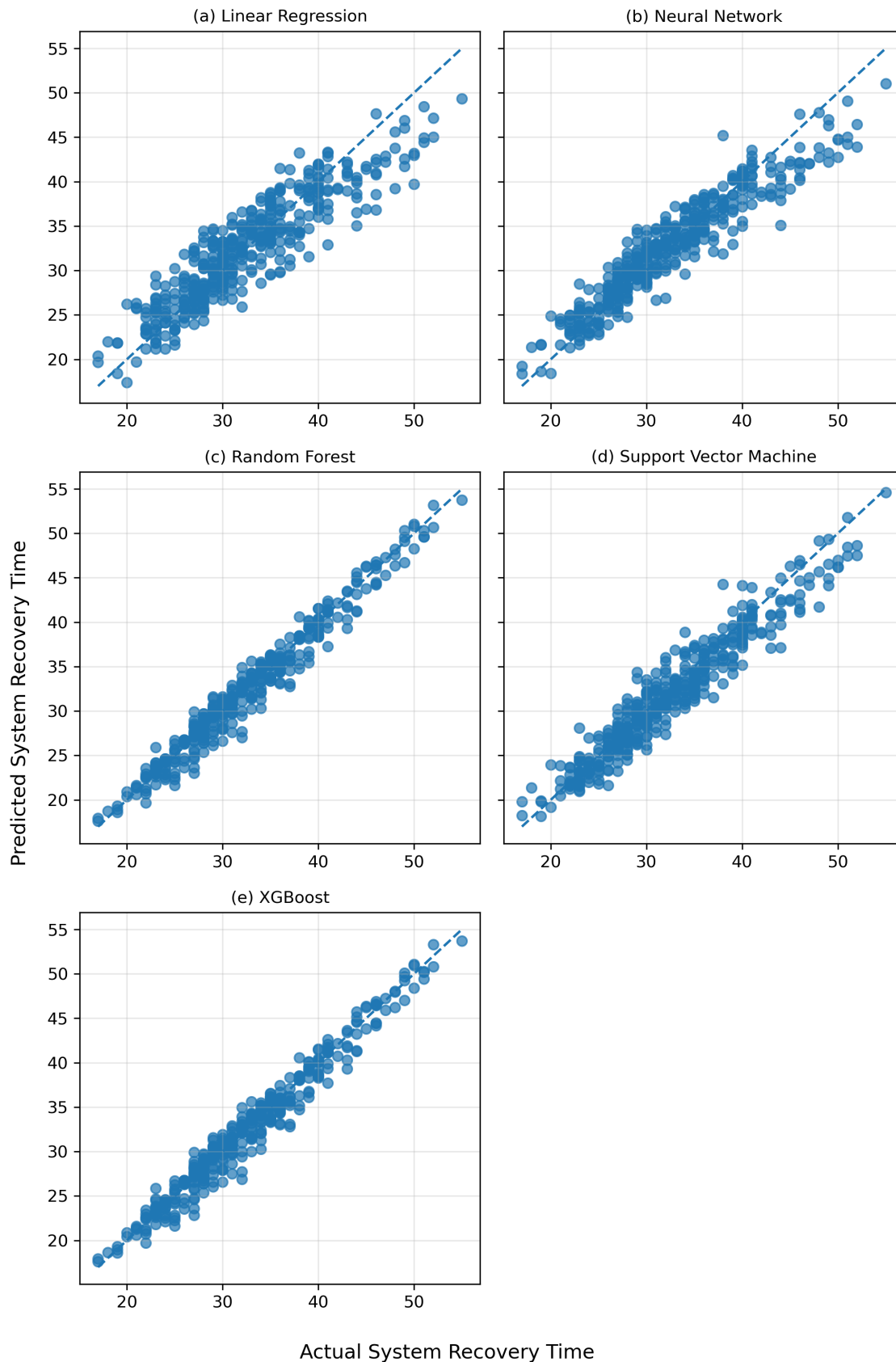


Figure 3: Actual versus predicted system-level recovery time (RT) for (a) Linear Regression, (b) Neural Network, (c) Random Forest, (d) Support Vector Machine (SVM), and (e) XGBoost. System recovery time is computed as the aggregate of substation-level recovery times for each damage simulation. The dashed line indicates perfect prediction.

