



Research Article

Innovative approaches and practical experiences: Post-disaster reconstruction with adhocratic architecture

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ABSTRACT

Reconstruction after a disaster is essential to the reconstruction of communities that have been ravaged by either man-made or natural disasters. Errors in data calibration persist even as issues and challenges with planning reconstruction techniques are becoming more widely acknowledged. This study examines methods and techniques for creating resilient societies and reconstructing them following such occurrences in order to get around this restriction. Adhocratic Architecture effectively improves the performance of the post-disaster reconstruction process. Initially assessment and data collection is used and to analyze the extent of damage, the availability of resources. Then Fuzzy logic algorithm used for feature extraction. After that we use Probability Graphics Models (PGMs) and Bayesian networks for analyzing the gathered data. subsequently Weakly Supplied training methods for classifying the general tags then Utilizing the Adam-Enhanced Squeeze and When a disaster strikes, the Excitation High-Resolution Network (SEHRNET) improves the precision of classifying structural damages. For balanced decision-making, the Preference Ranking Organization Method of Enrichment Evaluation (TOPSIS-PROMTHEE) technique and the Order of Preference by Similarity to Ideal Solution technique are utilized. Lastly, we employ Multi-time Stepping Rolling with Model Predictive Control (MPC) as a feedback loop to monitor the process. The proposed model is addressed utilizing several comparison metrics such as Accuracy, F1-score, Precision, Acceleration.

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INTRODUCTION

Over the past few decades, there has been a dramatic increase in the frequency, intensity, and severity of both natural and man-made catastrophes, such as hurricanes, earthquakes, and huge floods [1]. The built environment, the economy, and

society have all suffered short- and long-term consequences as a result of these occurrences [2]. The susceptibility of many countries to natural disasters has been highlighted by recent events [3]. For example, Gorleston's disastrous floods left the city's infrastructure severely and permanently damaged.

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In addition, cities are increasingly vulnerable to the direct consequences of natural disasters like floods due to population development and rising demand for infrastructure and structures [4,5]. Infrastructures can be disrupted by both natural and man-made disasters [6], even if they are built to withstand hazards. Although it is impossible to completely forecast hazards [7], one can mitigate their consequences by improving emergency response times and limiting the infrastructure's susceptibility. The resilience of infrastructure to damage and return to its original state has become more important in the context of risk management. Many academics have studied a variety of resilience tactics to lower the risk of disasters and assess the recovery period after calamitous incidents.

One of the most critical challenges in post-disaster reconstruction is the inaccurate assessment of damage and the difficulty in processing large amounts of data under uncertain conditions. Many traditional approaches rely on manually annotated datasets, which introduce errors due to subjective interpretations. Moreover, the decision-making process in reconstruction planning lacks a comprehensive framework that balances short-term and long-term recovery efforts.

Similar issues, including the damage from the most recent earthquake, have been documented recently all around the world. Consequently, a number of organizations are putting more pressure on researchers studying disaster management to create practical plans for building resilient cities [8]. The construction industry frequently provides a range of vital services in the wake of a disaster, such as building public infrastructure and temporary housing in the early aftermath [3]. However, one of the key problems that arise in disaster recovery is the lack of standardized methodologies for post-disaster assessment and classification of damages. Humanitarian organizations cannot choose and begin all possible reconstruction after a disaster due to a lack of resources [1]. Tasks Reconstruction current conditions, long-term objectives, and numerous other crucial elements Based on their primary strategy and overarching objectives, humanitarian organizations ought to pick post-disaster programs according to a suitable model [9]. Considering the restrictions and considerations of comprehensive and effective criteria, in addition to internal and environmental variables.

In this context, this study proposes an adhocracy architecture to enhance the accuracy of post-disaster construction activities by leveraging machine learning, Bayesian networks, and fuzzy logic. It thereby aims for a twofold advancement: automating damage classification and optimizing decision-making processes through a structured feedback loop. Managers may now overcome the challenges of project selection with the help of numerous techniques. To get a more reliable and accurate result when choosing the best project, it is essential to first precisely define the context of analysis and then use an efficient tool to analyze criteria that are at odds with the strategic goals of the

humanitarian organization. In multi-criteria decision-making (MCDM) systems, the fundamental issue concerns how the final decision is reached. This issue is often approached from the reverse perspective; that is, following a decision, it is necessary to examine the choices made via the MCDM method and provide a fair basis for that decision [1]. Although priority is given to the most important projects, there is strong evidence that incorrect choices negatively impact the effectiveness of many post-disaster recovery efforts [3]. The primary procurement strategies currently employed in reconstruction projects, as well as the key challenges encountered in post-disaster reconstruction initiatives, have been identified and documented [4]. Rebuilding transportation infrastructure following a natural disaster is generally a highly challenging process [10].

This study presents a creative and effective method by integrating various analytical and computational techniques to ensure a more resilient and adaptable reconstruction process.

The accuracy of damage detection is enhanced through fuzzy logic-based feature extraction.

Bayesian networks are employed to probabilistically model uncertainties in damage classification.

- An Adam-enhanced SEHRNET deep learning framework has been developed for use with high-resolution remote sensing imagery.
- A TOPSIS-PROMETHEE-based method is utilized to optimize the decision-making process.
- A Model Predictive Control (MPC) feedback loop enables real-time adjustments through continuous assessment.

In terms of biomimicry, parasitic architecture mimics the course that parasitism takes in nature. Furthermore, parasitism is acknowledged as a symbiotic lifeform [11]. Adhocracy is a type of organizational structure that is very adaptable, loosely connected, and frequently changed. Related Topics: public administration organization [12,13].

The process of reconstructing transport infrastructures after a natural event is a challenging endeavour generally post disaster architecture refers to the design and construction of structures as well as communities to aid in the recovery and rebuilding efforts following a disaster [14]. This might encompass both temporary and permanent constructions, as well as the restoration and repair of existing structures (see also Aziminezhad and Taherkhani [15] on BIM for deconstruction) The major activities in the post disaster phase include: Rehabilitation, Reconstruction and Recovery. Disaster affected communities will be made resilient and able to return to normalcy through these activities [8]. Searching for an alternative recovery condition for disasters can lead to the term disaster relief architecture. An aspect of architecture that is specifically focused on biopolitics is approaches that resemble nature. Currently, one of these biopolitical strategies is recognized as parasitic architecture [16, 17]. Effective disaster response after a natural disaster, such as an earthquake or hurricane, depends on

conducting a thorough and in-depth damage assessment of lifeline infrastructure. There has been a dramatic rise in the use of various tools for this in recent years [18].

Satellites, drone photos, LIDAR scans, water level sensors, structural strain gauges, and other instruments and datasets are examples of these. The goals, the accuracy of the data gathered, and the resources needed for data processing and gathering vary between various instruments. All too frequently, architects produce design solutions for post-disaster rehabilitation in developing nations with little understanding of the environments in which those solutions are expected to function. Reconstruction in the aftermath of a tragedy is complicated and uneven [19]. Language barriers, lack of resources, transportation challenges, rising building material costs, corruption in the distribution of aid funds and resources, and the challenge for architects to adhere to the specific socioeconomic and cultural norms of each community are just a few of the problems. In our research we used in this type of technique. To ensure balanced decision-making in the post-disaster reconstruction process we propose the Method for Sorting Preferences According to Likeness to Ideal Solution (TOPSIS-PROMETHEE) The Enrichment Evaluation Method of Preference Ranking Organization with Simulated Annealing method Finally, we utilize a feedback loop to monitor and feedback to the classifier and decision-making method to reduce the demands.

MOTIVATION AND OBJECTION

The primary challenge of the existing methods in post-disaster reconstruction lies in their inability to accurately assess damages, classify disaster zones, and prioritize reconstruction activities efficiently.

- **Inaccurate assessment:** Many existing methods face difficulty in dividing and data calibrating which leads to inaccurate assessment of disaster damage.
- **Short-term focus:** The existing approaches largely concentrate on short-term recovery rather than taking into consideration long-term reconstruction planning. This leads to a decrease in the efficacy of decision-making processes and has a significant influence on total disaster recovery and rebuilding plans.
- **Issue of categorization:** It is difficult to categorize building damage due to the poor accuracy of the suggested classification techniques, which is further complicated by the limited amount of imaging data that is available to the public for damaged buildings.
- **Impact of relief operations:** The growth in the need for relief, in conjunction with the higher rates of unmet demand, worries about the environment, and costs related to emergency situations, leads to a considerable deterioration in the overall performance of the system.

The primary objective of this research is to enhance the reconstruction process after a natural disaster using Adhocratic Architecture. The following are the specific objectives of the research:

- To implement an integrated approach for damage classification and data calibration.
- To establish a robust machine learning model that reduces manual annotation requirements.
- To optimize decision-making by considering both short-term and long-term post-disaster recovery strategies.
- To introduce a novel categorization method for multi-level building damage assessment.
- To develop a real-time monitoring framework that enhances reconstruction accuracy and responsiveness.

