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Department of Information Engineering, Computer Science and Mathematics

Reinforcement Learning And Social Based Approach to Post-disaster Reconstruction Planning

PhD in

Information and Communication Technologies
XXXIV Doctoral Cycle

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Submission Date: September 20, 2022

Declaration of Authorship

I, Ghulam Mudassir, hereby declare that this thesis titled, 'Reinforcement learning and Social based approach to Post-disaster Reconstruction Planning' *(REPAIR)* submitted by me, as my Ph.D. thesis at the University of L'Aquila and the work elaborated in it are my own. I assure that:

- Whole thesis has been written by myself under the supervision of Prof. Antinisca Di Marco at the University of L'Aquila.

- Overall proposed approach elaborated in this thesis is based on my work [91] [92] co-authored with Prof. Antinisca Di Marco. Chapter 4 contains mathematical model, Chapter 5 contains implementation and Chapter 6 [94] contains evaluation of our proposed model respectively.

- I further declare that this work has not been submitted for the award of any other degree or diploma in this institute or any other institute or university.

- All published works which is consulted or quoted during this research have been properly cited.

- I have acknowledged all main sources of help.

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Ghulam Mudassir

"Compromise for your Dream but NEVER Compromise on your Dream"

Imran Khan

Dedication

"I honestly did this research because I feel responsible as a researcher to contribute to post-disaster reconstruction planning in L'Aquila Italy. Dedicate this work to every person who lost their lives in that massive disaster (April 6, 2009 earthquake)."
"Also to my parents, family who have been my source of inspiration in this journey. Especially to my beloved late grandfather (Hafiz Yar Muhammad), who passed away just one day before when I flew to Italy to begin my doctorate."

"This work has been supported by the Territori Aperti, a project funded by Fondo Territori, Lavoro e Conoscenza CGIL CISL UIL"

The thesis and all the artifacts resulting from this research will be made available after the dissertation, through the Territori Aperti RI at the following links:
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Abstract

Natural disasters always have several effects on human lives such as in the form of causalities and destruction of the built environment. These kinds of situations always become challenging for the governments to tackle these incidents and to rebuild the economic, social, and physical infrastructures and facilities with the available resources, more specifically, in the defined budget and time. The governments always define plans and policies in accordance with the law and political strategies to reconstruct damaged infrastructure (buildings, roads, and bridges) that should maximize the social benefits of the affected community. Due to the severity of the damage, for-instance to assess all the needs of the involved citizens, private companies, and public institutions, the plans and policies definition is a critical and difficult task. That's why a huge amount of resources is always required to bring life back to normality, which makes reconstruction very challenging for all responsible stakeholders.

To this end, in this thesis, we develop an approach *(REPAIR)* to decision-support system by using deep reinforcement learning technique (Double Deep Q-Network) for the planning of post-disaster city reconstruction by considering available resources, meeting the needs of the broad community stakeholders (like citizens' social benefits and politicians' priorities) and keeping in consideration city's structural constraints (like dependencies among roads and buildings). In particular, from enriched GIS data, REPAIR elaborates a graph-based representation of the considered area and runs Double Deep Q-Network (DDQN) algorithm to generate a set of alternative reconstruction plans by satisfying the posed requirements. The generated plans are then provided to decision-making for the selection of which one to actuate.

To check the applicability of the whole approach, we applied it on two real use-cases, i.e. the historical center of Sulmona city (Italy) and L'Aquila city (Italy), using detailed GIS data and information on the urban land structure and buildings vulnerability.

The proposed approach for post disaster reconstruction planning *(REPAIR)* is generic, determines a set of alternative plans for local administrators who select the ideal one to implement, and it can be applied to areas of any extension as long as the decision-makers share the same goals.

The described approach is comprised of a more general data science framework which is developed to produce an effective response to natural disasters in post-disaster reconstruction planning.

Keywords: Decision-support System; Natural Disaster; Deep Reinforcement Learning; Social Benefits; City Reconstruction Planning; Data Science, Geographical Information Systems.

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List of Abbreviations

AI Artificial Intelligence

ANN Artificial Neural Network

C Cycle

CD City Data

CNN Convolutional Neural Network

CRED Center for Research on the Epidemiology of Disasters

DDQN Double Deep Q-learning Network

DL Damage Level

DNN Deep Neural Network

EM-DAT Emergency Events Database

EUG Enriched Undirected Graph

FUMCO Fuzzy Multicriteria Optimization

GDP Gross Domestic Production

GIS Geographical Information Systems

MCDM Multicriteria Decision Modeling

MDP Markov Decision Process

ML Machine Learning

PD Physical Dependencies

PDR Post-Disaster Recovery

PICOC Population-Intervention-Comparison-Outcome-Context

PP Political Priority

PO People Opinion

PRISMA Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PS Primary Studies

QGS Quasi-Gold Standard

RA Random Agent

RL Reinforcement Learning

RN Resident Numbers

RQ Research Question

SAR Search And Rescue

SARSA State-Action-Reward-State-Action

SDRC State Disaster Recovery Coordinator

SS Seismic Strength

TD Temporal Difference

UNDP United Nations Development Program

UNISDR United Nations Office for Disaster Risk Reduction

USRA L’Ucio Speciale per la Ricostruzione dell’Aquila

Chapter 1

Introduction

Disasters always lead to massive destruction which affects people's lives in various ways, for-instance destruction of the societies, disruption of livelihood, especially economies damage including infrastructure, people's homes also get damaged and in the meanwhile they lose dignity and self-respect because they look on for help towards other people and authorities in that difficult time. According to the research of the 'Center for Research on the Epidemiology of Disasters (CRED)' from 1900 to the present, almost 18000 mass disasters happened all around the globe. And just in the last two decades 510837 deaths and millions of people got affected by 6681 disasters (Centre for Research on the Epidemiology of Disasters - CRED, 2019). And damage cost is almost 67 billion dollars every year [51]. For example among those disasters Haiti earthquake in 2010, Cyclone Nargis in 2008, and in 2004 Asian Tsunami are the major ones.

Natural disasters each have a different kind of nature. They can develop slowly or suddenly and also can be predictable or unpredictable with respect to time and place. Damage level is directly proportional to the intensity of disaster and if it happened with high intensity (like an earthquake) near a residential area then destruction is supposed to be too much as compared to less magnitude disaster. On the other hand, if disaster striking location is away from residential then collateral damage might be less. United Nations defines a disaster as "A serious disruption of the functioning of a community or a society involving widespread human, material, economic or environmental losses, and impacts, which exceeds the ability of the affected community or society to cope using its own resources" (United Nations 2009, p. 9)

On the abstract level, the reconstruction process is categorized into two levels, first one is to rebuild damaged houses and the second one is the restoration of damaged infrastructure like roads, bridges, lifelines, electricity, and sanitation. Reconstruction of the damaged house is on the top priority in many countries whenever any disaster happens because it becomes a desperate requirement of victims, that's why governments also prioritize housing reconstruction instead of focusing on anything else. Additionally, in developing countries, most of the time affected people don't have home insurance or any financial assistance. For this purpose, it becomes the government's responsibility to provide seismic proof houses to victims. Freeman et al. [39] researched the allocation of financing for housing reconstruction in post-disaster situations according to their analysis allocation of 30-50% of overall expenditure is the best ratio.

On the other hand, governments have two ways for the reconstruction process. According to the first approach, housing reconstruction needs fewer technical people and other resources as compared to other infrastructures like roads and bridges for this purpose victims or affected people can reconstruct houses by themselves. In the second approach, the government allocates housing reconstruction to private contractors.

Is there any difference between normal reconstruction and post-disaster reconstruction? According to Mesurier et al. [73] concluded in their study, during the post-disaster reconstruction process major part is related to policy and legislation to rebuild damaged buildings and other infrastructure. Because most of the time existing legislation doesn't cover disaster situations and authorities need a lot of resources to overcome these disasters. Existing legislation might not be enough to handle the emergency phase and severe disaster. On the other hand, routine construction processes don't need these kinds of prerequisites.

According to Davidson et al. [27] post-disaster housing reconstruction projects have similar kinds of challenges in developing countries like low-cost housing, but still there exist some additional challenges which vary from country to country. These additional challenges are like the uncertainty of conditions after the disaster, the lack of resources to start the reconstruction process. At the same time, other local and international organizations that reconstruct housing projects simultaneously might be busy in some other places. Subsequently, the donors who finance reconstruction projects want to see the results as soon as possible. Also, the affected people expect the reconstruction projects to be more sustainable and vulnerability to be reduced for future disasters. Moe et al. [90] describe disaster management as a public management project in which the main aim is to create a unique product in a specific time and enhance the quality of living conditions of affected people.

To recover from these kinds of devastating situations is really difficult and requires a lot of time and effort because of damages suffered by public/private buildings including other infrastructures such as bridges and roads [123]. Requirement of resources during recoveries like material, labor force, and management of time and cost is another challenging factor in post-disaster situation [45]. For example, Hurricane Katrina in 2005 took five years in recovery and reconstruction. Overall one billion dollars were spent to complete the whole process. Similarly, during the Hyogoken-Nanbu earthquake in Japan, only highway reconstruction took 20 months to complete. In post-disaster situations, authorities need to take quick and efficient decisions to overcome these kinds of emergency situations, because if the restoration time took long it may affect the local community socially and economically. For this purpose, substantial management of resources including budget and time is required to reconstruct the damaged area. In post-disaster circumstances, the primary challenge for stakeholders is the lack of a comprehensive recovery plan to bring back normal life [63]. In fact, full recovery from a disaster always requires a long time, and this very badly affects local communities from both a social and an economical viewpoint. This challenging phase was defined by Contreras et al. [21] as a *complex multidimensional, long-term process involving planning, financing, decision-making, and reconstruction.* According to United Nations Development Program (UNDP) [110] post-disaster recovery phase is divided into four sub-phases which are: *relief*, *early recovery*, *recovery*, and *development*. *Relief* phase according to [3, 65], gives priority to save the lives of people with the help of search-and-rescue (SAR) operation; *early recovery* phase consists on rehabilitation of roads and damage buildings identification; *recovery* has the goal to bring back the basic services and to start reconstruction of buildings including roads by considering social relationship of effected communities; *development* focuses to strengthen the economy and improve quality of life.

Post-disaster situations are always like a nightmare for affected people and volunteers who used to work in an emergency because they can't access vital facilities and locations easily to evacuate and help the people. For example logistics personnel who participate in relief activities face too many difficulties (roads/bridges get damaged) to access the damaged area because it gets disconnected from road networks. And the ultimate purpose of volunteers is to help out people in minimum time and cost during the relief chain.

According to Phillips et al., [47] relief chain is divided into four activities or phases which are mitigation (reduce the impacts and risks hazards), preparedness (reduce the effects of disasters), response (the decisions and actions taken in immediate effects of an emergency), and recovery (set of policies adopted during recovery process). Kovecs et al. [72] divide the post-disaster phase into two steps which are response and reconstruction activities. Similarly, Paulsen and Cangelosi (1994) and Altaya et al [20] have described the typical occurrence of preparedness, response, recovery, and evacuation as activities in post-disaster phases.