- Figure 3a (Linear Regression) shows strong overall alignment with the 1:1 line across low-to-moderate system recovery times. However, predictions increasingly fall below the 1:1 line for larger recovery times ($RT \gtrsim 45$), indicating systematic underestimation of severe recovery scenarios. This reflects the limited capacity of linear models to capture nonlinear escalation effects arising from widespread and interacting damage.
- Figure 3b (Neural Network) exhibits greater dispersion around the 1:1 line across the full recovery time range. While general trends are captured, noticeable scatter and several large residuals indicate reduced stability and generalisation at the system level, consistent with its comparatively weaker quantitative performance.
- Figure 3c (Random Forest) demonstrates substantially improved predictive accuracy, with predictions clustering closely around the 1:1 line across most recovery times. Mild underprediction is observed at the upper tail, reflecting the tendency of bagging-based ensemble methods to smooth extreme outcomes while maintaining strong overall agreement.
- Figure 3d (Support Vector Machine) shows relatively stable predictions for moderate recovery times but increasing dispersion and underprediction for larger recovery durations. This systematic tail bias may result in optimistic recovery estimates under severe disruption conditions.
- Figure 3e (XGBoost) exhibits the closest agreement with the 1:1 line across the entire range of system recovery times. Predictions remain tightly clustered with minimal systematic bias, including at the upper tail of the distribution. This visual performance confirms the superior system-level predictive capability of XGBoost.

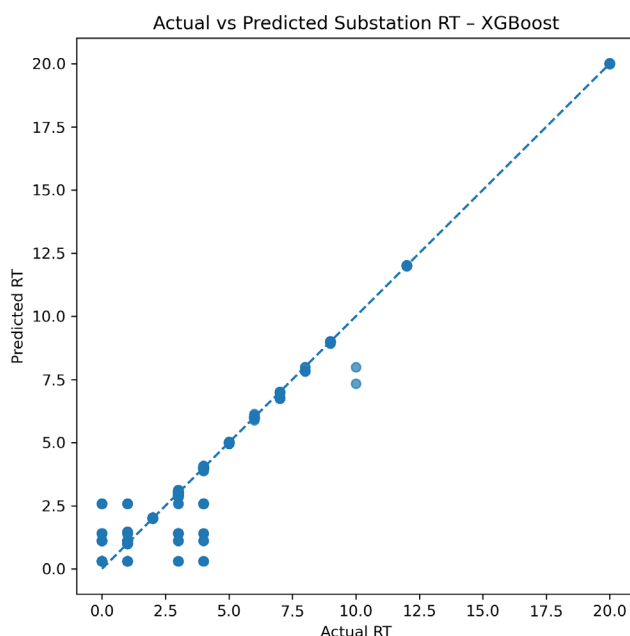


Figure 4: Actual versus predicted substation-level recovery time using XGBoost. The dashed line indicates perfect prediction and illustrates the model's ability to learn heterogeneous recovery behaviour at the component level.

Figure 4 presents the actual versus predicted substation-level recovery times (RT) for the XGBoost model, illustrating its effectiveness in capturing the diverse recovery behaviours across substations. The close alignment of the data points with the 1:1 line highlights that the model is performing well, with minimal deviation between predicted and actual recovery times. This indicates that the model not only accurately reflects the recovery dynamics at the substation level but also has a high degree of precision across a wide range of values. Importantly, the distribution of points at lower recovery times suggests that the model is particularly adept at predicting smaller recovery times. As the recovery times increase, the model's predictions continue to closely follow the actual values. This consistency supports the conclusion that the XGBoost model's predictions can reliably be aggregated to generate accurate system-level recovery time estimates.

4.2 Quantitative Performance Comparison

Following the visual assessment, model performance is evaluated quantitatively using two standard regression metrics:

- **Coefficient of Determination (R^2)**, measuring the proportion of variance in recovery time explained by the model; and
- **Root Mean Squared Error (RMSE)**, which penalises larger prediction errors and is particularly relevant for assessing recovery time underestimation in severe damage scenarios.

Performance metrics are reported at both the substation level, where models predict recovery time for individual substations, and the system level, where system recovery time is reconstructed by aggregating predicted substation-level recovery times across each damage simulation. Table 1 summarises the predictive performance of each ML model.

Table 1: Summary of substation-level and reconstructed system-level recovery time prediction performance.