Research Contribution

This study makes significant contributions to post-disaster reconstruction through the following innovations:

- To effectively process and extract the features from the collected data we propose the Probabilistic Graphical Models (PGMs) with Bayesian networks and fuzzy logic techniques.
- Utilizing the weakly supervised learning technique which effectively reduces the manual annotation of complex labels, in remote sensing scenarios.
- To implement the Adam optimization algorithm, which offers efficient gradient-based optimization, coupled with the SEHRNET architecture tailored for high-resolution remote sensing imagery, the methodology enhances the precision and reliability of damage classification.
- Using a feedback method known as Multiple steps Rolling with Model Predictive Control (MPC). This method allows for watching things as they happen and making decisions quickly, so help can be adjusted in a timely way.
- Integrates TOPSIS-PROMETHEE with Simulated Annealing to ensure comprehensive and balanced decision-making in post-disaster scenarios.

Literature Survey

This segment encapsulates and analyzes the core research inquiries tackled by earlier investigations. Current studies predominantly concentrate on singular elements of the post-disaster recovery process; yet, there is an absence of a holistic framework that incorporates processes like damage evaluation, decision-making, and resource distribution. Our research seeks to fill this need by introducing a decision support system that integrates human contributions with artificial intelligence to enhance post-disaster reconstruction initiatives.

A research conducted by Cremen et al. [5] suggested the application of Bayesian linear regression, utilizing a probabilistic modeling approach, to forecast and assess business growth and recovery. The framework evaluates four essential attributes related to a company's restoration and normalization post-disaster: the length of operational disruption, the schedule for revenue recuperation, and indicators pertaining to customer engagement and workforce retention. This research predominantly emphasizes

financial recuperation while neglecting the essential element of physical infrastructure resilience in post-disaster contexts. Our research tackles this constraint by combining infrastructure damage evaluation with probabilistic modeling to establish a comprehensive recovery strategy [20].

A study by Calle Müller and ElZomor [21] introduced two innovative approaches to address the difficulties encountered in low-income regions after a disaster. The aim of this research was to promote upward social mobility and enhance learning efficacy within the community by employing educational resources and techniques. Nonetheless, these regions continue to be exceedingly susceptible to natural calamities owing to constrained financial means, elevated poverty rates, and the existence of informal housing. The research in focus emphasizes socioeconomic weaknesses but fails to provide a structured method for incorporating disaster resilience strategies into urban development. Our study complements this by developing a decision-support system that incorporates both socioeconomic and infrastructural resilience. In the work of Zhang et al. [22], a method was proposed to determine hazardous gathering regions and evaluate the areas with the highest concentration of earthquake victims. The study assessed building damage conditions and analyzed geographical features by mapping casualty distribution and employing grid data for hotspot evaluation and spatial autocorrelation analysis. While this research provides valuable insights into damage distribution, it lacks an adaptive feedback mechanism for real-time modifications. In our methodologies, we utilize a feedback mechanism referred to as Model Predictive Control (MPC) to continually modify resource distributions and damage evaluations over time [20]. Research by Zhang et al. [22] indicates that fluctuations in ground motion were overlooked in the assessment of potential building damage. This exclusion may result in considerable inaccuracies in damage assessment, especially when the research zone includes an urban or metropolitan area. To improve precision in extensive disaster evaluations, our research integrates an AI-driven remote sensing analysis that continuously adjusts damage forecasts utilizing real-time seismic and ground motion information [23]. A study by Zokaee et al. [10] introduced a resilience-focused strategy for site selection and routing that leverages public-private partnerships to enhance post-disaster reconstruction supply chain (PDRSC) efforts. Although this approach improves logistics and supply chain efficiency, it lacks a structured methodology for integrating real-time disaster response adaptation mechanisms. Our study builds upon this by implementing an optimization model that allows real-time adjustments in supply chain distribution based on updated disaster severity levels [24].

The study by Zokaee et al. [10] assessed the impact of limited resources on rebuilding costs and aimed to minimize the reduction in the efficiency of distribution partnerships. The model's effectiveness was tested using a real-case study. While this study provides a strong cost

analysis framework, it does not fully address decision-making complexities under uncertainty. Our research employs a Bayesian probabilistic approach to enhance the decision-making process as disaster conditions evolve. The study by Zokaee et al. [10] explored the possibility of redistributing surplus reconstruction resources between locations via a Temporary Disaster Recovery Warehouse (TRDW) to reduce disaster response times. That study focused on agent-based reinforcement learning for repair team assignment without incorporating real-time adjustments. Our approach is based on integrating a Multi-Step Moving Horizon Model Predictive Control (MPC) strategy to dynamically update repair team assignments in response to evolving real-time damage assessments [20]. In the study by Sun and Zhang [25], an agent-based modeling (ABM) approach was presented to evaluate infrastructure network resilience and propose effective recovery methods following extreme events; however, the study highlighted certain limitations regarding the accuracy and reliability of the infrastructure connectivity model. Our study overcomes these limitations by integrating a graph-based deep learning network to improve prediction accuracy in assessing infrastructure network failures.

The study by Cremen et al. [26] investigated the role of adaptability in corporate recovery processes, noting that such processes can be multi-stage and continuously evolving. However, that study views the recovery process in binary terms—as an “all-or-nothing” phenomenon—an approach that may fail to fully capture long-term corporate performance. Our study employs a fuzzy logic-based dynamic alignment framework to enable a more detailed and continuous examination of the recovery process of companies. The research by Wearing et al. [27] presented an initial examination of the potential role of volunteer tourism in post-disaster recovery processes. The study has addressed the ethical aspects of post-disaster volunteer tourism and proposed an approach that involves stakeholders in the process. While emphasizing the social dimensions of the recovery process, our research further develops this approach by incorporating a participatory decision-making model that enables affected communities to actively make decisions regarding post-disaster planning and resource allocation.

The needs of economically disadvantaged populations were examined in the study by Calle Müller and ElZomor [21], which investigated post-disaster vulnerabilities, essential needs, and the competencies required for temporary employment and housing (TEH). Its emphasis on immediate support leaves scope for a more developed account of long-term recovery. Our study responds by proposing an adaptive framework that brings economic resilience and infrastructure restoration into a shared recovery perspective. Connecting these dimensions provides a basis for examining how short-term interventions might support more durable rehabilitation.

The study by Islam et al. [28] quantitatively examined factors influencing community participation in recovery programs organized by non-profit organizations and government agencies. Community participation and physical damage assessment, however, capture different dimensions of recovery. The physical condition of an affected area cannot, by itself, establish the demographic characteristics or needs of its residents. Reliable differentiation between damaged and intact structures remains a complementary technical requirement. Our study contributes to this aspect of recovery planning by employing probabilistic modelling to improve damage classification, while recognizing that such classifications must be interpreted alongside social information.

The study by Wang et al. [29] explored the use of unmanned aerial vehicles (UAVs) in post-disaster recovery, proposing a framework that draws on the spare processing capacity of unmanned ground vehicles (UGVs) to support computationally demanding UAV tasks. This arrangement offers a practical means of sharing computing resources, although its scalability across extensive disaster zones requires further consideration. Building on this approach, our study proposes AI-based task allocation within coordinated UAV-UGV operations to improve the efficiency of disaster response. The central concern is how computational resources can be assigned as operational demands change.

A related challenge concerns the continuity of interconnected infrastructure. The study by Wei et al. [30] developed

a multi-agent integrated energy system (IES) that incorporates road networks into post-disaster recovery planning. Although it established operational indicators and the system topology, the treatment of cascading failures associated with climate-related disasters remained limited. Our proposed model addresses this issue through real-time monitoring and predictive risk analysis, with the aim of strengthening resilience to widespread outages. This extends the focus of recovery planning to the dependencies through which disruption can spread between infrastructure systems.

Resource allocation introduces a further set of trade-offs [31]. The recovery framework presented by Ransikarbum and Mason [23] used an evolutionary algorithm to address two objectives simultaneously. Its mixed-integer linear programming formulation sought to balance financial considerations with fairness and equity during reconstruction. This perspective is relevant because recovery priorities involve decisions about both the use of limited funds and the distribution of assistance. Technical assessments therefore need to be considered alongside the consequences of those decisions for affected communities.

However, this method does not adequately account for transportation network issues that delay reconstruction efforts. Our study addresses this gap by optimizing the deployment of repair crews and integrating dynamic traffic flow models to minimize delays in the post-disaster recovery process. Table 1 presents a general summary of the literature review conducted [10-41].