According to Alexander et al. [4] as shown in Fig.1.1 *mitigation* and *preparation* are pre-disaster phases. On the other hand *response* and *recovery* are the two major phases starts right after disaster happened. *Recovery* phase initiated after *response* phase. *Response* consists of emergency based rescue actions which need to be taken for short term after the disaster to save the people lives and fulfill affected people needs. *Recovery* phase is bit longer process which consists of restoration of services, repairing and reconstruction of damage buildings and roads in post-disaster situation.

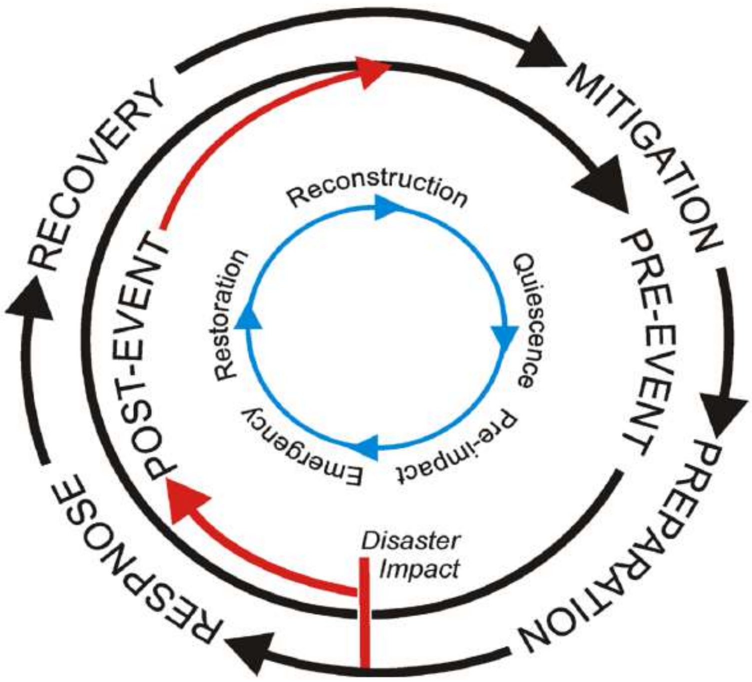


Figure 1.1: Disaster management cycle

According to Shaw et al., [117] usual duration to initiate rescue, relief, restore services and start the reconstruction of facilities is determined within seven days, three months, and five years subsequently. *Rescue* phase is started by local residents straight away after disasters occurrence and then professional staff from government departments joined them for search and rescue operations. Additionally, international teams also arrived after one or two days depending upon the convenience to access the disaster area as well as political stability in the affected country. *Relief* phase starts right after the rescue phase which takes around one to three months depending upon the damage level and availability of resources from corresponding authorities. *Recovery* phase starts as soon as the relief phase end, this phase consists of removing debris from roads, houses, restoration of infrastructure, and long-term reconstruction activities to make a safe and vulnerable building infrastructure. *Reconstruction* phase is the next level of the recovery phase, which plays a vital role in overall disaster management e.g restoration of affected communities, restoration of new houses, and restoration of damaged infrastructure. Because this phase is considered as an opportunity for the affected community to start a new life by improving their living condition e.g reconstruction of their living in a better way. Additionally, during reconstruction must keep in mind future disasters by applying structural and non-structural measures. Good quality houses/ buildings would be vulnerable enough to face any kind of natural disaster in the future. Public decision-makers (politicians, servants, and citizens) always face difficulties to define a comprehensive recovery/reconstruction plan which covers all formal and informal requirements to the damaged area in the minimum possible time [93]. They need to take care of critical aspects like the benefits of the local community, the vulnerability of buildings, the budget, and the time required to complete the plan. Additionally, decision-makers also need to make sure reconstruction plan should increase the resiliency of both physical infrastructures and communities to consider stability factors to handle any kind of future disaster [91]. Another aspect often not tackled by public decision-makers deals with the social benefits that local communities can obtain from the recovery plan implementation. In fact, social impact and benefits are different for different plans, so the plan itself can play a vital role in all post-disaster phases. A traditional reconstruction approach is not suitable for this purpose, and we need a reconstruction framework that encompasses social benefits for the communities affected by the disaster [135]

In this thesis, our focus is on the post-disaster phase, specifically in the reconstruction planning of infrastructure including damaged buildings, roads, and bridges. According to Coppola et al. [22] recovery is the activity in which "returning victims' lives back to a normal state following the impact of disaster consequences". As we know roads and bridges get damaged during the disaster and some of them get blocked by debris, these kinds of situations become a real threat to the affected community because transportation infrastructure gets damaged. Additionally, road connections between cities and other places also get damaged like hospitals, fire brigade stations, shelters, police stations, and social buildings that's why it becomes really difficult to rescue injured people. In the meanwhile, emergency departments also face difficulties to approach and evacuate affected people. According to Sharkey et al.[139] "Operational interdependencies occur when a component of one infrastructure requires services provided by another infrastructure in order to properly function". For this purpose, it's compulsory to make a mechanism for reconstruction order of damaged buildings and physical dependencies like damaged roads/bridges. According to order policy firstly those buildings are reconstructed where most of the affected people get benefits like hospitals, universities, schools, and other public buildings. Additionally, Sharkey et al.[139] also mentions that"Restoration interdependencies occur whenever a restoration task, process or activity in one infrastructure is impacted by the restoration (or lack thereof) of another infrastructure"

The work presented in this research uses a reinforcement learning algorithm called Double Deep Q-learning Network (DDQN) to solve reconstruction planning problems. By using DDQN we are able to reconstruct damaged buildings and physical dependencies successfully in a specific order. Additionally, this work is also helpful in the post-disaster situation to make alternative reconstruction plans for damaged buildings, roads, and bridges by considering all basic attributes like time, cost, political priorities, physical dependencies, and social benefits of affected people. The name of this reconstruction planning model is "Reinforcement learning and Social based approach to Post-disaster Reconstruction Planning *(REPAIR)*", and we have validated on L'Aquila (Italy) earth-quack dataset that happened back in 2009 and Sulmona (Italy) dataset. The overall purpose of this approach is to take a quick and efficient decision for reconstruction planning and to reconstruct those damaged buildings, roads, and bridges which takes less time cost and is more beneficial for victims' lives "back to normal" as soon as it is possible. The mathematical model identifies damaged buildings and roads and defines priorities including physical dependencies which are equally important to rehabilitate to access damaged buildings. The treatment of this multi-dimensional problem and relative implementation was very challenging. To handle the problem's complexity, we proposed an approach that leverages a mathematical model and uses a DDQN algorithm to define post-disaster reconstruction plans according to the defined model.

We have collected damage infrastructure data from Geographical Information System by using GIS to graph algorithm [59] and then extracted information is saved in .CSV and .XLSX files. By using .CSV and .XLSX files we have created an undirected graph to visualize damaged buildings, roads, and bridges including the number of people living in each building and the political priority of each unit.

1.1 Thesis Structure

The remainder of the dissertation proceeds as follows. In Chapter 2, the background of this problem and reinforcement learning is provided. Chapter 3 contains a systematic mapping study of literature review related to post-disaster reconstruction planning. Chapter 4 contains mathematical modeling and Chapter 5 presents the implementation of the proposed approach including comparison of DDQN with other other reinforcement learning algorithms. Chapter 6 explains the evaluation on behalf of two case studies; which are the historical center of Sulmona city (Italy) and L'Aquila city (Italy). Finally, we conclude the thesis in Chapter 7 have described conclusion and future work.

Furthermore, in Appendix A, we have described the details of different technologies which we have used during the implementation of our proposed approach presented in this thesis.

1.2 Contribution

This dissertation highlights the following major contributions to our proposed approach.

Contributions to post-disaster reconstruction planning

- Addressing to an up-to-date state of the art approach that proposes building reconstruction plans taking into account multiple aspects of different stakeholders in a post-disaster situation.
- Approach takes care of constraints such as time, budget, and city physical dependencies (damaged roads and bridges).

- The novelty of the proposed approach is the usage of a model that explicitly formalizes political strategies, political priorities, and social benefits of affected people.

Algorithmic contribution

- The application of deep reinforcement learning approach, namely Double deep Q-learning network (DDQN) is used to determine reconstruction plans. And our approach name is *"Reinforcement learning and Social based approach to Post-disaster Reconstruction Planning (REPAIR)"*.

- To the best of our knowledge, it is the first time that the Double Deep Q-Learning (DDQN) approach is used to determine post-disasters reconstruction planning.

Evaluation/experimentation contribution

- Have evaluated *REPAIR* approach on real case studies of Sulmona city and L'Aquila city datasets.

- Have evaluated DDQN by making a comparison with Q-learning, SARSA, and deep SARSA, at the end we proved with the results that DDQN is the most suitable option for our research problem.

Chapter 2

Background

This chapter presents a brief overview of the main concept and background of post-disaster situations including core works that are used to handle these kinds of circumstances on the basis of research works which is presented in this thesis. We start this chapter by giving an overview of *international disasters* (Section 2.1). This is followed by a machine learning overview (Section 2.2) with details of those techniques which are used in this thesis. Additionally, we have used random agent to verify the training accuracy of the trained agent. We have explained all these concepts in this section. On an abstract level, our approach is used to solve post-disaster reconstruction planning problems. In the last Section 2.3, there is an explanation for the details of case studies that are used for the evaluation of the proposed research methodology in this thesis.

2.1 International Disasters

In 2021, according to International Disaster Database (EM-DAT) from 1900 to 2020 almost 1442 natural disasters happened in the top 10 disaster-affected countries from four different continents (Americas, Europe, Asia-Pacific, and Africa). The total calculated impact of these disasters was around 2.4 million deaths, 200 million people affected, and in the meanwhile total economic damage is $1.3 trillion [19] as shown in Fig. 2.1.