Model	Substation R^2	Substation RMSE	System R^2	System RMSE
Linear Regression	0.8852	1.1080	0.8141	3.1092
Random Forest	0.9798	0.4653	0.9645	1.3592
Support Vector Machine	0.9493	0.7360	0.9132	2.1242
Neural Network	0.9350	0.8337	0.8822	2.4753
XGBoost	0.9802	0.4598	0.9649	1.3514

At the substation level, tree-based ensemble models clearly outperform linear and kernel-based approaches. XGBoost and Random Forest achieve the highest predictive accuracy, with R^2 values of 0.9802 and 0.9798 and substantially lower RMSE values of 0.4598 and 0.4653, respectively. These results indicate that substation recovery dynamics exhibit strong nonlinear behaviour that cannot be adequately captured by linear models alone. In contrast, Linear Regression achieved lower accuracy ($R^2 = 0.8852$), reflecting its limited ability to represent heterogeneous recovery mechanisms across substations.

At the system level, reconstructed by aggregating substation-level predictions, XGBoost and Random Forest again achieve superior performance, with system-level R^2 values exceeding 0.96 and RMSE values close to 1.35. This demonstrates that accurate component-level prediction propagates effectively to system-level recovery estimation. In contrast, Linear Regression shows a substantial degradation in system-level performance, despite reasonable substation-level accuracy, highlighting the limitations of linear aggregation when recovery dynamics vary across network components.

Overall, the results demonstrate that learning recovery dynamics at the component (substation) level, followed by aggregation to reconstruct system-level recovery time, yields substantially improved predictive accuracy compared with direct system-level learning. These findings support the selection of XGBoost as the primary predictive model within the proposed hybrid topology–ML decision-support framework, with Random Forest providing a viable alternative where model interpretability is prioritised.

4.3 Integration with traditional CI recovery approaches

In the authors' previous work (Syed, 2021), recovery prioritization was derived primarily from network topology, with components ranked using graph theory measures such as centrality, connectivity, and network efficiency. These topology-based approaches provide valuable structural insight into component criticality and are computationally efficient and highly interpretable. They are particularly effective for identifying elements whose failure disproportionately affects network connectivity and service delivery. However, topology-based recovery models implicitly assume that structural importance directly translates into recovery impact and typically rely on predefined or simplified recovery times (Ouyang, 2013). As a result, components with similar topological importance are often treated equivalently, even when their actual recovery requirements differ substantially due to heterogeneous damage states or asset configurations.

The results of the present study demonstrate that ML-based recovery time prediction captures additional dimensions of recovery behaviour that are not explicitly represented in topology-based models. Both the actual versus predicted recovery time plots (Section 4.1) and the quantitative performance metrics (Section 4.2) show that recovery duration is not solely a function of topological importance but also depends on nonlinear interactions between damage states across substations, cables, and poles. Substation-level learning reveals significant variability in recovery time among components that would otherwise be considered similarly critical from a purely topological perspective. The integration of ML into recovery planning offers several advantages over purely topology-based approaches.

- First, ML models provide quantitative estimates of recovery time, rather than relative importance rankings alone. This distinction is critical for operational recovery planning, as realistic scheduling, repair crew assignment, and resource allocation depend directly on the expected duration of repair activities.
- Second, ML models capture nonlinear and threshold effects that arise under severe disruption conditions, such as cascading hazards that can cause concurrent damage to multiple asset types. These effects are difficult to encode explicitly in topology-based heuristics but are naturally learned through data-driven approaches. The superior performance of XGBoost in predicting both substation-level and reconstructed system-level recovery times demonstrates the importance of accounting for such nonlinear recovery dynamics.
- Third, ML-based recovery models can be updated as new damage assessments or operational information becomes available, allowing recovery strategies to adapt dynamically. In contrast, topology-based rankings are typically static unless recomputed from scratch and therefore offer limited flexibility in rapidly evolving post-disaster contexts.

Despite the demonstrated advantages of ML, topology-based approaches remain essential for interpretability, transparency, and situational awareness. Network metrics provide intuitive explanations of why certain components are structurally critical and support communication with infrastructure operators and decision-makers. For this reason, the objective of this study is not to replace topology-based recovery models, but to augment them. Therefore, we propose a hybrid framework in next section that integrates topology-based prioritisation with ML-based recovery time prediction. Topological analysis is used to identify structurally critical components and candidate restoration sequences, while ML models refine these sequences by incorporating predicted recovery durations derived from component-level damage characteristics. By learning recovery dynamics at the substation level and reconstructing system-level recovery trajectories, the framework preserves structural insight while improving predictive accuracy and operational realism.