Table 1. An overview of the literature review

Ref.	Objective	The method or the model utilized the algorithm	Restrictions
[10]	With cooperation from the public and private sectors, this study suggests creating a resilience location-routing model to support the Post-Disaster Reconstruction Supply Chain (PDRSC) programs.	Supply chain during post-disaster reconstruction: An empirical optimization study	• Unneeded rebuilding resources
[18]	Displacement Damage Analysis Using Remote Sensing Data	SAM-VQA system for post-disaster damage evaluation using remote sensing photographs.	• It is very expensive method.
[20]	Emergency Recovery During a Disaster in Distribution System Applying Model Predictive Control	Rolling Optimization Strategy with Multiple Time Steps	• Plan losing optimality • Recovery period is lengthy
[21]	The objective of a comprehensive and enduring plan construction trade education	Origami infrastructure and construction trade education	• High levels of poverty • Informal buildings
[22]	building damage and analysis of geographical features	Spatial autocorrelation analysis	• Ground input was not considered
[23]	The hybrid technique, referred to as Hybrid NSGA-II (HNSGA-II), depends on the non-dominated sequencing genetic algorithm-II	Evolutionary formula.	• Issues in damage for the roads,

Table 1. An overview of the literature review

Ref.	Objective	The method or the model utilized the algorithm	Restrictions
[24]	This research presents a novel (“N-BBB”) theoretical method for empirical recovery analysis after earthquakes in different countries	Building Back Better” and Post-Earthquake Needs for Recovery and Reconstruction	• Did not consider long-term reconstruction planning
[25]	Post-Disaster unique methodological framework that can evaluate infrastructure network	Reinforcement learning with ABM, methodological framework	• Limited. reliability
[26]	This project aimed after earthquake seismic events an impact on company recovery.	Modelling Post-Earthquake Business Recovery Time: An Analytical Framework.	• Not accurately long-term performance
[27]	The aim of this research has been to offer a first exploratory investigation into the potential role that volunteer tourism may play in the aftermath of a catastrophe.	Engaging volunteer tourism in post-disaster recovery	• Inefficient
[28]	Factors influencing community participation in recovery from disaster managed by non-profit and government organizations using quantitative analysis	That five factors govern decision-making participation and eleven main factors govern community engagement in sustainable disaster recovery programming (SDRP).	• Materials region not entirely correct
[29]	Offloading Cooperative UAV Computation Challenges for Post-disaster Rescue by VFC-Based Technique	Adaptable mobility, unmanned aerial changes the compute task issue into a matching puzzle with both sides.	• Minimize the number of iterations
[30]	Coordinated Method to Post-Disaster Recovery and Assessment for the Integrated Energy, Gas, and Transportation System	Repairing damaged roads was recommended, considering various energy sectors’ perspectives and the condition of the highways.	• IES to the rising frequency
[32]	Building Damage Detection using Mechanism from Pre- and Post-Disaster Remote Sensing	Siamese neural network	• Difficult to split the damage itself, which leads to errors in data calibration
[33]	Unsupervised domain adaptation applying self-attention to identify post-disaster building degeneration	Unsupervised self-attention domain adaptation “(USADA)	• Accuracy of the proposed classification method is low
[34]	In order to solve the problem, a hybrid global criteria technique that combines a branch-and-bound strategy, expected value, and primal-dual algorithm is developed.	“fuzzy tri-objective bi-level integer”	• The overall percentage of unfulfilled demand and all potential environmental issues
[38]	Post-disaster business recovery	A probabilistic modelling technique for the use of Bayesian linear regression	• Wide range of hazard intensities
[39]	This study was designed to determine whether GEE was useful for recovery analysis and monitoring.	Post-Disaster Recovery Monitoring with Google Earth Engine	• Hard in some situations to discern actual damage and visually separate damaged
[40]	A Framework for Spatial and Temporal Evaluation of Network Disaster Recovery	Such as adaptive reorganization and topology rebuilding, are also included.	• Number of network components impacted by the catastrophe
[41]	The study’s goal is to come up with a multi-stage dynamic healing method for distribution networks (DNs) after a disaster.	Multi-phase Dynamic Recovery Plan for Distribution Networks after a Disaster Taking Integrated Transportation and Energy Networks into Account	• Issues within traffic allocations • Transportation system

Problem Statement

The explicit works now in existence, together with methods for monitoring and mapping forest health, are compiled in this area. Additionally, this study offers research solutions for the mentioned issues.

Specific problem definition

Wu et al. [32] to develop a Siamese neural network that is capable of simultaneously localizing and classifying damaged structures. Many attention U-Nets backed by different backbones are the most crucial parts of this network. The following is a list of the issues with certain methods. It is difficult to split the damage itself, which leads to errors in data calibration. Even expert find it challenging extend damage to certain aspects. Additionally, inconsistencies in sensor data and remote sensing imagery further complicate the classification of structural damage, increasing the need for probabilistic calibration methods.

Sarkar [18] proposed the purpose of post-disaster damage assessment based on drone footage, the visual question answering (VQA) framework, specifically supervised attention-based VQA (SAMVQA), is the primary subject of this paper. By offering a VQA dataset and proposing a unique SAM-VQA method for post-disaster damage appraisal utilizing remote sensing images, this work enhances the field of storm assessment. These are the problems with this work: However, their proposed need for human annotation for remote sensing data leads to high time consumption and a very expensive method. To address this limitation, weakly supervised learning is utilized to reduce the dependency on extensive human annotation, making damage classification more efficient and scalable.

Shi et al. [24] suggested a novel (“N-BBB”) theoretical method for empirical recovery analysis after earthquakes in different countries. It is based on the global “building back better” (BBB) agreement and an evaluation method for post-disaster needs. Factor analysis proved the model’s dependability. The main issues are: the proposed method did not consider long-term reconstruction planning it only focused on short-term recovery which led to reduced decision-making process effectiveness and also affected the disaster recovery and reconstruction plans. To address this gap, our approach integrates a hybrid decision-support system that ensures both short-term emergency response and long-term sustainable recovery strategies.

Li et al. [33] explained an “unsupervised self-attention domain adaptation (USADA) model as a solution to the previously described difficulty. This strategy would convert instances from the source realm into the desired area in pixel space. Three components make up the proposed USADA: collection GANs (generative adversarial networks), a classifier, and a self-attention module. The problems encountered in those approaches are: the accuracy of the proposed classification method is low so the categorization of building damage is a difficult problem since there is a limited amount of publicly accessible imaging

data including damaged structures, and it is difficult to determine the extent of damage based on images simply. To improve classification accuracy, this study incorporates a graph-based deep learning model that enhances feature extraction and damage categorization.

Cao et al. [34] described a “fuzzy tri-objective bi-level integer” program method whose bottom level maximizes the pleasure of enduring persons while the higher-level addresses unmet demand, environmental concerns, and emergency expenses. In order to solve the problem, a hybrid global criteria technique that combines a branch-and-bound strategy, expected value, and primal-dual algorithm is developed. The main issues are: as a result of the rise in the need for relief, the overall SPS decreases significantly while the total missing demand rate, the total amount for possible environmental problems, and the whole amount of emergency expenses all rise. To mitigate this issue, a hybrid optimization framework incorporating stochastic modelling is utilized to balance supply-demand fluctuations and optimize emergency resource allocation. In both instances, it is shown that the fluctuation in the supply and demand does not possess sufficient strength to prevail over the selection of decision modes

Research solutions

To address the problem by putting together probabilistic graph models, Bayesian networks, and fuzzy logic, the problem of separating damage and reducing data calibration can be solved successfully.

Additionally, an AI-enhanced resource allocation system is employed to dynamically prioritize reconstruction efforts based on real-time disaster severity levels and accessibility constraints.

It uses fuzzy logic to pull out features that capture uncertainty and probabilistic graphical models with Bayesian networks to calibrate the data. To make weakly supervised learning easier, it’s enough to have labels for object groups that are more general and easier to find at the image level. So, the training network with weakly supervised learning makes it easier for people to label complex labels for remote sensing, which lowers the need for a lot of human labelling during reconstruction after a disaster. To solve this problem, we suggest a mix of TOPSIS-PROMETHEE and a decision-making method based on simulated annealing to make sure that both short- and long-term healing plans are carried out. To get around this problem, we’re using Adam-Enhanced SEHRNET to correctly identify the damage to buildings after a disaster. To get around this problem, a feedback system called Multi-time-step Rolling with MPC is being used to help with tracking and making decisions in real time. This good method makes sure that the relief efforts are responsive, flexible, and able to meet the changing needs of the communities that were harmed. The Problems are verified to the above solutions

Proposed Work

People usually get back to rebuilding quickly after a natural disaster. The goal of adhoc architecture is to make the rebuilding process more flexible and quicker after a disaster. As part of this plan, the following important things are done:

- Initial assessment and data collection
- Processing and feature extraction
- Training
- Classification
- Decision-making
- Feedback loop

Initial assessment and data collection

To identify the needs and priorities of the affected community first we conduct the initial assessment. This assessment is used to analyze the extent of damage, the availability of resources, and the population that is most susceptible, based on the collected data. Engaging in communication with many stakeholders [35], including local community members, government officials, non-governmental organization (NGO) representatives, and subject matter experts, to gather information on the challenges encountered throughout the reconstruction process. Hence, the restoration

endeavors are guided by the preferences and requirements of those who have been directly impacted by the catastrophe. We are using a disaster dataset from Kaggle, (<https://www.kaggle.com/datasets/varpit94/disaster-images-dataset>). Figure 1 shows the final methodologies of architecture.