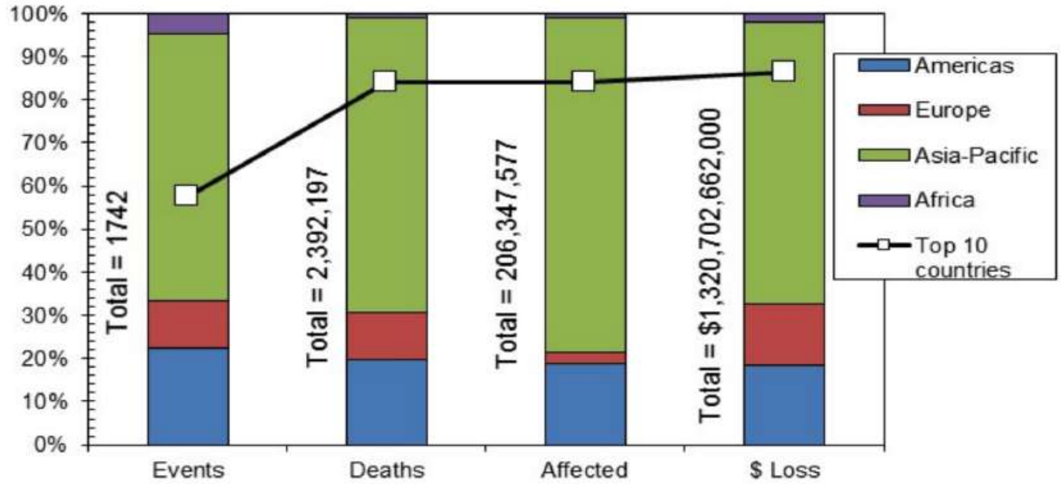
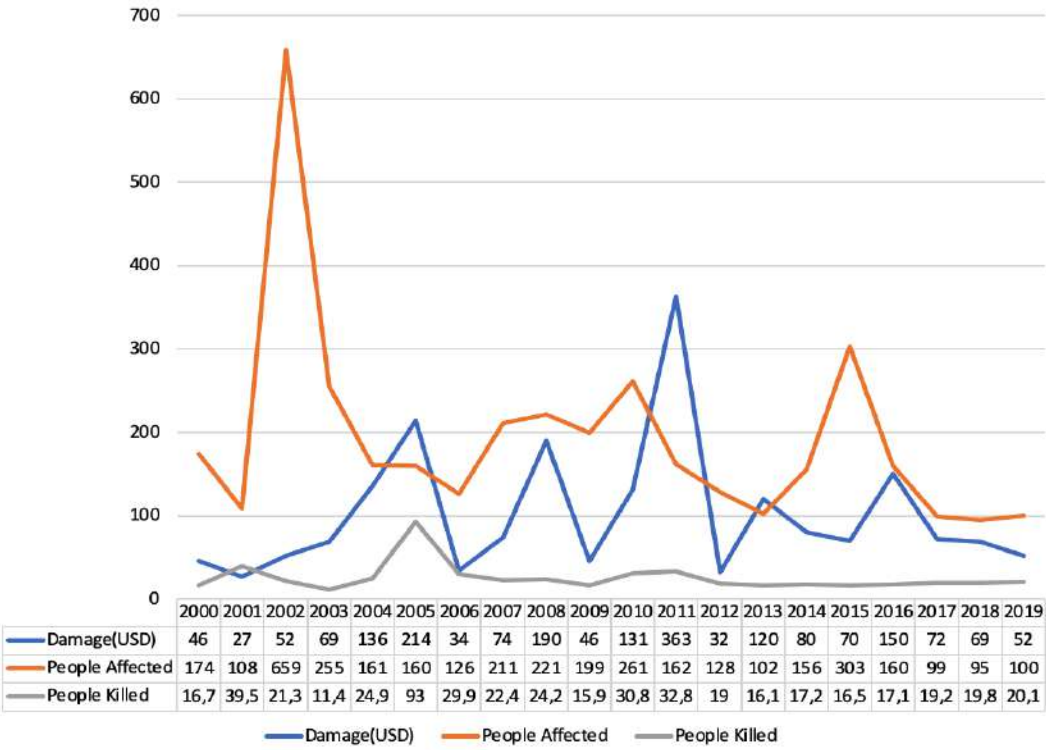


Figure 2.1: Distribution of natural disasters across the globe during the period 1900–2020 AD.

Additionally, in recent years many natural disasters have been reported which severely affected a lot of places [140]. According to one estimate in the last decade, damage cost was almost 67 billion dollars every year [51]. The ratio of economic loss due to these disasters has increased 14-folds since 1950 [140]. Additionally, these disasters not only effects the economy but at the same time, thousands of people also lost their lives. From 1994 to 2003 almost 54000 people lost their lives in different kinds of natural disasters. According to one survey, just in 2003, due to natural disasters, almost 1 person out of 25 get affected [50]. The United Nations Office for Disaster Risk Reduction (UNISDR) also presented a report about different types of disasters in the last two decades. Statistics show in UNISDR most of these disasters occur in developing countries as compared to developed countries. For example in August 2002 drought happened in China, in December 2004 Tsunami affected millions of people in Indonesia, Sri Lanka, Malaysia, and other countries, in October 2010 massive earthquake in Pakistan, and also in May 2008 same kind of earthquake happened in China. According to the UNISDR report, among all these 44% were flooded, 28% storm, 8% earthquake, 6% extreme temperature, 5% landslide, 5% drought, 3% wildfire, 1% volcanic activity, and <1% mass movement [24]. Subsequently, humans and economic loss in the same duration is also massive as shown in fig.2.2 and poor preparedness to tackle natural disasters also leads to massive destruction [50].

Natural disasters always have various kinds of impacts on the local community but major ones are *social impact, demographic impact, political impacts* and *economic impacts*. *Social impacts:* means the vast majority suffered from psychological problems like during Hurricane Andrew there were not any significant trends between births, marriages, deaths, and divorce applications [102]. *Demographic impacts:* is related to infrastructure which gets damaged during disasters and the majority of people don't come back to that area even after reconstruction. For example, after Hurricane Katrina, only 78% people returned back [78]. *Political impacts:* is about political disruption due to social activism during natural disasters. *Economic impacts:* is about damages of property in this way people lose their asset values that can be measured by the cost of repair or reconstructions [23].

Right after disaster post-disaster recovery (PDR) phase starts which is the combination of three entities called *goal, phase* and *process* [79]. And all these entities are really important for long-term process reconstruction (infrastructure). According to world bank [61] "Post Disaster Reconstruction begins with a series of decisions that must be made almost immediately. Despite the urgency with which these decisions are made, they have long-term impacts, changing the lives of those affected by the disaster for years to come". Furthermore, poor post-disaster recovery (PDR) often leads to many problems like vulnerability and instability which is evident from many countries that got affected by disasters and couldn't follow a proper recovery process [36]. PDR stage is so critical but still missing a comprehensive definition with detailed aims, characteristics, and contents [87]. It is also referred with other name like Post Disaster Recovery [95], Post Disaster Rebuilding [97], and Post Disaster Redevelopment [118]. All these terminologies have differences but still, no one did a mapping study to find out the difference between all these concepts. But ultimate goals of these terminologies are to restore household/infrastructure, business, and government activities to the "normal" level the way it has existed before the disaster. By focusing on the mapping study of reconstruction planning techniques after natural disasters, this thesis has the potential to find out the gaps as well as summarize the improvements among all proposed techniques which can be more useful to tackle any kind of future natural disaster.



	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Damage(USD)	46	27	52	69	136	214	34	74	190	46	131	363	32	120	80	70	150	72	69	52
People Affected	174	108	659	255	161	160	126	211	221	199	261	162	128	102	156	303	160	99	95	100
People Killed	16,7	39,5	21,3	11,4	24,9	93	29,9	22,4	24,2	15,9	30,8	32,8	19	16,1	17,2	16,5	17,1	19,2	19,8	20,1

Figure 2.2: The Economic and human impact of disasters between 2000 and 2019.

2.2 Machine Learning

Rapid advancement in cutting-edge technologies is bringing a revolution in daily life. That's why we have also used machine learning (reinforcement learning) techniques in this research to solve the post-disaster reconstruction planning problem. Following we have explained the basic concepts of machine learning and artificial intelligence (AI).
Artificial intelligence is one of the most demanding research fields which has already been applied to different practical applications [53]. According to Figure 2.3 overall artificial intelligence can be categorized into three different domains which are *Artificial Intelligence, Machine Learning*, and *Deep Learning*. Machine Learning got more popularity among all these domains because of its broad application scope. Because most of the techniques which are used in different applications belong to Machine Learning (ML) domain [53]. In other words, all these domains lie under the artificial intelligence umbrella. Here, we have given an overview of ML techniques in-depth including those techniques which are used in this dissertation.

2.2.1 Definitions

Machine Learning has different definitions which keep evolving since it emerged over the years. In simple terms, Machine Learning is a type of artificial intelligence (AI) that improves software/system/processes through continuous experience without being explicitly programming. In the other words, ML is a collection of computer programs that access the data and used to learn itself by following defined instructions.

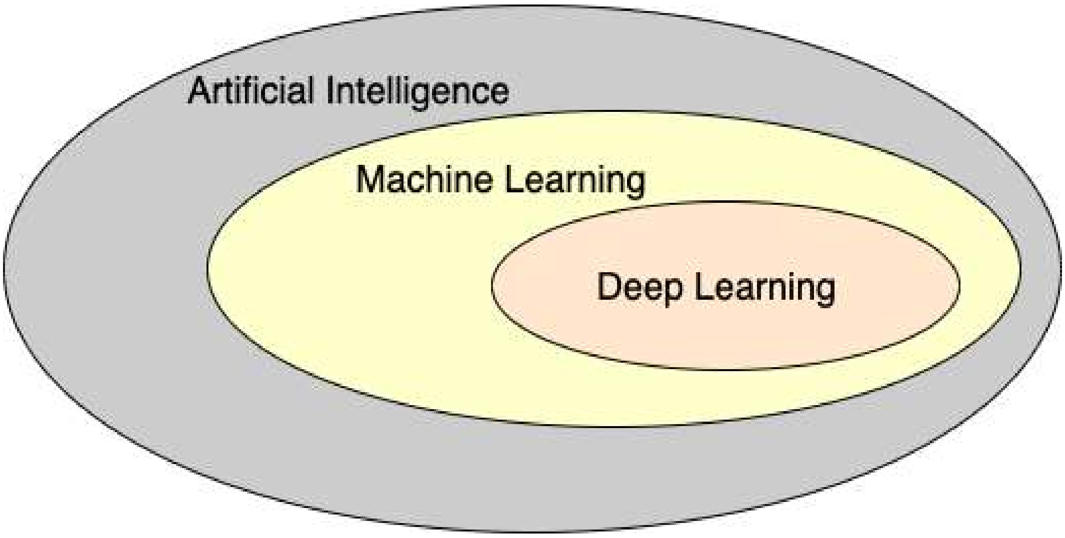


Figure 2.3: Venn diagram of overall field of artificial intelligence

The learning process starts with environment observation or from data. So here following are some concrete definitions of machine learning (ML):

- According to Tom Mitchel [88] Machine Learning is a computer program is said to learn from *experience* E with respect to some class of *tasks* T and *performance* measure P if its *performance* at *tasks* in T, as measured by P, improves with *experience* E.
- According to Alpaydin [5] Machine learning is programming computers to optimize a performance criterion using example data or past experience.