5 HYBRID DECISION SUPPORT FRAMEWORK FOR CI RECOVERY

Building on the results presented in the previous section, this study proposes a hybrid decision-support framework that integrates topology-based recovery analysis with substation-level ML prediction. The framework is designed to support infrastructure operators in planning and executing post-disruption recovery actions by combining structural insight, quantitative recovery time estimation, and adaptive prioritisation. The framework consists of five sequential steps:

Step 1: Network Representation and Damage Characterisation

CI networks are represented as network models in which nodes correspond to substations and edges represent physical or functional connections through cables and poles. Damage scenarios are generated following a disruptive event, with damage states assigned to each substation and its associated assets.

Step 2: Topology-Based Identification of Structurally Critical Components

Topology-based metrics, such as centrality, connectivity, and network efficiency, are used to identify structurally critical components. This step provides an initial prioritisation that reflects the role of each component in maintaining overall system connectivity and service delivery.

Step 3: Substation-Level Recovery time Prediction Using ML models

ML models are applied at the substation level to predict recovery time based on damage characteristics. Using damage indicators for substations, cables, and poles as input features, the models estimate recovery time for each substation under the given damage scenario. Results from this study demonstrate that XGBoost and Random Forest provide the most accurate and robust predictions, capturing nonlinear recovery dynamics that are not represented in topology-only approaches.

Step 4: Reconstruction of System-Level Recovery and Prioritisation Refinement

Predicted substation-level recovery times are aggregated to reconstruct system-level recovery trajectories. This aggregation enables estimation of total recovery duration while preserving the underlying component-level predictions. Topology-based prioritisation is then refined by incorporating predicted recovery times, allowing differentiation between components that are structurally similar but operationally.

Step 5: Adaptive Recovery Planning and Resource Allocation

The reconstructed system-level recovery estimates are integrated with operational constraints, such as crew availability, repair capacity, and logistical considerations. Recovery plans can be updated dynamically as new damage information becomes available or as restoration progresses. By combining structural insight with quantitative recovery-time prediction, the framework enables adaptive, data-informed decision-making.

The proposed decision-support framework demonstrates how topology-based recovery analysis and ML-based prediction can be combined to address complementary aspects of infrastructure recovery. Topology-based methods provide interpretability and structural awareness, while ML supplies quantitative and adaptive recovery-time estimates. The results of this study show that substation-level learning followed by system-level reconstruction generates superior predictive performance and greater operational relevance than direct system-level modelling. From a practical perspective, the framework supports infrastructure providers in prioritising repairs, allocating resources, and anticipating recovery timelines under diverse damage scenarios. By integrating established network-theory concepts with data-driven learning, the framework offers a scalable and implementable approach for enhancing the resilience and recoverability of CI networks.

6 CONCLUSIONS AND FUTURE RESEARCH

This study investigated the integration of topology-based recovery modelling and ML techniques to enhance post-disruption recovery planning for CI networks. Building on the authors' prior topology-based recovery framework, the study reformulated recovery-time prediction at the substation level and evaluated multiple ML algorithms using simulated damage scenarios.

The results demonstrate that modelling recovery dynamics at the component level substantially improves predictive performance compared with direct system-level learning. Tree-based ensemble models, particularly XGBoost and Random Forest, consistently achieved the highest accuracy in predicting substation-level recovery times and in reconstructing system-level recovery trajectories. By contrast, linear and kernel-based models, while capable of capturing general recovery trends, exhibited systematic underestimation of severe recovery scenarios. The comparison between topology-based and ML-based approaches highlights their complementary strengths. Topology-based models provide transparent and interpretable insight into structural criticality and network vulnerability, while ML models deliver quantitative, data-driven estimates of recovery duration that capture nonlinear and heterogeneous recovery behaviour. The proposed hybrid framework integrates these strengths by combining topology-based prioritisation with substation-level recovery-time prediction and system-level reconstruction. Overall, the findings confirm that a hybrid topology–ML approach offers a more accurate, adaptive, and operationally meaningful solution for CI recovery planning than either method alone.

Several avenues for future research emerge from this study. First, the incorporation of additional topological and functional features such as flow capacity, interdependency measures, and dynamic network states may further improve recovery-time prediction accuracy. Second, extending the framework to larger and more complex networks would support assessment of scalability and generalisability. Third, future work could integrate explicit resource-constrained scheduling and optimisation models with the proposed framework to translate predicted recovery times into detailed restoration schedules. Fourth, incorporating uncertainty quantification and probabilistic recovery modelling would enable risk-informed decision-making under incomplete or evolving damage information. Finally, applying the framework to real-world post-disaster datasets and multiple infrastructure sectors would provide valuable validation and support broader adoption of hybrid, data-driven recovery planning tools for resilient infrastructure systems.

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