Processing and feature extraction

Once the data-gathering procedure is finished, we progress to analyzing and extracting the characteristics from the dataset related to the disaster zone. A recommended approach involves using a combination of Probabilistic Graphical Models (PGMs) and Bayesian networks for analyzing the gathered data. It's important to use a combination of PGMs with Bayesian networks and foggy logic strategies for processing and extracting features in post-disaster constructions. One kind of probabilistic graphical model (GM) is the Bayesian Network (BN). It is also called the Bayesian Belief Network or the Causal Probabilistic Network. It is based on Bayes' theory, which lets you show how a set of variables is likely to be related visually. Subjective probabilities can be used to show the errors in a BN model, which means that the method can be used with experts' knowledge. It is possible to figure out the probability distribution

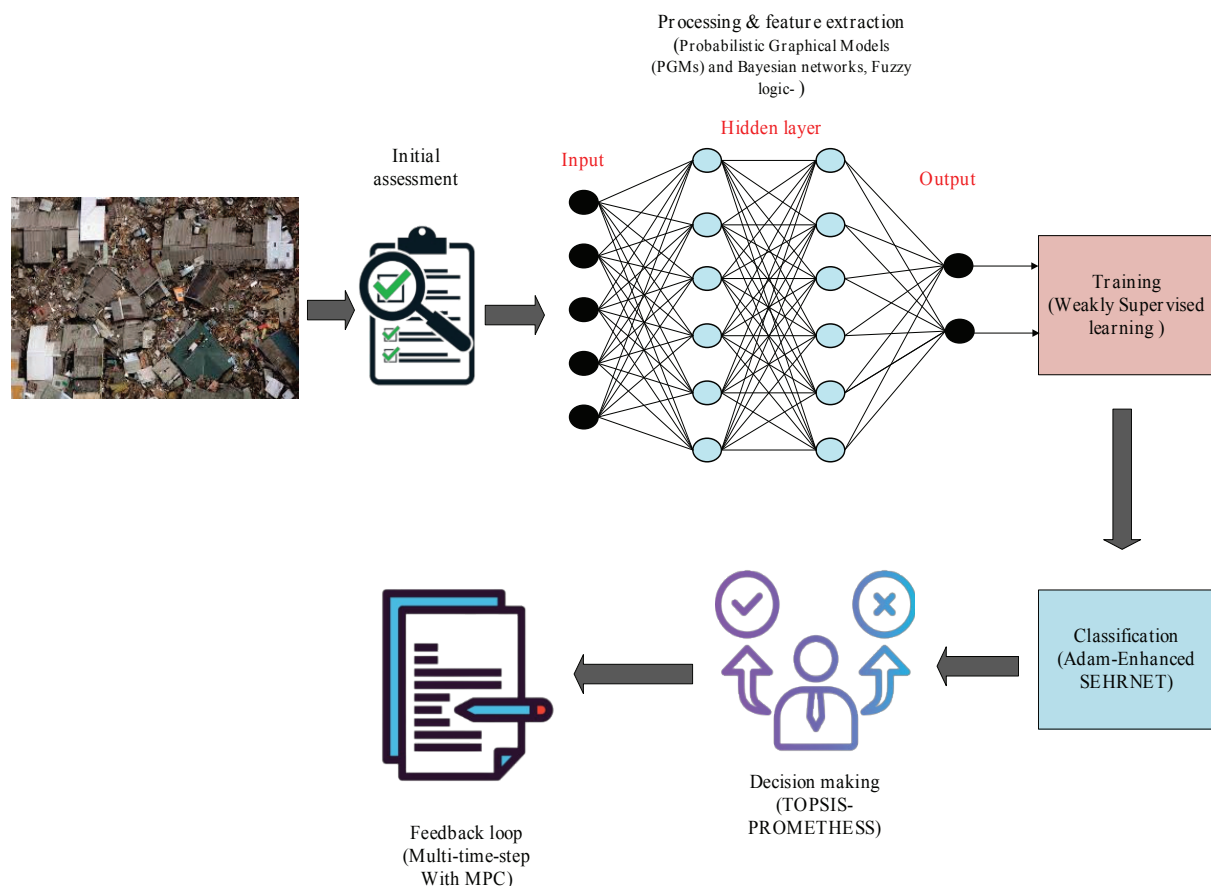


Figure 1. Final proposal architecture.

of variables by using BNs and variables that both quantitative and qualitative data have shown.

- A BN can have variables that are quantitative (low, medium, high) or Boolean (yes, no). collection of random variables that are connected to one another by arrow-shaped linkages is one component of a binary network (BN).
- A list of states that can't happen together for each variable (for example, E, F and G) that describe what could happen.
- A table of probabilities with and without conditions for each kid node and a table of probabilities without conditions for every additional node.

Variable to change. Z, it means that variable Y (the child) depends on variable (the parent). A directed acyclic graph is made up of edges and nodes. Most of the time, Conditional Probabilities Tables (CPTs) are used to show how the factors in a BN are related to each other. These tables show how likely it is for a child node to take on a certain state if its parent node is in a certain state. For variables that are not based on any other variables an unconditional probability table (UPT) replaces the CPT. A particular kind of probabilistic graphical model (GM) is the Bayesian Network (BN). It is also called the Bayesian Belief Network or the Causal Probabilistic Network. It uses Bayes' theorem to show how statistical relationships between a set of variables subjective probabilities can be used to show the errors in a BN model, which means that the method can be used with the knowledge of experts With BNs, one may determine the random distribution of variables depending on variables that have The Bayes theorem, which states that two nodes A (parent) and B (child) have the following relationship, is the fundamental source of inspiration for the BN.

$$P\left(\frac{C}{D}\right) = P\left(\frac{D}{C}\right) P(C)P(D) \quad (1)$$

where $P(C/D)$ is the probability of seeing C if D is true, $P(D/C)$ is the probability of seeing D if C is true, and $P(C)$ and $P(D)$ are the probability of seeing C and D separately. The probability that C/D will happen is called the posterior probability, and the probability that C will happen is called the prior probability. After a set of links have been used to connect the variables, both unconditional and conditional odds are given. To determine the unconstrained probability (UPs) of parent nodes whose states are unknown, the notion of insufficient reasoning is applied. This indicates that a weight of $1/n$ where n is the number of states, is assigned to each fundamental input. One example is if the variable $X1$ has three states: Low (L), Medium (M), and High (H). Then, $P(X1 = K) = 1/3$, $P(X1 = L) = 1/3$, and $P(X1 = M) = 1/3$. You can get an idea of the conditional probabilities (CPs) by asking experts for their knowledge and teaching them with data that already exists. The procedure can be divided into three parts:

- Putting first parent variables: The first stage involves assigning a weight number to each parent variable in order to determine its relative importance to the child nodes.

- What do combinations mean? By examining the various configurations that the child nodes can take, distinct states are identified for every variable.
- Guessing the chances of different outcomes: The last step is to guess the chances of all the possible outcomes for each set of conditions.

An example is given to help you understand the process better. Take a look at a system that has a kid node called Impacted Area and three further nodes named Extreme weather, urban areas, and mobility and access. Following the first phase of the recommended procedure, variables are arranged according to their impact on the child node. The three states are Extremely Bad (for Extreme Weather), Hard (for Mobility and Access), and Large (for Urban Area). (IAS, IAM, IAL) = (0.9, 0.1, 0) are the conditional probabilities associated with the variable "Impact Area." To determine the whole conditional probability table of the father node based on the various states in which the kid nodes can be in, alternative combinations are employed from the worst-case scenario. From now on, this method will be used to figure out the conditional odds for every node in the DT network. The conditional odds for the DT variable, on the other hand, are found in a different way. The conditional probabilities of the DT are calculated using restoration fragility curves based on the size of the earthquake.

Selection of variables Thirty-one indicators are chosen to create the BN for the DT estimation after a thorough analysis of previous work on important downtime parameters and literature publications. The indicators chosen provide a detailed description of each component of the framework. All indicators identified in the literature have been gathered and subsequently sorted to provide indicators that are mutually exclusive. Variable identification:

- Variable clustering: the variables are grouped into clusters to be properly organized once they have been recognized.
- Variable connection: Using Bayesian parent-child relationships, the variables are connected in the last phase

Training

Weakly supplied training methods are used to teach people how to do harmful rebuilding in the future. These steps make getting ready for classification easier by adding general tags for object types to the picture level. Weakly supervised learning only needs more coarse-grained labels, which are labels for object types at the image level.

Classification

Utilizing the Adam-Enhanced SEHRNET enhances the accuracy of categorizing structural damages in the event of a catastrophe. The objective of this approach is to overcome existing barriers and categorize multi-tiered damages with greater precision. SEHRNet achieves a significant reduction in network parameters while maintaining high accuracy by suppressing useless information and accurately identifying regions of interest. This leads to higher accuracy in aircraft

key point detection and reduces the risk of potential apron conflicts. Our proposed model also improves real-time performance in the key point detection process in Figure 2.