2.2.2 Machine Learning Types

Usually, Machine Learning techniques are categorized based on learning performed. According to Louridas et al. [82] primarily ML categorized into two types which are supervised and unsupervised but in more depth further, it is more extended into four different types which are *Supervised Learning, Unsupervised Learning, Semi-supervised Learning and Reinforcement Learning* [71, 122] as shown in Fig. 2.4 [1].
Furthermore, all these types have different kinds of algorithms that are used to solve the problems depending upon the nature of the task, problem type, and statistical data. Detail description of each type of ML is provided as follows:

Supervised Learning: In supervised learning, algorithm/program learns the way, how to perform some specific task by using different kinds of well-defined examples which are available in the form of data. Basically, these algorithms are trained on input data that contain specific output which is called *training* data, and attributes of this data are called features. Model training continues until the relationship between input data and the corresponding output is not found. Supervised learning is used for three types of problems which are (i) Classification (ii) Regression and (iii) Estimation

[1] SVM - Support Vector Machines, PCA - Principle Component Analysis, DQN - Deep Q-Network, DDQN - Double Deep Q-Network, MDP- Markov Decision Process, ANN - Artificial Neural Networks

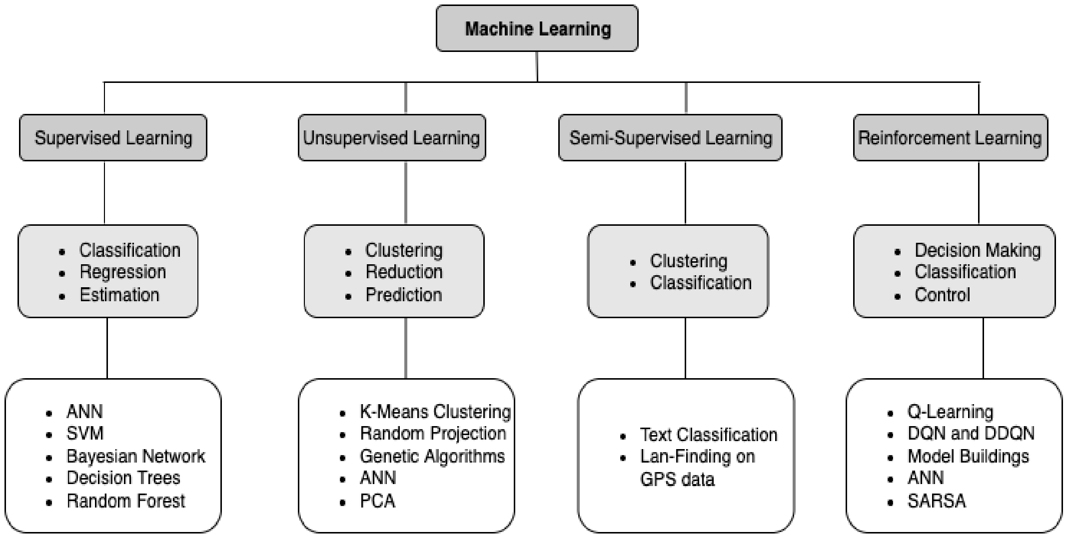


Figure 2.4: Types of machine learning

Classification algorithm aim is to sort the input into one of the defined categories on behalf of labeled data that was trained on. In the other words, data samples are provided in this algorithm which contains different kinds of input features including output variables to represent the categorical values. The ultimate objective of the classification algorithm is to make a mapping function that is capable enough to map the input to output. When new input is given to the classification algorithm then it will be capable enough to predict the expected category. There are various real-life problems that are solved with the help of a classification algorithm. e.g weather forecast (yes or no) and prediction of various diseases.
Regression algorithm is used to predict real number values on behalf of the given input. The only difference of regression algorithm from the classification is which output variable represents a real number. The ultimate objective of this algorithm is to generate a mapping function that is capable to predict the expected value on given a new input. There are so many applications of regression algorithms in our daily life e.g stock prediction.
Estimation is also called *density estimation.* Basically, it is used for fitting probability or picking the "best" and most likely accurate data model to find the distributions of each class. Additionally, it is also used to classify new observations based on the distribution. For example, it is used for finding extreme outliers in data.

Unsupervised Learning: In contrast to supervised learning, it is a type of Machine Learning algorithm where the program learns from training data which consists of input parameters without any output labels or real numbers. It automatically defines the pattern in hidden relationships amid input data. When new input data is given then the algorithm explores and find hidden relationship from unlabeled data then action is performed on it. An unsupervised learning algorithm is used to solve three types of problems which are (i) Clustering (ii) Reduction and (iii) Prediction
Clustering is a data mining technique in which a given set of inputs is divided into different groups based on their similarities or differences. In these kinds of problems, data samples with unlabeled inputs are provided to a clustering algorithm to identify relationships among the input data and divide them into different categories. When new input data will be given then the algorithm uses

learned knowledge and generates a new category. Clustering techniques play a vital role in our daily life e.g fake news identification.
Reduction is also called dimensionality reduction. This technique is mostly used during pre-processing the training data to remove irrelevant or redundant features from input training data. The ultimate purpose of these kinds of techniques is to identify the best relationships among training data features without much loss of information. The practical application of the reduction technique is image processing.
Prediction is a technique that is used for fitting shapes that are close to the data as possible after applying the classification technique to separate data into classes.

Semi-Supervised Learning: As it is obvious, this type of ML fall somewhere in between supervised and unsupervised learning. In this technique, the process learns by using both labeled and unlabeled data for the training of both supervised and unsupervised input samples. The ultimate role of this technique is to find the relationship between unlabelled data based on labeled data samples. This type of ML is used in different kinds of practical applications like Speech analysis and web-content classification. Semi-supervised learning is used for two types of problems which are (i) Clustering and (ii) Classification
Clustering and *Classifications* are already explained in supervised and un-supervised learning.

Reinforcement Learning: is also called "learning with a critic" [6]. In this type of ML technique, programs learn by interacting with the environment by possible actions that are performed to achieve the task. Then feedback/reward is received with respect to the action performed. On behalf of the feedback/reward program, it selects a better action next time for the same task. This improvement process is called program/agent training and it will go on until it becomes expert. The ultimate objective of this algorithm is to select the best action to maximize the overall reward. Reinforcement learning is used for three types of problems which are (i) Decision Making (ii) Classification and (iii) Control

Decision Making is also known as Markov Decision Process (MDP). MDP or decision making is discrete discrete-time stochastic control process based on three things: *action* , *state* and *reward*. In MDP when agent interact and performed an *action* $'A_t'$ with the environment at each time step 't' and get information about environment *state 's'*, at the same instant agent receives numerical *reward* 'R_{t+1}'. The agent keeps repeating the action and gets the value of every state/action of an MDP for all possible combinations of actions that can be picked. Then, in the end, we pick simply the highest value for the states and actions with the help of optimal function. Simple applications of MDP are robots or the Chess-playing agent.
Classification is already explained in supervised learning.
Control algorithm is based on value function (Monte Carlo) and the goal is to adjust the policy to choose the best action on every step. In the end, we get optimal policy and expect future rewards by using that optimal policy.

In this thesis we have used reinforcement learning type of ML, to be more specific used Double Deep Q-learning Network (DDQN) algorithm, Convolutional Neural Networks (CNN), Loss function, optimizer and comparison of other Reinforcement Learning algorithms (Q-Learning, Deep

Q Network (DQN), State–Action–Reward–State–Action (SARSA), Deep-SARSA) with DDQN to solve post-disaster reconstruction planning problem. These all concepts are explained following.

2.2.3 Artificial Neural Networks (ANN's)

Basically artificial neural network (ANN) is the biological-inspired information processing system that is used for computation. The first neural network model was invented by McCullough and Pitts in 1944 [26] which was called McCullough Pitts model or the MCP model. This innovative invention of the MCP model becomes the foundation of modern machine learning. Artificial neural network consist on three major components which are *neurons, weight* and *output.*

- A set of units which are simply used for information-processing are called *neurons.*
- Neurons are connected to each other through links and each link has specific value (number) which is called *weight.* And these weight represent amount of relevance of particular connected link.
- Each input information is processed by neurons by using activation function (a non-linear function) to produce *output.*

Key Concepts

In the following section, we have given some basic concepts of commonly used terminologies in neural networks, and also these will be sued in the remainder of the thesis.

- *Features:* Input variables are called *features.*
- *Activation Function:* A function which is used to get the output of node through weighted sum of input features called *activation function* and it is also known as *transfer function.* Furthermore, it is categorized into different types such as *Rectified Linear Unit (ReLU), logistic sigmoid, tanh, softmax, etc.* But in this thesis, we have used *Rectified Linear Unit (ReLU.*
- *Training:* The learning process of neurons when it is provided with different data samples is called *training.*
- *Hidden Layers:* A layer between input and output called *hidden layers.* Hidden layers are used in a complex data model.
- *Forward Propagation:* When data move from the input layer to hidden layers during training then it moves from hidden layers to output layers is called *forward propagation.*
- *Feedforward Neural Net:* When data moves just in one direction from input layers to hidden and then towards output layer is called *feedforward neural net.*
- *Backpropagation:* When data information moves from output layers back to the hidden layers to adjust weight appropriately on behalf of feedback called *backpropagation* [54].
- *Model:* A mathematical function and parameter values obtained as an output of the training process called *model.*

- *Batches:* Splitting of the dataset into small chunks called batches
- *Iterations and Epochs:* Continuously passing of each batch or small chunks of training data through neural networks and on every passing model updates the parameters this process is known as *iteration*. Similarly, continuous training of the entire dataset through the neural network is called *epoch*. That's why a single epoch consists of multiple iterations which is depend upon the number of batches or batch size.
- *Loss Function:* Difference between predicted value and actual value is called *loss* and function which is used to calculate the difference value called *loss function*. There are different types of loss functions e.g. Mean Absolute Error, Root Mean Squared Error, etc [46].
- *Optimization:* A process which minimizes the loss is known as *optimization*. For example *Gradient Descent* [12] and *Adam Optimizer* [67] are commonly used as an *optimization* function.
- *Selection:* When agents interact with the environment and select the best action to maximize the reward called *selection*.

In this thesis, we have used deep neural networks (DNNs), more specifically convolutional neural networks (CNNs) in Double Deep Q-learning Networks (DDQN). So we have explained the basic concepts of all these in the following subsection.

2.2.4 Deep Neural Network (DNN)

A Deep Neural Network is a type of neural network and the most efficient tool of deep learning with a certain level of complexity. Basically, DNN consisted of more than two layers to learn some key features from data and aggregate all those for the object recognition in the images. Generically, DNN has three building blocks which are following:

- Neuron model which is used for computation
- Learning rule for updating weights/synapses between the neurons,
- Network architecture that specifies how neurons are interconnected

2.2.5 Convolutional Neural Networks (CNNs)

Convolutional neural networks are a type of deep neural network model for processing data related to pattern recognition and computer vision [40]. CNN was first introduced in the 1980s by Yann LeCun a postdoctoral computer science researcher, also known as ConvNets. CNN has the ability to learn spatial hierarchies of features with the help of backpropagation and by using multiple building blocks (Fig. 2.5) such as hidden layers, convolution layers, pooling layers followed by one or more fully connected layers. That's why it has become very popular and surpassed traditional techniques, especially in radiology [137]. Additionally, CNNs also contain multiple layers of artificial neurons and these artificial neurons are mathematical functions that are used to calculate the weighted sum of various inputs and outputs as activation values. The process of weighting and summing is called "convolution".

In CNN final classification layer takes the output of the final convolution layer as input and higher convolution layers detect complex objects.

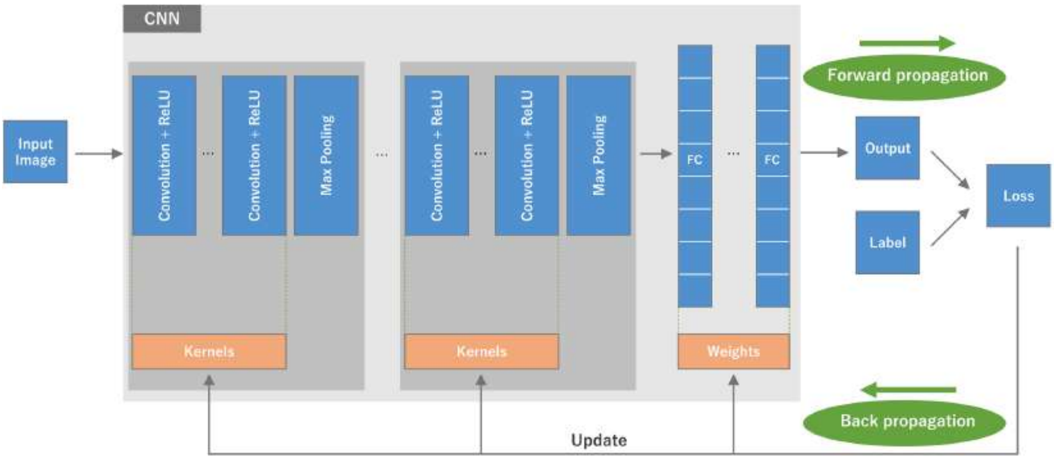


Figure 2.5: Overview of CNN and training process

For example when we give any image as input in CNN then each layer generate various activation map to highlight the related features of the image. Then each neuron takes a group of pixels as input, multiplies color values by their weights, sums them up, and then runs through the activation function. Usually first or bottom layer of CNN finds basic features like horizontal, vertical, and diagonal edges. The output of the first layer becomes the input of the next layer which extracts more features. Further going down into a more convolutional neural network, then layers detect higher-level features e.g objects and faces.

Limitations of CNNs: Even though CNNs are the backbone in pattern-recognition machines. But still, CNNs have some limitations like difficulties to detect and block inappropriate content of social media vast repositories of images and video where they are trained on, fail to detect objects under different lighting conditions and from different angles, inability to understand relationships among different objects and also CNNs can't develop mental models like humans.

2.3 Case Studies

In this section, we have discussed the case studies which are used for the evaluation of our approach in Chapters 6.

2.3.1 Reconstruction Planning of Sulmona City

To explain the feasibility and applicability of our proposed approach, we use the dataset of "Sulmona" city of Abruzzo region (Italy) to verify the results in Chapter 6. We have extracted the required information and converted it into .XLSX and .CSV formats. On behalf of extracted information, we have found 597 buildings out of 1214 are damaged and 470 roads out of 3476 are damaged. The proposed approach suggests five different cycles to reconstruct all damaged units/roads by considering maximum social benefits and others constraints.

2.3.2 Reconstruction Planning of the historical city center of L'Aquila

We have validated our approach to the historic city center of L'Aquila, in the Abruzzo region which was severely affected in 2009 by the earthquake, to explain the feasibility and applicability of our approach in Chapter 6. In this case study, we considered a small area extending towards the northwest of the crossing of three main streets: Corso Vittorio Emanuele (north-south axis of the city), Corso Principe Umberto, and Via San Bernardino, for a total land size of 246,684.28 m^2. According to dataset information, we have found 37 buildings out of 133 are damaged including 20 damaged roads out of 150. The aim is to provide more details on the implementation and check the results of the reconstruction planning model.

Chapter 3

State of the Art and Systematic Mapping Study

The main aim of a systematic mapping study is to identify and classify studies related to post-disaster reconstruction planning. In all this extensive systematic mapping study selection process, we have picked 52 papers among 43552 filtered studies. After this, we applied the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach as shown in figure 3.2 and PICOC (Population, Intervention, Comparison, Outcome, Context) criteria for classification and extraction to select and analyze the most related information. The remainder of this chapter proceeds as follows: Section 3.1 reveals mapping study process, Section 3.2 systematic mapping study results, Section 3.3 potential research areas, 3.4 threat to validity and Section 3.5 close the chapter and discuss conclusion.

3.1 Mapping Study Process

In this section we have described the process followed throughout during conduction of this systematic mapping study according to Fig. 3.1 by considering guidelines for conducting secondary studies proposed by Durelli et al. [32],Petersen et al. [105] and Wohlin et al. [132]. In Figure. 3.1 rounded rectangle represents *process* and grey colour simple rectangles representing *outcomes* of each process. Overall systematic mapping consisted on six process which are *definition of research questions*, *conducting research*, *screening of papers*, *keywords and themes* and *data extraction & mapping process*. Similarly six outcomes for each process which are *research scope*, *retrieved papers*, *relevant papers*, *classification scheme* and *systematic map*.

Additionally, our mapping study is inclusive and included relevant articles as much as we can from different digital libraries and also performed systematic review quality assessment to determine the relevance of primary studies.

Here following sections describe overall mapping study process with outcomes including guidelines to respond to the research questions which we have defined in this mapping activity.

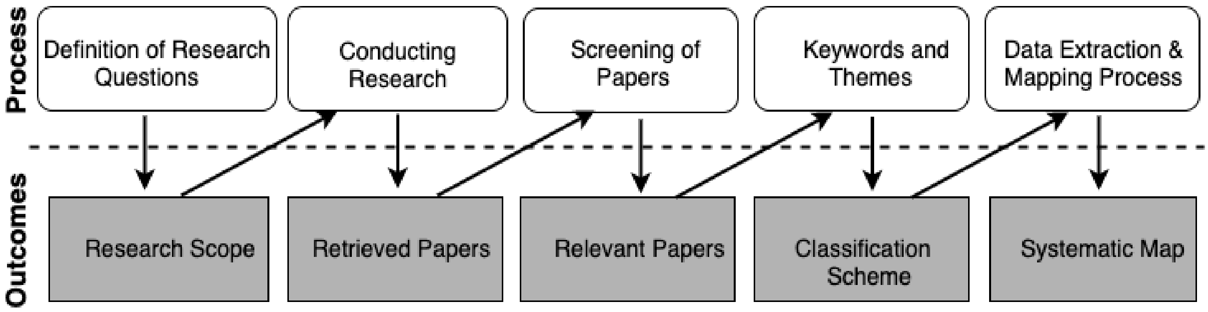


Figure 3.1: The Systematic mapping process

3.1.1 Definition of Research Questions

The main aim of this mapping study is to provide an overview of the research scope related to the post-earthquake situation and the results available in it. This thing leads us towards the following research questions which are based on literature/articles related to post-earthquake situations and methodologies they have used, that would be interesting for researchers and practitioners to get summarized studies. We have used Goal-Question-Metric approach [106] to formulate the scope and goals of our papers. Here following is the Goal-Question-Metric approach query.

> **Analyze** the state-of-the-art post-disaster approaches **for the purpose of** infrastructure reconstruction planning **with respect to** the social benefits of affected people, politicians role, physical dependencies, time and cost for reconstruction, to **what extent** these methodologies have been evaluated, latest active research in this domain **from the point of view of** researchers, and practitioners **in the context** of post-earthquake situation.

According to Kitchenham et al. [70] research question should be goal-oriented to find out appropriate material for mapping study. For this purpose *Goal-Questioned-Metric* approach also highlights goal-oriented keywords for making comprehensive search strings to find relevant articles as well as to define research questions. The main aim of this mapping study is to determine how systematic mapping processes have been executed to manage the post-earthquake situation. According to the goal of our paper, we have defined the following research questions (RQs) including the aim and rationality of every question to explain this whole study:

- **RQ1:** What kind of problems have been addressed in our research domain?
  Aim (RQ1): The aim of this RQ is to define the domain of our mapping study which is just considering only articles related to the post-earthquake situation.

  Rationale (RQ1): As our mapping study is based on post-earthquake problems, with the help of this question, we have defined our search string accordingly to filter out only those studies which are related to our domain.

- **RQ2:** What approaches are used to address these problems?
  Aim (RQ2): The aim of RQ2 is to just focus on proposed approaches whether these are algorithms, mathematical models, review of implemented approach, or just theoretical proposed approach to handle the post-earthquake situation.

  Rationale (RQ2): On behalf of RQ2 we have clearly defined the criteria about the inclusion of primary studies, anything outside of this criteria will be excluded.

- **RQ3:** Which parameters are used in proposed approaches?
  Aim (RQ3): Main aim of this question is to consider key attributes which are used in different approaches like time required to overcome the disastrous situation, required cost, number of affected people, damaged houses, roads, bridges, and other infrastructure.

  Rationale (RQ3): With the help of RQ3; firstly we can filter all those attributes which are used in all proposed models and secondly we can easily compare all those proposed models which are helpful in finding the research gaps.

- **RQ4:** What kind of limitations (i.e., threats to validity and limits) have been observed in our research domain?
  Aim (RQ4): RQ4 aim is to focus on limitation and threat to validity in proposed approaches.

  Rationale (RQ4): With the help of RQ4; we can find the exhaustive level or maximum capacity of the model where it can be applied and can get satisfactory results. In this way, we can also discuss the threat to the validity of the considered primary study approach.

- **RQ5:** What are the top publishing/ popular venues for the considered research domain (venue, the trend over the time, the expertise required - computer science mathematics civil engineering, etc)? Further, it is divided into sub-questions:
  Aim (RQ5): Aim of RQ5 is to note down all venues which are publishing articles related to computer science and social sciences to handle the post-earthquake situation. Additionally, with the help of this question, we will come to know the research interest and expertise of researchers in this domain during the period of 2000 to 2021.
  Rationale (RQ5): Purpose of RQ5 is to figure out those venues which are publishing most of the primary studies related to our research topic because these venues are really helpful for analysis and trends regarding selected studies. Additionally, it's also helpful to know the researcher's expertise whether they are computer scientists, civil engineers, or mathematicians when they wrote articles.

  - **RQ5.1:** What are the top published venues?
  - **RQ5.2:** What are the research trends in a time span of the last two decades?
  - **RQ5.3:** What is the expertise required in this research domain?

- **RQ6:** What are the main research gaps (i.e., open issues) in the research domain?
  Aim (RQ6): RQ6 is the end of the mapping study process and describe research gaps or grey area which has not been explored so far.
  Rationale (RQ6): With the help of RQ6; we can find the directions of unexplored areas.

3.1.2 Conducting Research

In this step, we will apply the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach as shown in fig.3.2 that makes sure all relevant studies have been considered and it consists of four stages (represented in left side light blue vertical column) which are *Conducting Research, Screening* and *Included*. *Conducting Research* stage is about the development of research protocols by defining research questions, keywords, and bibliographic databases to perform the search operation. *Screening* is about to set inclusion and exclusion criteria to select papers including type whether these are from conferences or journals and putting limit of time frame (publication years) as well. *Included* step contains remaining articles after applying screening criteria.