Adam's method involves determining the ratio of the squared moving averages of the gradient $\nabla\epsilon(\tau)$ to the moving averages of the gradient $\nabla\epsilon(\tau)$ in order to immediately change the learning rate at each repetition. Specifically, in the $(\tau+1)$ the iteration, the moving averages $m(\tau+1)$ and the squared moving averages $v(\tau+1)$ may be obtained by,

$$\begin{cases} a(\tau+1) = (1 - \beta_1)\nabla\epsilon(\tau), \\ b(\tau+1) = (1 - \beta_2)\nabla\epsilon^2(\tau), \end{cases} \quad (2)$$

The exponential decline rate parameters of m and v from the previous iteration of the loop are represented by β_1 and β_2 .

$$\begin{aligned} \hat{a}(\tau+1) &= a(\tau+1)/(1 - \beta_1), \\ \hat{b}(\tau+1) &= \frac{b(\tau+1)}{(1 - \beta_2)}, \end{aligned} \quad (3)$$

Update the partial derivative operator $\nabla\mu(\tau+1)$ as follows with the new values for $\hat{a}(\tau+1)$ and $\hat{b}(\tau+1)$

$$\nabla\epsilon(\tau+1)\alpha.\hat{a}_a(\tau+1)/\sqrt{\hat{b}_a(\tau+1)} + \varphi \quad (4)$$

Decision-making

In order to successfully manage the difficulty of balancing immediate and long-term rehab measures, we suggest using a hybrid decision-make approach. This method combines the TOPSIS-PROMTHEE technique with Simulated Annealing to provide accurate and sufficient

decision-making in situations after a tragedy. An analogy with solid-state physical annealing is employed to propose SA. Kirkpatrick et al. [36] made it popular, and it has since been used to solve numerous challenging combinatorial optimization issues in networks.

The neighbourhood search method, often known as the SA algorithm, is a random process that increases the possibility of local optima and processing time by giving each decision variable an equal chance of changing. Therefore, the following are the benefits of RD optimization:

$$\sum_{i=1}^L \sum_{t=1}^M lu_i \times (dp_i^t) \quad (5)$$

$$0 \leq x_{ij} \leq y_{ij} \quad (6)$$

$$\sum_{i=1}^L \sum_{j=1}^L x_{ij} \leq Total \quad (7)$$

The initial RD for the SA algorithm is found in Eqn (7) using the equal division approach. The decision variables are limited to the parameters in X whose values are modifiable according and their quantity is indicated by R_x . There are two stages involved in applying this approach. In the initial stage, every decision variable is raised by the value of aver, which is $\text{floor}(Total/(lu \times Lx)) \times lu$, where $\text{floor}(a)$ is a function that, up to a certain value, produces the largest integer. The remaining portion of $Total$ is arbitrary allocated to the decision variables in the second phase. The two stages are displayed as. Determine the value of $Avex$ in

- step one; raise each of the choice variables to $avex$.
- step two; determine the residual.
- step three. $Total - avex \times L = Rem$.

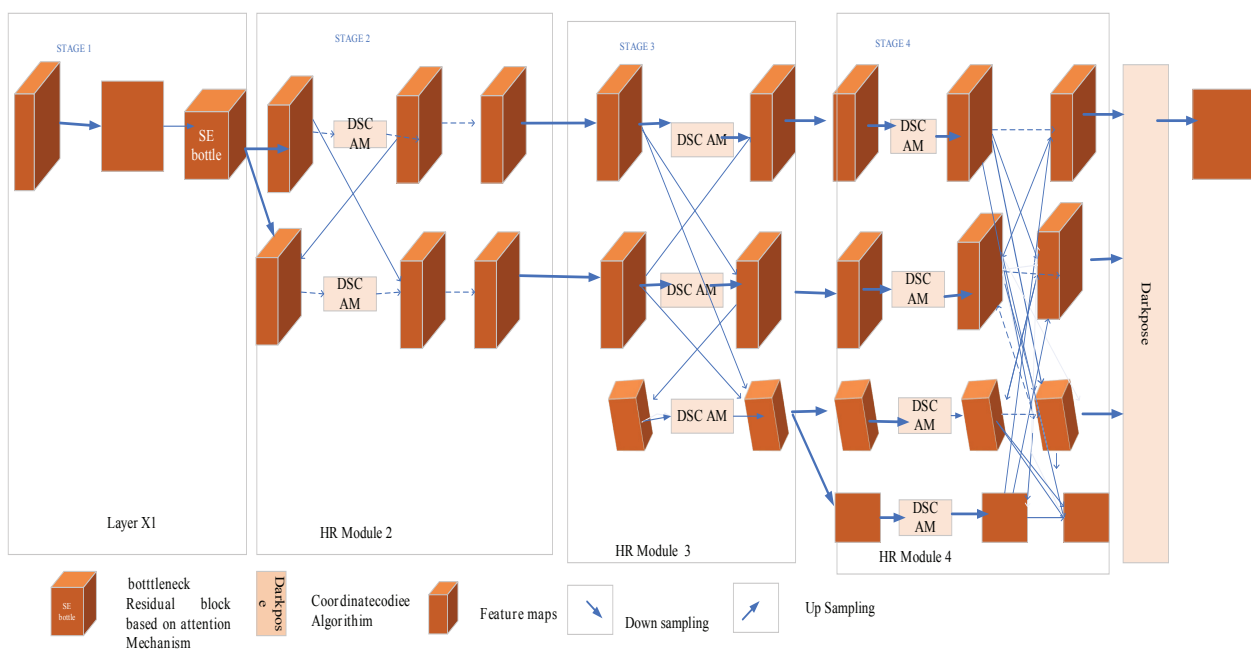


Figure 2. SEHR Net architecture.

- Step 4: Take the current $y = x_{ija}$ as the initial RD and terminate the procedure if Rem is smaller than not equal to zero.
- Step 5: Choose a decision variable Y_{ij} at random, and if Y_{ij} . By using the quantitative significance to improve its neighbourhood search, the SA is made better. $S = [L_{ij}]$ For example, risk i is represented by RIN node i , and its quantitative importance relates to risk i 's impact on project risk loss. If a node

$$IP_{tm} = \left(k_1 + \frac{M_{ij}}{\sum_{l=1}^N \sum_{m=1}^N L_{ij}} \right) / (1 + k_1) \quad (8)$$

Where k_1 is constant;

$$IP_{tm} IP_{tm} rand(0,1) \quad (9)$$

more quickly and effectively, the enhanced SA method is used to find the feasible domain of the decision variables, which is represented by Y in the pseudocode in below algorithm. Our pseudocode is a development of the typical SA-related code provided in Eqn [9].

The result of the RIN simulation model is the stable value of total risk loss L under which is called by $ob.(Y)$. The group of RIN nodes and edges that have a quantitative significance is represented by

$$S = \{L_{ij}\} \quad (10)$$

The number of iterations that the neighbourhood search should run at a particular temperature is indicated by the term $Iter$. T_0 and T_f , respectively, are the starting and finishing temperatures. We may compute the likelihood of adopting a worse solution using the Boltzmann constant, K . The corresponding coefficient relating to the α .

When the temperature drops to or equals T_f , or when the optimal solution is no longer superior than $N_{non-improving}$ consecutive times, the algorithm comes to an end.

Pseudocode for Improved SA Algorithm

$SA(I_{iter}, R_{non-improving}, T_0, T_f, \alpha, k, S)$

Begin

Generate an initial solution by the equal division method

$Y_{best} = Y; F_Y = obj(Y); F_{best} = F_Y;$

$T = T_0; R_1 = 0;$

While ($T > T_f \& N_1 < R_{non-improving}$) {

$I = 0; R_1 = R_1 + 1;$

While (I_{iter}) {

$l_1 = random(0,1); S$

if ($l_1 > 0.5$)

{Generate a new solution Y' from Y through the improved neighborhood search method with in S ;

else { Generate a new solution Y' from Y through the improved neighborhood search method randomly;

$l_2 = random(0,1);$

if [$l < exp(-\Delta)/(k \times T)$] $\{Y = Y'; F_Y = F_Y;\}$

```

}
if( $F_Y \leq F_{best}$ ) {  $Y_{best} = Y; F_{best} = F_Y;$  }
 $S = S + l;$ 
}
 $T = T \times b;$ 
}

```

end

Fuzzy Topsail is believed that fuzzy TOPSIS is a suitable approach for handling decision-making issues in a fuzzy setting. This methodology's procedures and formulas are below.