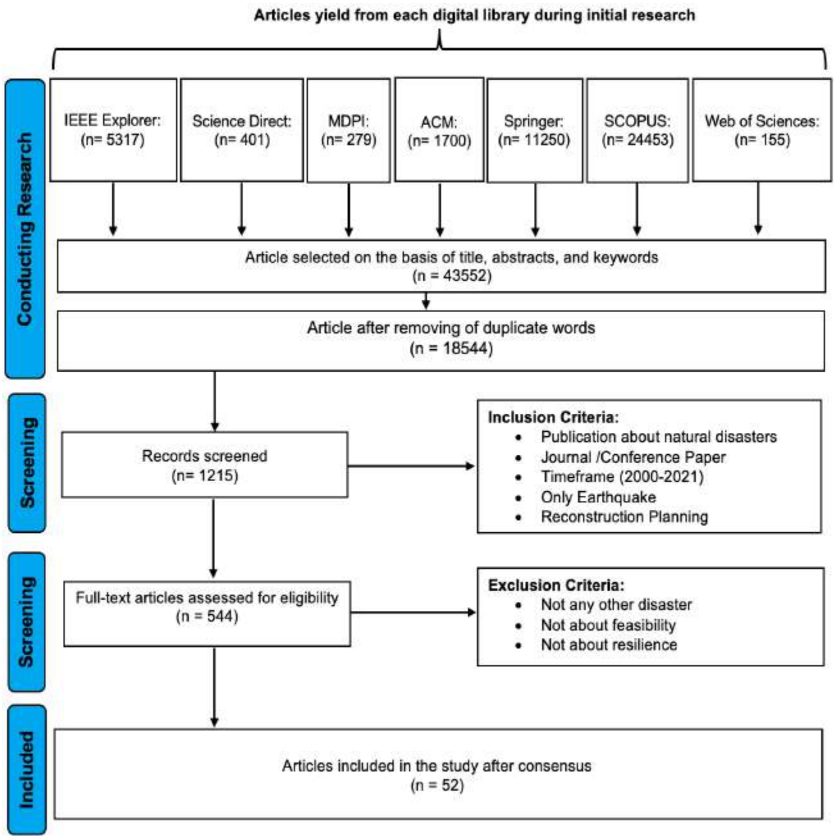


Figure 3.2: PRISMA flow diagram showing the process of selection of articles

To identify keywords for conducting meaningful research and to retrieve the most relevant work for mapping studies for this purpose we have used PICOC (Population, Intervention, Comparison, Outcome, Context) [107] criteria to identify keywords as well as to formulate search strings from research questions.

- **Population:** Here population means all those people who get affected directly due to earthquake. These people might have lost their houses and other properties.

- **Intervention:** Intervention is the software methodology/ tool/ technology/ procedure that is used to solve an issue. For example which technology or algorithm is used to handle a post-earthquake situation.

- **Comparison:** In this study we compare different methodologies of the 'Intervention" step. Although, at this level alternative strategies are identified instead of empirical comparison.

- **Outcome:** Outcome means we are supposed to focus on factors of importance in considered methodology which is quite worthy for practitioners to enhance reliability or functionality.

- **Context:** In context we need to define the kind of comparison supposed to consider whether it's academia or industry. But in our mapping study, we have considered both.

As we know our mapping study is based on the analysis of post-disaster earthquake approaches which are used to overcome those kinds of terrible situations.

To find out the most relevant studies that were published over the last two decades (2000 to 2021), we have performed automatic search as the main search strategy from seven selected digital libraries which are IEEE Explore[1], ACM[2], Science Direct[3], Springer Link[4], Web of Sciences[5], SCOPUS[6] and MDPI[7] these have covered most of the literature about post-disaster earthquake situation. All these databases have selected based on the experience reported by Zenun et al. [64]. To search the most relevant studies we have identified some keywords as well as synonyms of keywords to ensure search query should be exhaustive and then we have constructed search strings by using Boolean operators (i.e., AND and OR). Quasi-gold standard (explained in the following paragraph) also used to search maximum relevant primary studies for a specific time span (2000 to 2021) in conferences and journals [143] to answer defined research questions. Search string consists of identified keywords that are used in all databases mentioned in Table. 3.2, and have been used in all fields. Among selected databases IEEE and ACM Digital Libraries have been chosen because these two contain leading international journals and prime conferences/workshops about data sciences and disaster handling situations. Additionally, we have considered ScienceDirect and SpringerLink digital libraries because these two are most comprehensive as well as contain online scientific collections and index-based international journals. On the other hand, the Web of Sciences (WoS) is also the oldest citation index for the sciences and contains a collection of scholarly publishing journals, proceeding and data compilations [11]. To enhance the domain of our work to social prospects, we run search string queries in SCOPUS digital library because its developers claim 4000 publishers from social science titles and state that it is the "largest single abstract and indexing database ever built" [15]. At last, we have also considered MDPI digital library because it offers high-quality articles from leading publishers.

Quasi-Gold Standard (QGS): According to Zhang et al. [143] it is based on two constraints which are venues (where) and period (time span). In this way, we have identified relevant publications from mentioned seven venues/databases as shown in Table.3.2 by using automated and manual search. Additionally Quasi-Gold Standard (QGS) also has the capability to evaluate search strategies for finding relevant literature in a specific time span. With the help of QGS, we have found a set of studies from the related venues, e.g., domain-specific conferences and journals recognized for a given time span from 2000 to 2021. After that, we have listed down top publication venues (computer science/social sciences) with respect to digital libraries as shown in Table.3.3.

[1] https://ieeexplore.ieee.org/Xplore/home.jsp
[2] https://dl.acm.org/
[3] https://www.sciencedirect.com/
[4] https://link.springer.com/
[5] https://apps.webofknowledge.com/
[6] https://www.scopus.com/
[7] https://www.mdpi.com/

Another factor to use QGS because it filters out related studies by just reading the title and abstract of papers but manual and automated searches are really time-consuming to filter out relevant data and to narrow down the venues. After finding out relevant studies by using QGS we have applied inclusion and exclusion criteria subsection 3.1.3. In the end, we have selected only 52 primary studies from available venues.

Furthermore, we have also applied the backward snowballing technique not to miss out on any relevant primary studies which are published from 2000 to onward [131]. The backward snowballing technique is explained following.

Backward Snowballing: To make sure that any potential material shouldn't be missed, for this purpose we have used backward snowballing to find more relevant articles and to include them in our selected studies. The major benefit of this technique is to check the references of relevant papers in this way there is always a high chance to find an important paper because authors refer to each other [143]. Essentially it is an iterative process, and its initial input is relevant studies which are consisted of a subset of selected studies. Every iteration checks for new studies and this process will go on until no new studies are selected. In this whole process, we follow the guidelines of Wohlin [143].

3.1.3 Screening of Papers

In this section, we have defined inclusion and exclusion criteria for those studies which are retrieved from automated and manual search and evaluated by two authors *(Ghulam Mudassir and Antinisca Di Marco)* to decide whether these articles should be included on behalf of title, abstract, and keywords or not. For inclusion, we have applied the following criteria.

Table 3.1: Inclusion and exclusion criteria

Inclusion Criteria	**Exclusion Criteria**
I1: Studies which are about research methods and results of the considered research domain.	E1: Studies that are not focused on earthquakes.
I2: Studies must have gone under peer-review process and published in leading venues such as journals, conferences proceedings, and workshops proceedings.	E2: Grey literature like working papers, white and short papers, or presentations that are published in the form of some panel discussion.
I3: Studies about the earthquake.	E3: Studies that are just about proposing guidelines, recommendations about disaster situations.
I4: Studies that were published from 2000 to 2021.	E4: Secondary studies (such as mapping studies).
I5: Studies written in English.	E5: Studies that are not peer-reviewed.
	E6: Studies that are not written in English.
	E7: Duplicate studies which are published in different venues on various stages of their evolution.

We have applied inclusion and exclusion criteria on relevant studies (which have been found

from digital libraries) just to verify whether these could be included in our search or not, and in the meanwhile time span (2000 to 2021) also validated. So during full-text reading, we have removed extra articles which were not in the scope of inclusion and exclusion criteria. We performed snow-balling technique on the remaining articles after that we have found 5 more relevant articles.
Furthermore, we have reassured the reliability of included studies for the systematic mapping by applying Fleiss' Kappa [38]. It is a statistical method that is used to access the reliability agreement (independent observer) between a fixed number of raters (classification on behalf of nature of information) during items classification. It measures the score in binary form like 0 (called poor agreement) and 1 (called full agreement). During all this process we took the help of 4 different independent raters for the classification of 30 random sample studies out of those 20 were already included in the mapping study and 10 were not. In the end, Fleiss' kappa calculated result was 0.94. So the obtained result indicates the acceptance level of agreement among the raters.

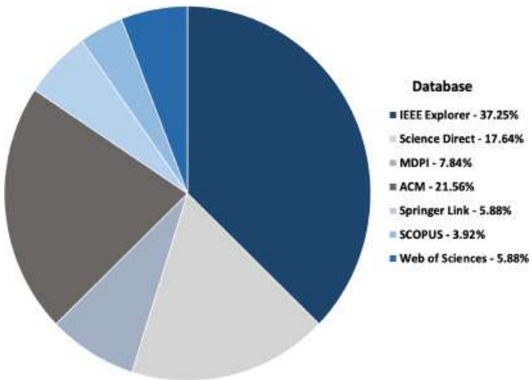


Figure 3.3: Primary studies percentage in each database

3.1.4 Keywords and Themes

We have selected 52 articles after a thorough review process and applied inclusion and exclusion criteria with the help of the PRISMA technique as shown in fig.3.2. According to Fig 3.4, the proportion of primary studies from each digital library is: from "IEEE explorer" we found most of the primary studies which are 18 then "ACM" and "Science Direct" 10 and 9 articles respectively. Similarly from MDPI digital library, we have found only 4 articles, and then "Springer Link" and "Web of Sciences" contain 3 articles each subsequently. SCOPUS has the least contribution in primary studies which contain only 2 related articles. There are few articles that exist in two different libraries like IEEE and ACM have two articles in common. Similarly, SCOPUS also shared 2 articles with the IEEE explorer digital library.

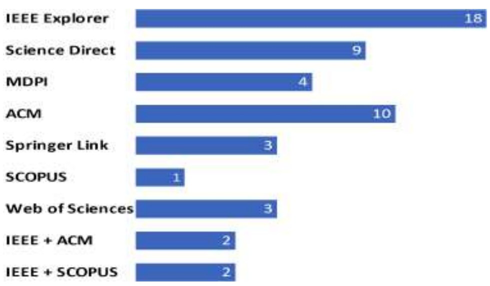


Figure 3.4: Selected primary studies

Table 3.2: Search strings in databases.

Database	Search String
IEEE Explorer	("Post disaster" OR "post-disaster" OR "reconstruction planning" OR "earthquake") AND ("Housing" OR "city" OR "system" OR "building" OR "facilities" OR "road OR "bridge" OR "infrastructure") NOT ("Detection" OR "rescue" OR "cyclone" OR "eruption" OR "tsunami" OR "resilience" OR "temporary" OR "feasibility" OR "authentic" OR "war" OR "flood" OR "tornado"))
ACM	("Post disaster" OR "post-disaster" OR "reconstruction planning" OR "earthquake") AND ("Housing" OR "city" OR "system" OR "building" OR "facilities" OR "road OR "bridge" OR "infrastructure") AND NOT ("Detection" OR "rescue" OR "cyclone" OR "eruption" OR "tsunami" OR "resilience" OR "temporary" OR "feasibility" OR "authentic" OR "war" OR "flood" OR "tornado"))
Science Direct	("Post disaster" OR "post-disaster" OR "reconstruction planning") AND("City" OR "building" OR "road") AND NOT ("Cyclone" OR "Tsunami")
Springer Link	("Post disaster" OR "post-disaster" OR "reconstruction planning") AND ("Housing" OR "city" OR "system" OR "building" OR "facilities" OR "road" OR "bridge" OR "infrastructure") AND NOT ("Detection" OR "rescue" OR "cyclone" OR "eruption" OR "Tsunami" OR "resilience" OR "temporary" OR "feasibility" OR "authentic" OR "war" OR "flood" OR "tornado")
Web of Sciences	("Post disaster" OR "post-disaster" OR "reconstruction planning") AND ("Housing" OR "city" OR "system" OR "building" OR "facilities" OR "road OR "bridge" OR "infrastructure") AND NOT ("Detection" OR "rescue" OR "cyclone" OR "eruption" OR "Tsunami" OR "resilience" OR "temporary" OR "feasibility" OR "authentic" OR "war" OR "flood" OR "tornado")
SCOPUS	("Post disaster" OR "post-disaster" OR "reconstruction planning" OR "earthquake") AND ("housing" OR "city" OR "system" OR "building" OR "facilities" OR "road" OR "bridge" OR "infrastructure") AND NOT ("detection" OR "rescue" OR "cyclone" OR "eruption" OR "tsunami" OR "resilience" OR "temporary" OR "feasibility" OR "authentic" OR "war" OR "flood" OR "tornado")
MDPI	("Post disaster" OR "post-disaster" OR "reconstruction planning" OR "earthquake") AND ("Housing" OR "city" OR "system" OR "building" OR "facilities" OR "road OR "bridge" OR "infrastructure")

Quality Assessment: Once the set of 52 relevant studies has been selected we have performed quality assessment by using used most developed quality assessments model of Adams et al. [1],

Table 3.3: Venues investigation during creation of Quasi-Gold Standard.

Publication Venue	Subject Area	Type	Databases
ISCRAM	Computer Sciences / Social Sciences	Conf.	IEEE Explorer
CACIE	Computer Sciences / Social Sciences	Journal	Web of Sciences
Disasters	Social Sciences	Journal	ACM
ICT-DM	Computer Sciences / Social Sciences	Conf.	IEEE Explorer
RCIS	Computer Sciences / Social Sciences	Conf.	Springer
Journal of Big Data	Computer Sciences	Journal	Springer
Decision Support Systems	Computer Sciences	Journal	ScienceDir.
Advanced Engineering Informatics	Computer Sciences	Journal	ScienceDir.
ICAISC	Computer Sciences	Conf.	Web of Sci.
Expert Systems with Applications	Computer Sciences	Journal	ScienceDir.
Big Data and Society	Computer Sciences / Social Sciences	Journal	IEEE/ACM

Yasin et al. [138], Kitchenham et al. [68] and Tyndall [124]. On behalf of suggestions provided in these models, we developed the quality assessment checklist as shown in Table. 3.4 which is consisted of six different criteria and questions (subjective and objective) to verify source validity, suitability and make sure it should be free of bias.

With this checklist, we have checked the quality of selected literature but in principle with the help of selection criteria, we already have excluded all irrelevant studies with certainty and less effort have required for time-consuming quality assessment activity [41] which is based on producer authority, methodology, scope, objectivity, novelty, and impact.

Additionally, we can use the same selection criteria for other types of research methods like surveys, case studies, or experiments for further assessment of quality studies. For example Host et al. [57] proposed a quality assessment checklist for case studies which can also be used for case studies in formal literature.

3.1.5 Data Extraction & Mapping Process

To extract data from selected primary studies and to answer RQs which are defined in subsection 3.1.1 we have defined Table. 3.5 which is consisted of key "Data Items" on behalf of defined research questions. According to Brereton et al. [13] it's really useful if one researcher extracts the data and the other reviews the extraction. So we also performed an extraction mechanism by two authors. Because extraction verification by the authors is common practice in systematic mapping studies [107]. A defined data extraction strategy ensures the same criteria for all selected papers including their classifications.

Table 3.4: Quality assessment checklist of relevant literature for mapping study .

Criteria	Questions
Producer Authority	• Is publishing institution/platform reputable? E.g., Progress of Disaster Science • Is the author associated with a publishing institute? • Has the author published any other work in this field? • Does the author has expertise in this area? (e.g. job title principal software engineer or expert civil engineer)
Methodology	• Does proposed methodology have clearly stated aim? • Does proposed approach is supported by authentic references? • Any limitation of proposed methodology clearly stated? • Does proposed work based on specific research questions and all question responded effectively? • Does the proposed methodology validated by real case study?
Scope	• Does this work related to our mapping study domain?
Objectivity	• Is this work balanced in presentation and clearly stated? • Is problem statement clearly state the objective? • Is this work refer to a particular vendor? • Are conclusions of this work supported by data?
Novelty	• Does this work introduce a new idea?
Impact	• Check the impact of the considered study with respect to the following criteria. - Number of paper citations - Number of paper backlinks - Number of paper views /read

Analysis and classification:

The extracted information are explained and visually illustrated in subsection 3.1.5. For example, during the analysis of the study identification phase, extracted strategies were grouped like search strategy, developing the search, evaluation of search, and inclusion and exclusion. Then all these groups have given themes and sub-themes. The sub-themes are used for the inclusion and exclusion process (also known as a priori) which are based on strategies like resolving a disagreement between researchers and reducing bias [103]. At last, selected papers were counted belonging to each of their themes and sub-themes.

Data Synthesis:

In data synthesis we have extracted and summarized data in a meaningful way to respond to defined RQs. For this purpose we use various kinds of techniques for data synthesis like B.Kitchenham and S.Charters' guidelines for SLRs [66] including synthesizing evidence in software engineering research by Cruzes et al. [25]. These techniques cover different domains like descriptive synthesis, quantitative synthesis, qualitative synthesis, thematic analysis, and meta-analysis. Further, we have also used descriptive technique as shown in fig. 3.5 for describing publications types of selected studies with respect to venue and fig. 3.6 describing publications ratio of selected studies in the time span of the last two decades (2000 to 2021). Additionally, we have defined a classification scheme on behalf of keywords-related topics to respond to some research questions. Furthermore, these classifications

Table 3.5: Data extraction

Data Item	Value	RQ
Article ID	Integer	
Author Name	Author's name list	
Title of Articles	Name of the article	RQ1
Keyword	Keyword study indexing	RQ1
Publication Year	Calendar year	RQ5
Venue	Publication venue name	RQ5
Reconstruction	Reconstruction of buildings , infrastructure (roads, bridges), economics, education and health	RQ1
Phase	Rescue phase (to evacuate the people)	RQ1
Social Benefits	Social benefits of affected people	RQ3
Planning	Reconstruction planning of buildings	RQ1
Emergency management	Rescue and facilitate people in post-disaster situation	RQ1
Contribution type	whether this article is based on some tool, solution methodology or consist of case study	RQ2
Optimization model	Optimization model is used in proposed study	RQ2
Machine learning	Machine learning algorithm is used in the proposed study	RQ2
Mathematical model	Mathematical model is used in proposed study	RQ2
Characteristic	Which parameters are used in proposed study/ algorithm	RQ3
Search Strategy	Guidelines about search strategy that which is followed to select the studies	RQ4
Visualization Type	Which technique is used to visualize the data	RQ3
Classification schemes	How were articles classified	RQ2
Search Type	Manual or automated	RQ4
Open Issues	Limitation of proposed study	RQ4
Domain Expertise	Keywords extracted from the venue description	RQ5

are really useful for the mapping process.

3.2 Systematic Mapping Study Results

We have performed a mapping study according to section 3.1 guidelines and RQs. During this process in the first search, we have found 43 papers according to year, countries, affiliations, venue, and topic by applying inclusion criteria. Once we updated the searches according to systematic mapping protocols [106] have found new 9 new papers which met defined inclusion criteria. So in the end we have finalized 52 primary studies. A brief summary of all considered studies is mentioned in Appendix A.

Additionally, Fig. 3.7 presents detailed information's selected primary studies from seven different digital libraries. This information consisted of digital libraries where it gets published including the type of solution which authors have proposed (like its Social Economics (social eco.), data sciences, modeling or civil engineering (see in subsection 3.2.3)) and publication year. The last

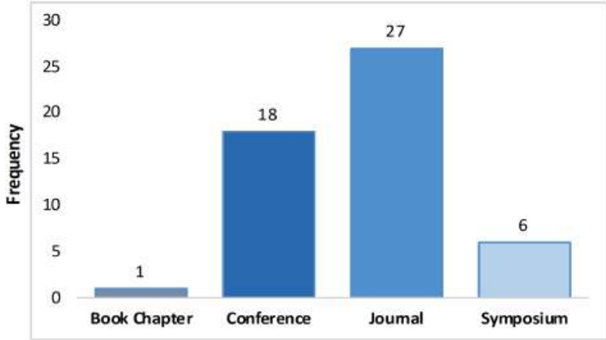


Figure 3.5: Distribution of selected studies with respect to publication type

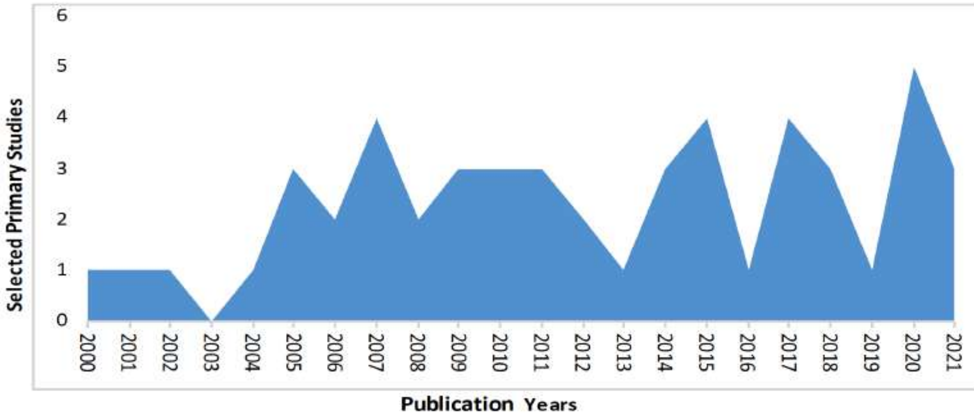


Figure 3.6: Distribution of selected studies with respect to time span

donut circle presents the references of relevant primary studies.

3.2.1 Publication Type and Trend

We have considered primary studies that were published in different platforms like book chapters (1 study), conference papers (18 studies), journal papers (27 studies), and symposiums (6 studies). The studies that contributed are shown in fig. 3.5 with respect to publication type. Here, journals are one of the most popular platforms for publications which is almost 52% of overall selected studies related to handling reconstruction planning in a post-disaster situation. Similarly, conferences contain 34.6%, symposium contains 11.5%, and book chapter is the least common type which has a contribution of around 1.92%.