- Adapted with changes from the fuzzy TOPSIS is summed up in the stages that follow. Certain the evaluation criteria's weights.
- Construct the fuzzy decision matrix ($\sim D$) and work out the relative weights of each alternative in relation to the $l \times m$ criterion. In this case,
- $\sim y_{ij} = l_{ij} m_{ij} n_{ij}$. For $i = 1, 2, \dots, l$ and $m = 1, 2, \dots, n$.

$$\tilde{D} = \begin{bmatrix} B_1 & y_{11} & y_{12} & y_{1n} \\ B_2 & y_{21} & y_{22} & y_{2n} \\ B_m & y_{m1} & y_{m2} & y_{mn} \end{bmatrix} \quad (11)$$

$$y_{ij} = \frac{1}{q} (y^1_{ij} + y^2_{ij} + \dots + y^q_{ij}) \quad (12)$$

$$y^q_{ij} = (l^q_{ij} m^q_{ij} n^q_{ij}) \quad (13)$$

q is the number of responds. y^q_{ij} ; Performance criterion
The equation is expressed below,

$$y^q_{ij} = (l^q_{ij} m^q_{ij} n^q_{ij}); k=1, 2, \dots, q.$$

compute normalized fuzzy matrix value

$$\tilde{P} = [p_{ij}] l \times m \quad (14)$$

$$P_{ij} = \frac{l_{ij}}{c_j} + \frac{m_{ij}}{c_j} + \frac{n_{ij}}{c_j} \quad (15)$$

$$I = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n$$

Determine the fuzzy decision matrix that is weighted. The normalized values continue to be fuzzy triangles. We use the fuzzy-ANP approach to determine weights. The following formula is used to get the weighted normalized values P_{ij}

$$V_{ij} = \omega_i \times P_{ij}; i = 1, 2, \dots, m \text{ and } j = 1, 2, \dots, n \quad (16)$$

$$\tilde{V} = [p_{ij}] mn \quad (17)$$

Determine the optimal fuzzy-positive and fuzzy-negative solutions. The normalized fuzzy-decision matrix's

weights determine $\tilde{v}^+$ and $\tilde{v}^-$; $\tilde{v}ij$, which has a normalized positive value, should be $0 \leq \tilde{v}ij \leq 1$. Then, the following formulas are used to get B^+ and B^-

$$B^+ = \tilde{v}1^+, \tilde{v}2^+, \dots, \tilde{v}n^+ \quad (18)$$

$$B^- = \tilde{v}1^-, \tilde{v}2^-, \dots, \tilde{v}n^- \quad (19)$$

Determine the distances d_i^+ and d_i^- for every alternative (B^+ and B^-) using FPIS and FNIS.

$$d_i^+ = \sum_{j=1}^n d(\tilde{v}ij, \tilde{v}j^+) \quad i=1,2,\dots, \text{ and } l \text{ and } j=1,2,\dots, n$$

$$d_i^- = \sum_{j=1}^n d(\tilde{v}ij, \tilde{v}j^-) \quad i=1,2,\dots, \text{ and } l \text{ and } j=1,2,\dots, n$$

Determine the relative proximity of ideal solutions for $i = 1, 2, \dots, m$, and $0 \leq q_i \leq 1$ and $i = 1, 2, \dots, m$. The similarity between ideal solutions is resolved by the equation

$$q_i = d_i^- / (d_i^+ + d_i^-) \quad (20)$$

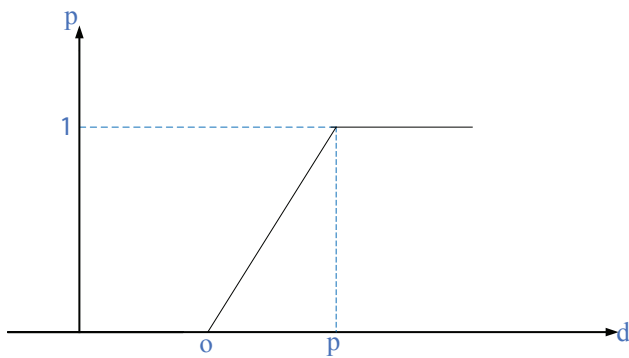


Figure 3. Preference Function in PROMETHEE method.

PROMETHEE is a compromise approach that chooses the optimal choice by utilizing the preference function. It is applied in many different domains. This method often gives solutions and criteria, weights each indicator so that the overall weight equals one, and transforms qualitative data into quantitative indicators.

$$P_k(b_i, b_j) = P[s_k(b_i, b_j)] \quad (21)$$

preference function (b_i, b_j). In this equation S represent the distance. Distance between the two-preference function. The value of preference function shown in this equation below

$$[s_k(b_i, b_j)] = f_k(b_i) - f_k(b_j) \quad (22)$$

R stands for incomparability with respect to A_{15} . When option A completely outperforms option C in a set of criteria, and option C completely outperforms option D in a set of criteria, we are unable to decide which option is best.

The degree to which option A is superior to option D cannot be inferred from the aforementioned relationships. The PROMETHEE approach uses preference functions to get rid of this problem and control how much the options are superior. Based on a number of preference functions, the degree of preference improves with the size of the difference between the two possibilities in a criterion. If the criterion is positive, then there is a positive difference between the two options with $s_j(c, d)$. Figure 3; Represent the Preference function of PROMETHEE Method.

$$s_j(c, d) = g_j(c) - g_j(d) \quad (23)$$

- The degree of preference for an over c according to criterion denoted (c, d). Figure 4.

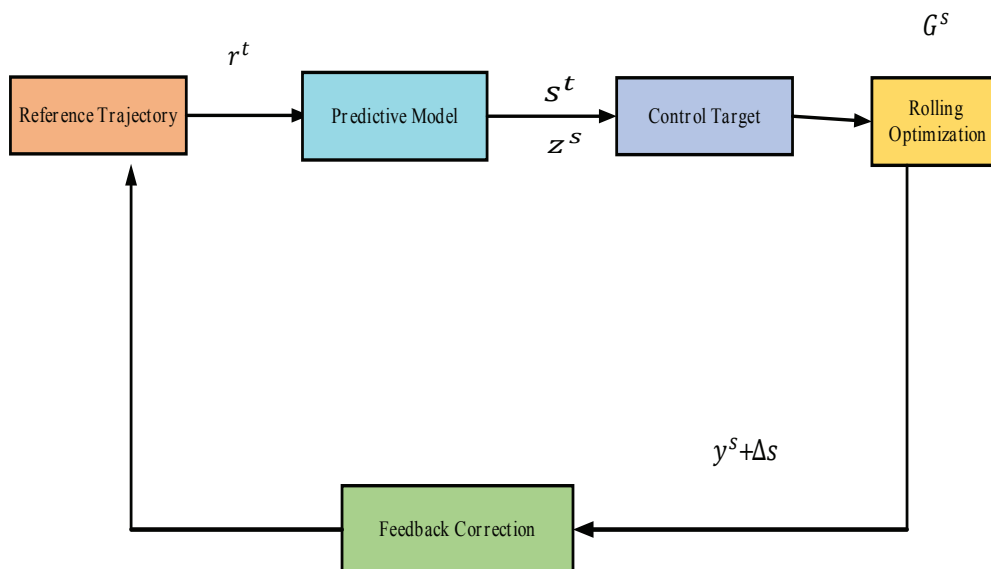


Figure 4. Basic flowchart for MPC.

- d or $d_j(c, d)$ is the distance, according to criteria j , between c and d .
- The midway between r and s , the preference threshold, and the indifference threshold is symbolized by the symbols σ , p , and s , respectively.

$$\pi(c, d) = \sum_{j=1}^n o_{j(c,d)} \omega_j / \sum_{j=1}^n o_j(c,d) \omega_j / \sum_{j=1}^n \omega_j \quad (24)$$

$$\pi(d, c) = \sum_{j=1}^n o_{j(d,c)} \omega_j / \sum_{j=1}^n \omega_j \quad (25)$$

$$\pi(c, c) = 0 \quad (26)$$

$$0 \leq \pi(c, d) \leq 1 \quad (27)$$

$$0 \leq \pi(c, d) + \pi(d, c) \leq 1 \quad (28)$$

Compute implied dominance flows in step two. The implicit dominance flows, both positive and negative, for each choice are computed in this particular section. The following equation shows the positive implicit dominie.

$$\varphi^+(c) = \frac{1}{m} - 1 \sum_{\substack{y \in B \\ y \neq b}} \pi(c, x) \quad (29)$$

demonstrates the negative implicit dominance flow equation. The average level of competence of the other selections in comparison to B is displayed.

$$\varphi^{-d} = \frac{1}{m} - 1 \sum_{\substack{y \in B \\ y \neq b}} \pi(x, b) \quad (30)$$

Lower $\varphi^+(b)$ and higher $\varphi^-(b)$ indicate a better alternative. Step 3: To rank the data, use PROMETHEE II. A thorough ranking in the form of equations is generated using the PROMETHEE II technique, the I I I and P I I interface, and the findings from the first and second steps.

$$b^{pII} c \Leftrightarrow \varphi(b) > \varphi(c) \quad (31)$$

$$b^{lII} c \Leftrightarrow \varphi(b) = \varphi(c) \quad (32)$$

Eqn (32) represents the implicit dominance of option B , denoted as $\varphi(b)$ or net flow.

$$\varphi(b) = \varphi^+(b) - \varphi^-(a) \quad (33)$$

In general, PROMETHEE II states that φ must be found for every option, and the benefit must be subtracted from the failure to achieve net domination. This φ increases with improvement. With this procedure, we get a final and thorough ranking and can determine the location of each option.

Feedback loop

Optimization Model Based on MPC. MPC is otherwise called as rolling time domain control basic model is given below and basic flowchart of MPC IS Also given below.

E , F , G and A ; Indicates the state space of Matrix; s^i ; Input Vector; r^i ; Output Vector; y^s ; State vector; G^s ; disturbance input vector; z^s ; Output Vector; $y^{s+\Delta s}$; State Vector

$$y^{s+\Delta s} = E y^s + F z^s + G x^s \quad (34)$$

$$z^s = A y^s \quad (35)$$

Figure 4 represent the basic flow chart of MPC. We propose to use Multi-time stepping Rolling with Model Predictive Control (MPC), a feedback loop evaluation technique, to address the shifting demands of impact populations. This technique makes it easier to make strategic decisions and conduct real-time monitoring which enables quick adjustments to relief operations. The methodology employs the MPC principle and continuously evaluates input from different time steps to guarantee responsiveness and effective relief effort.

Stakeholders will be able to make well-informed decisions based on the most recent circumstances and changing demands by employing these iterative methodologies. This ultimately improves the effectiveness and efficiency of the recovery efforts following disasters. Rolling Optimization Model Making Use of MPC Emergency recovery durations might last for several hours or days, during which the traffic flow, solar production, load demand, and topology of the distribution system. Figure 5 represents the flow chart on multi step rolling optimization.

RESULTS AND DISCUSSION

This section presents the experimentation analysis and performance evaluation of the suggested study plan. This part is divided into three subsections: simulation study, comparative analysis, research overview.

Simulation Study

To simulate the proposed research method, python tool is utilized. This tool has an efficient network topology and provides all specifications for the proposed technique. Table 2 indicates the system specifications.

Comparative Analysis

This section discusses the suggested approach with a number of available methods. Including Fuzzy Bi-Level Optimization Method (FBLom) [34]. Squeeze-and-Excitation dual High-Resolution Network (SEDHRNet) [37], Federal Emergency Management Agency (FEMA), The evaluation i.e. validation is performed by considering the performance metrics such as Accuracy, Precision, F1Score, and Acceleration.

Number of Epochs vs. Accuracy (%)

The degree of agreement between a measurement and its actual value is known as accuracy. The equation of accuracy is (assumes a simple linear relationship between the

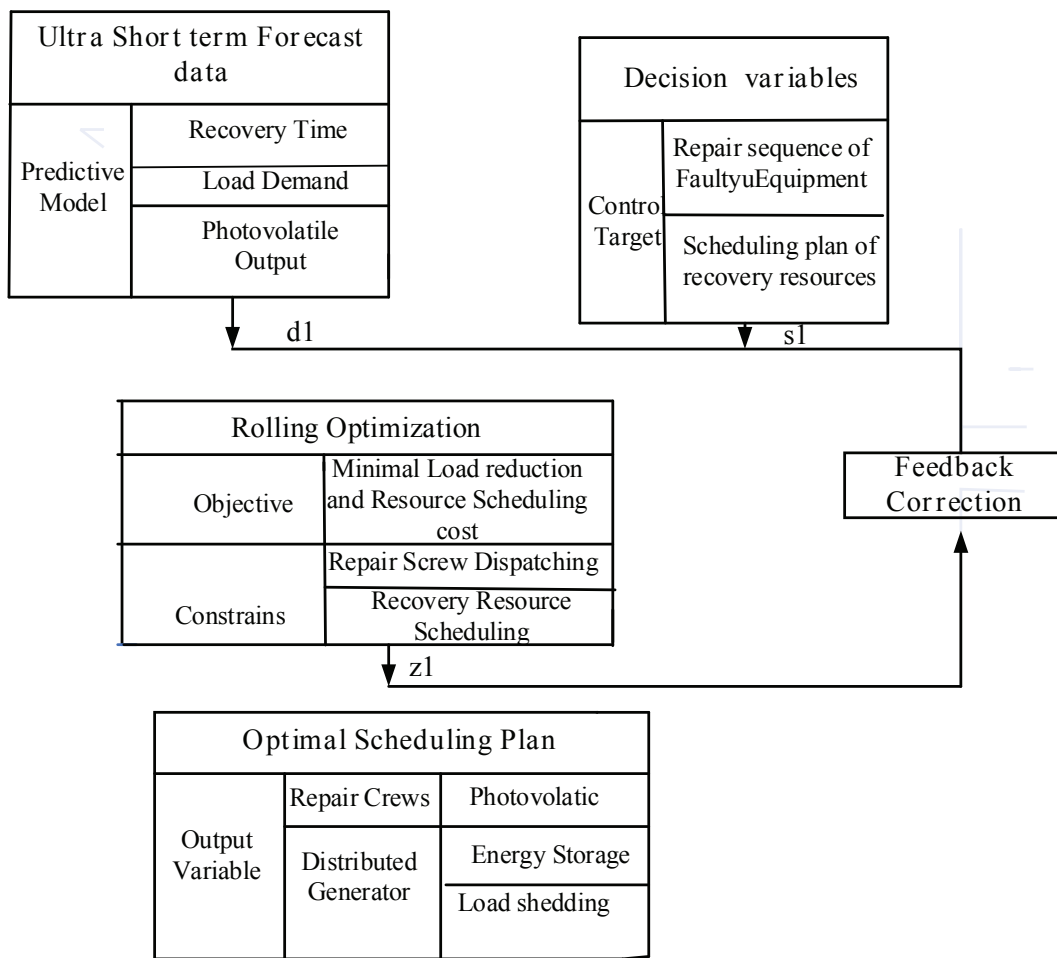


Figure 5. Flow chart for MPC.

Table 2. System specification

Software specification	OS	Windows 11-(64 bit)
	Tool	Python – 3.11.4
Hardware specification	RAM	4 GB
	Hard Disk	500 GB

(X) axis's number of epochs and the (Y) axis's percentage of accuracy (Fig. 6). Below is the equation.

$$A = \frac{Rp + Rn}{Rp + Rn + Wp + Wn} \quad (36)$$

Rp- True positive; Rn- true negative; wp- false positive; Wn- false negative.

As shown in Figure 6 and Table 3, classification accuracy increases with the number of training epochs for all three methods. At 20 epochs, SED-HRNet, FBLOM, and the proposed method achieve accuracy values of 85%, 86%, and 90%, respectively. At 40 epochs, these values increase to 87%, 88%, and 93%. At 60 epochs, the corresponding

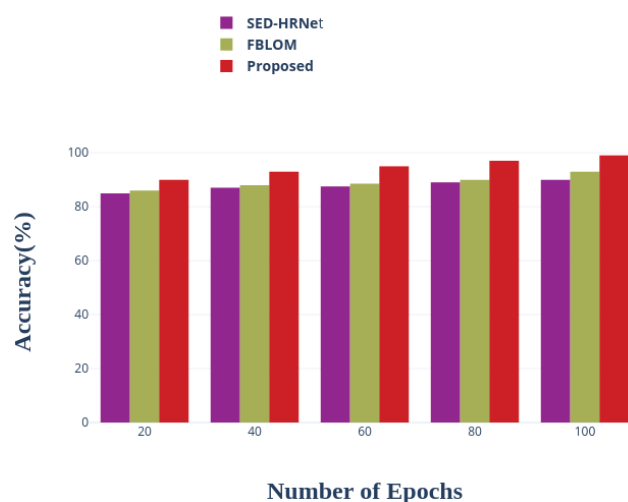


Figure 6. Number of epochs vs. accuracy.

values are 87.5%, 88.5%, and 95%, rising to 89%, 90%, and 97% at 80 epochs. At 100 epochs, SED-HRNet achieves an accuracy of 90%, FBLOM reaches 93%, and the proposed

Table 3. Numerical outcomes of accuracy (%)

(x-axis) – Number of Epochs	Accuracy (%) - (y-axis)		
	SED-HRNet	FBLOM	Proposed
20	85	86	90
40	87	88	93
60	87.5	88.5	95
80	89	90	97
100	90	93	99

method attains 99%. The proposed method achieves the highest accuracy at every reported epoch count.

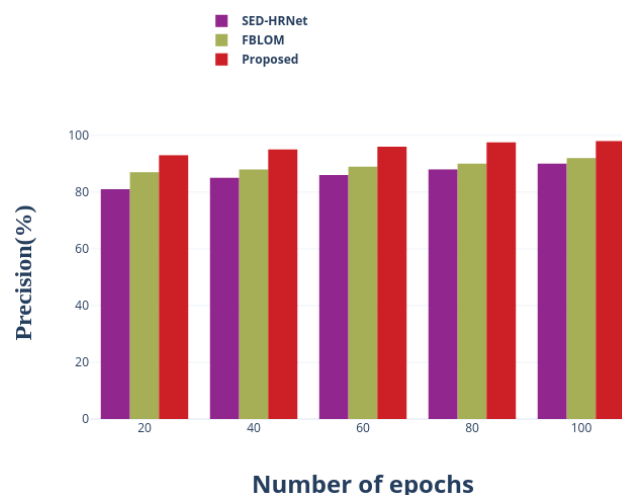
Number of Epochs vs. Precision (%)

Precision refers to the amount of information that is conveyed by a number in terms of its digits; it shows the closeness of two or more measurements to each other. It is independent of accuracy.

Figure 7 indicates the % of precision in the (Y) axis and the number of epochs in the (X) axis. The following is the mathematical relationship for precision.

$$Precision = \frac{Rp}{Rp + Rn} \quad (37)$$

Rp represent True positive; Rn represent true negative Initially 20% of epochs the percentage of precision in Existing level 85% & 89%. Proposed level is 94%. Further 60% of epochs the Percentage of precision in the SED-HRNet in 86%. FBLOM is 89% and proposed level is 96%. Then 80% of epochs the percentage of precision in the existing level 88% and 90% further increase in Proposed level 97.5%. Finally, 100% of epochs the percentage of Precision in the SED-HRNet 90%, FBLOM 92% and proposed level is

**Figure 7.** Number of epochs vs. precision.

98%. The proposed method is high percentage of precision so this method is better to other two method.

Number of Epochs vs. F1 Score

The F1 score is an alternative machine learning evaluation statistic that evaluates a model's predictive power by looking at how well it performs on each class separately as opposed to taking performance as a whole into account like accuracy does.

Figure 8 displays the percentage of F1Score on the (Y) axis and the number of epochs on the (X) axis.

$$F1score = \frac{2 \times \beta \times \delta}{\beta + \delta} \quad (38)$$

β - Precision;

δ - indicate Recall

Initially 20% of epochs with F1score achieved in existing level 85% and 89%. Proposed level is achieved 94%. 60% of epochs SED-HRNet in the F1 score level 88.5% and FBLOM reach the F1 score 91%. The proposed level is reach 95.5%. Then 80% of epoch will reach the F1 score level 89%, 91.5% and 96%. Finally, 100% of epochs will reach the F1 score 90%, 92% in the existing level. The highest F1 score is proposed method 97%.

Time vs. Acceleration

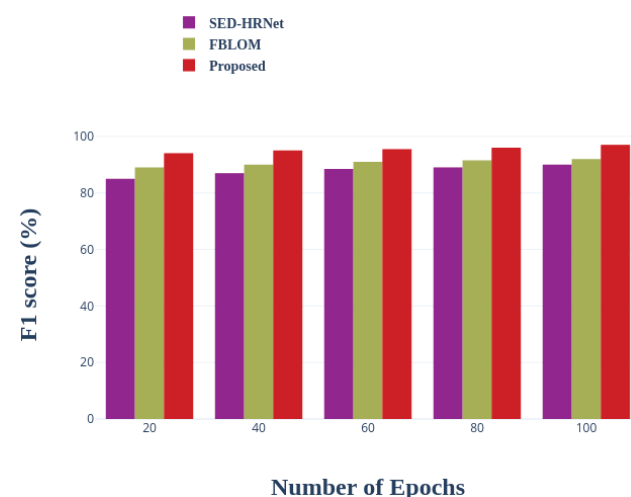
The velocity's rate of change with regard to time. Since acceleration has both a magnitude and a direction, it is a vector quantity. It can alternatively be thought of as the first derivative of velocity with respect to time or the second derivative of position with respect to time. Figure 9 represent Time in the (X) axis and Acceleration in the (Y) axis. This can be derived in mathematically

$$\bar{a} = S - S_0 / \Delta T \quad (39)$$

$\bar{a}$ = acceleration

$S - S_0$ = Speed of the velocity

ΔT = Change in the time

**Figure 8.** Number of epochs vs. F1 score.

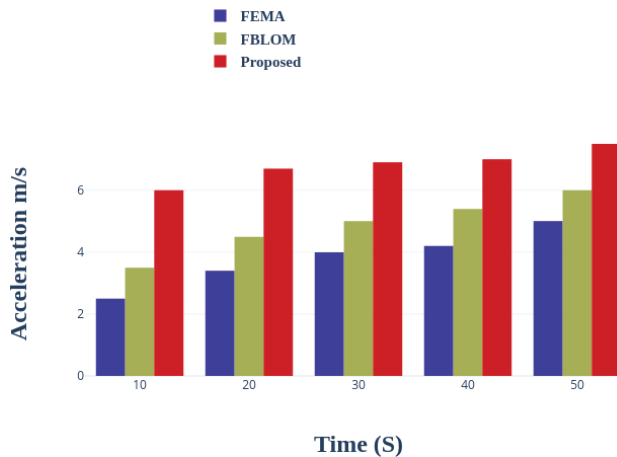


Figure 9. Time vs. acceleration.

Figure 9 represents initially 20s in FEMA method the acceleration in 2.5s. FBLOM 3.5s further increasing the speed of acceleration in proposed level 6s. reached. After 60s the acceleration in the existing level 4s,5s and proposed level is 6.9s. After 80s the acceleration speed is increasing in existing level 4.2s, 5.4s gradual increase in proposed level 7s. Finally, acceleration m/s in the existing level 5s and 6s. proposed levels 7.5s. Proposed level is higher speed of acceleration.

Research Summary

Initially we started the process data collection. Next processing and feature extraction and training then classification, decision making and feedback loop method. Next, we used fuzzy bilevel optimization. then implement Adam-Enhanced SEHRNET Algorithm enhance significant reduction in network parameters while maintaining high accuracy. Further we implement. Technique for Order of Preference by Similarity to Ideal Solution and Preference Ranking Organization method of Enrichment Evaluation (TOPSIS-PROMTHEE) then we implement SA algorithm and by constantly assessing input from various time stepping and using Multi time stepping rolling with model predictive control. The numerical results of proposed and actual outcomes are shown in Tables 3-6. The success metrics for the suggested approaches are shown in Figures 6-9.

Table 4. Numerical outcomes of precision (%)

(x-axis) Number of Epochs	Precision (%) - (y-axis)		
	SED-HRNet	FBLOM	Proposed
20	81	87	93
40	85	88	95
60	86	89	96
80	88	90	97.5
100	90	92	98

Table 5. Numerical outcomes of F1 score (%)

(x-axis) Number of Epochs	F1 Score (%) - (y-axis)		
	SED-HRNet	FBLOM	Proposed
20	85	89	94
40	87	90	95
60	88.5	91	95.5
80	89	91.5	96
100	90	92	97

Table 6. Numerical outcomes of acceleration(m/s)

(x-axis) - Time(s)	Acceleration(m/s) - (y-axis)		
	FEMA	FBLOM	Proposed
20	2.5	3.5	6.0
40	3.4	4.5	6.7
60	4.0	5.0	6.9
80	4.2	5.4	7.0
100	5.0	6.0	7.5

CONCLUSION

We began gathering data for the process at first. The steps that follow include training, feature extraction, processing, and finally classification, decision-making, and feedback loop technique. This study emphasizes the necessity of integrating advanced computational models into post-disaster recovery processes to enhance the efficiency of reconstruction efforts. Fuzzy bilevel optimization was then employed. Subsequently, we implemented the Adam-Enhanced SEHRNET Algorithm to markedly diminish network parameters while maintaining exceptional accuracy. We persisted in applying the TOPSIS-PROMETHEE methodology, which offered an organized framework for decision-making to prioritize rehabilitation initiatives in regions impacted by disasters. The Multi-time stepping Rolling with Model Predictive Control (MPC) method was utilized to consistently assess inputs from various time intervals, facilitating a more dynamic and adaptable response system in post-disaster recovery.

The proposed framework achieved an accuracy of 99%, a precision of 98%, and an F1 score of 97% in the reported evaluation. Performance assessments also indicated shorter response times and improved prioritization of reconstruction areas compared with the conventional approaches examined. These findings support the framework's potential to assist post-disaster decision-making, although its performance should be interpreted within the conditions of the study. High classification scores provide a basis for further investigation; their practical value ultimately depends

on whether the resulting decisions remain useful when evidence is incomplete and recovery needs change.

A central contribution of the study is its use of a hybrid probabilistic approach to damage classification and reconstruction planning. The methodology draws on weakly supervised learning and probabilistic graphical models, including Bayesian networks. This provides a means of representing uncertainty within the decision process and offers scope for revising classifications as additional evidence becomes available. Its contribution therefore concerns how damage assessments can inform decisions under uncertain conditions, alongside the predictive performance observed in the evaluation.

For recovery planning, the framework offers a potential link between automated damage assessment, resource allocation, and operational feedback. Such a link could help planners identify areas requiring attention and reconsider priorities as conditions evolve. The reduction in response time observed during evaluation is encouraging, but establishing its operational significance requires testing in actual recovery settings. Faster classification must be accompanied by sufficiently reliable information to support the decisions that follow. Local verification and professional judgement would remain necessary, particularly where an incorrect assessment could delay assistance or divert scarce resources.

Several limitations warrant further investigation. Performance may vary with disaster type, damage severity, and the availability and quality of photographic evidence. The reported scores cannot establish how well the model would perform in locations or disaster conditions absent from the evaluation data. Independent testing across geographically and operationally distinct settings is therefore needed. Future research could examine whether semi-supervised or self-supervised learning reduces dependence on labelled imagery while preserving sensitivity to consequential forms of damage. Reporting performance by damage category would also help clarify whether aggregate scores conceal weaknesses in less frequent cases.

The decision framework could be extended to account for population displacement, economic disruption, and access to essential services. These considerations matter because the extent of physical damage alone cannot determine the urgency of reconstruction. A moderately damaged facility may require immediate attention if it serves a population with few alternatives. Incorporating such factors would require explicit prioritization criteria and careful consideration of the trade-offs between competing recovery needs.

The study provides a basis for further development of probabilistic decision support in post-disaster recovery. The next step is to establish whether the observed performance can be sustained when data are uneven, infrastructure is disrupted, and priorities must be negotiated under pressure. Progress should be judged by the quality of the recovery decisions the framework supports, together

with its classification accuracy. Without that connection, improvements in predictive performance may yield limited benefits for the communities awaiting reconstruction.

DATA AVAILABILITY STATEMENT

The author confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

Artificial intelligence was not used in the preparation of the article.

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