Appendix B shows details of all 52 selected studies like published venue, type of studies, research topics, number of selected studies in each type, and reference of published studies. All these studies are from 47 different quality venues, while most of them are from journals (27 studies from 23 different journals), second-most are from conferences (17 studies from 14 different conferences) and third most are from the symposium (6 studies from 6 different symposia) including 1 primary study from book chapter.
Overall, bar chart in fig. 3.5 indicates that all these forums contains most related studies and make an immense contribution to our systematic mapping.

The distribution of selected studies regarding publication years over the time span from 2000 to 2021 is shown in fig 3.6. X-axis showing publication years and Y-axis showing selected primary studies. According to results, researchers have started considering post-disaster reconstruction plan-

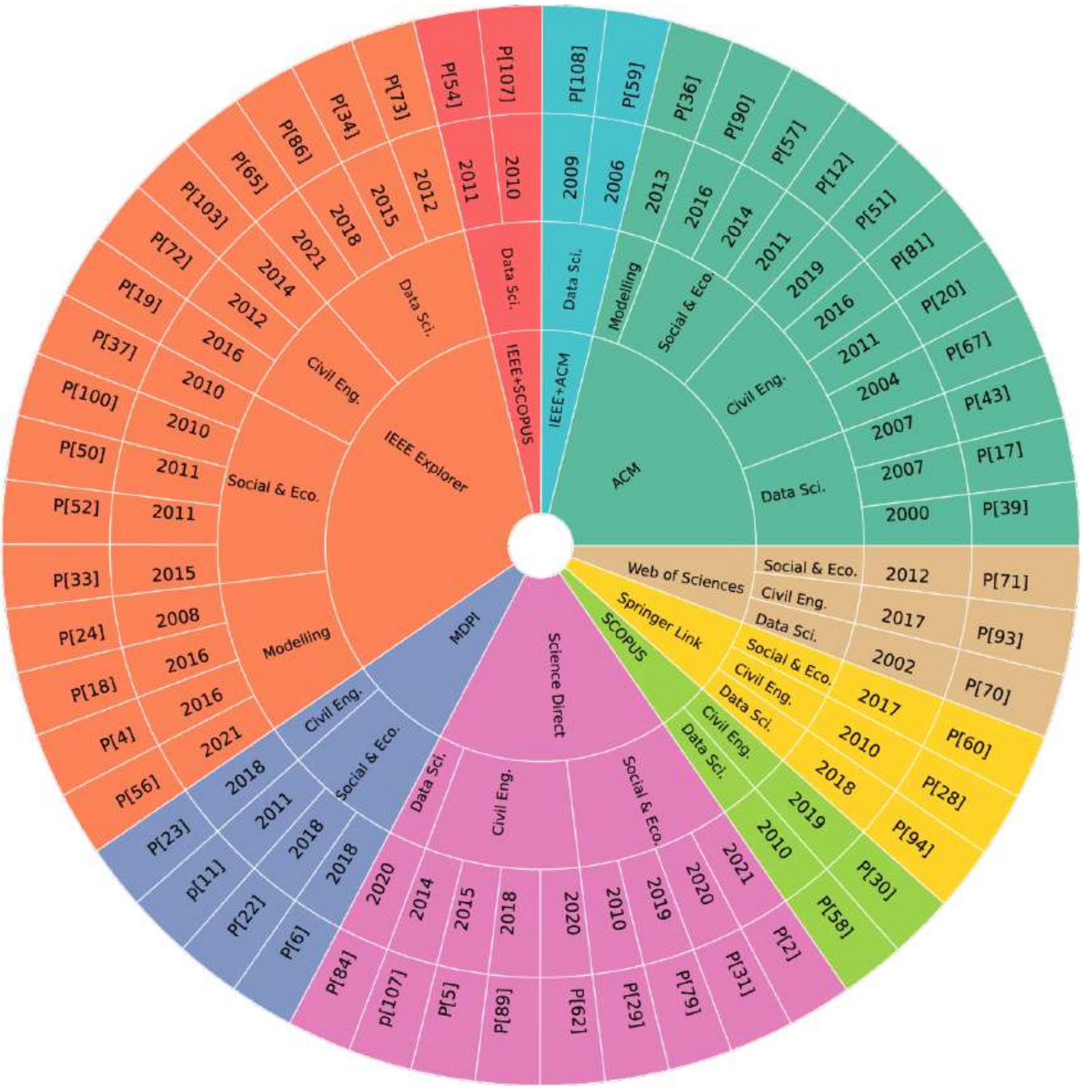


Figure 3.7: Distribution of publications techniques used for sentiment analysis across years

ning from 2000 to 2002 by using technical algorithms. Then we don't see any further enhancement in 2003 but in 2004 researchers have started remarkable work which goes on till 2007 then we can see slightly fall down in 2008. In 2009 research work and publications goes up which remain consistent till 2011. In the meanwhile, we can see research trend goes down very quickly in 2013, 2015, and 2019 then again goes up very fast in subsequent years in the post-earthquake reconstruction domain.

3.2.2 Primary Studies Classification based on Research Facet

For the research facet[8], we have used the classification scheme proposed by Wieringa et al. [130] and Durelli et al. [32] to categorize primary studies according to nature or type of research. These classifications are very simple and straightforward as shown in Table 3.6. All these classifications are explained in the following:

Solution Proposal: These kinds of papers propose a novel solution to the problem without a full-

[8]Facet is mini-investigation process with respect to defined criteria or research question from subset of studies which are part of overall selected studies.

Table 3.6: Studies classification according to research type

Research Type	**Number of Studies**
Solution Proposal	15
Solution Proposal and evaluation research	16
Solution Proposal and validation research	19
Philosophical papers	1
Opinion and Personal Experience	1

blown validation. Because these solutions are explained by proof of concept with the help of an example, a sound argument, or by some other means. We have found 15 solution proposals from selected studies.

Evaluation Research: Evaluation research is categorized as empirical research and it is based on research methods to evaluate novel solutions. All those studies that are based on formal methods such as hypothesis testing and performed experiments on real-world case studies are considered evaluation research. Our 16 primary studies lie in the 'solution proposal and evaluation research' category.

Validation Research: Validation research provides preliminary empirical evidence of the solution proposal that has been implemented. It is based on very deep and methodological sound research steps to verify all relevant studies. These research steps like quasi-experiments, prototyping, mathematical analysis, and case studies are used to collect evidence as well as for thorough investigations. We have found 19 primary studies in this category of research type.

Philosophical Papers: According to Wieringa et al [130] these studies are based on a new conceptual framework or a new way to look at current research. Only 1 primary study exists in this criteria.

Opinion Papers: These articles just describe the opinion of authors about some research area like whether it's wrong, or it is good or needs to improve by using some other methods or techniques. Only 1 'opinion paper' exists in our primary studies.

Personal Experience Papers: These studies are based on the author's personal experience from one or more projects like on *What* he/she has learned and not on *Why.* These articles mostly come from industry practitioners or some researchers who used to work practically on some tool and don't have discussion and methodology sections. In these types of studies, authors mentioned their experience is in the form of a list. Thus, the evidence in these papers is often anecdotal in nature.

We can create more categories instead of five as shown in Table.3.6 but some combinations are not worthy. For example, there could be a paper that proposes a new technique as well as validation and ends up with a discussion section where the author provides opinions on what other people/researchers did, so these kinds of papers do not fit in defined categories. Due to these kinds of limitations, we can not define more categories [130]. Selected primary studies related to reconstruction planning in a natural disaster are mentioned in Table. 3.6 and have been classified into relative category. Almost 28.8 % of papers doesn't provide any full-blown validation and empirically grounded evidence apart from proof of concepts so these (15 papers) studies were classified into solution proposals. From these states we can claim relevant studies with respect to reconstruction planning in the natural disasters domain is relatively weak with respect to scientific research.

Second research type of primary studies in Table. 3.6 is solution proposal and evaluation research where 16 studies fall into this category. These studies describe high-quality pieces of evidence like experiments on real case studies regarding the applicability of novel solutions.

Validation research studies analyze the potential contribution of selected studies with respect to the experimental setup and mathematical analysis. These kinds of studies are a bit more than solution proposals because some researchers have started working in this domain in the last few years that's why we have found 18 studies as shown in Table. 3.6.

Only 1 primary study is classified in the philosophical papers category because currently, not many people propose a new conceptual framework in this domain.

Similarly, only 1 primary study falls into the opinion and personal experience category.

Furthermore, we have used another evaluation classification scheme of Durelli et al. [32] to classify selected primary studies more in depth into two category *real case study* and *limited experiment* as shown in Table. 3.7.

Table 3.7: Evaluation methods in primary studies

Evaluation Method	**Primary Studies**	**Total**
Real Case Study *(Application of solution on real data as real context)*	PS6, PS9, PS13, PS15, PS23, PS17, PS21, PS10, PS3, PS47, PS32, PS19, PS22, PS36, PS45, PS26, PS18 , PS35, PS48, PS30, PS20, PS31, PS33, PS39, PS43, PS5, PS7, PS46, PS52	29
Limited Experiment *(Application of solution unsolicited data on very simple case study)*	PS11, PS14, PS24, PS1, PS25, PS8, PS2, PS50, PS41, PS44, PS49, PS51, PS38, PS29, PS37, PS34,, PS42, PS12, PS16, PS4, PS28, PS40, PS27	23

Most of the primary studies have empirical strategies to claim and evaluate their proposed technique. However, during reading the selected studies we have found different papers have a section like *case study* or *experiment* to validate their proposed solution. For this purpose, we have categorized selected studies into two evaluation methods (real case study and limited experiment) as shown in Table 3.7.

Real Case Study: is just a research method where the researcher explores the proposed solution or topic in-depth and validated on real data set.

Limited Experiment: is another research method where different variables are used in algorithms to test the hypothesis.

3.2.3 Mapping of Primary Studies According to Reconstruction Planning Solution Domain Facet

Mapping and classification of primary studies with respect to post-disaster reconstruction planning (PDRP) solution domain start right after data extraction and collected detailed information about current research in post-earthquake reconstruction. It has been defined by two reviewers in two different steps, in the first step systematic mapping was conducted and in the second step they have created the solution domain facet classification which is consisted of four types (i.e social and economics, data science, modeling, and civil engineering) as shown in Table 3.8. Here we have explained all these categories with respect to primary studies.

Table 3.8: PDRP solution facet in primary studies

PDRP Domain	Res. Topics	Primary Studies	Total Count
Social & Economics	1- Social Sciences, 2- Social and Economic Experts, 3- Management Experts.	PS13, PS46, PS45, PS30, PS39, PS21, PS28, PS15, PS37, PS33, PS27, PS42, PS9, PS35, PS48, PS10, PS44, PS25,PS5	19
Data Sciences	1- Data Sciences, 2- Data Analytics, 3- Intelligent Master Planning, 4- Reinforcement Learning.	PS8, PS17, PS11, PS7, PS12, PS19, PS47, PS22, PS29, PS1, PS50, PS34, PS24, PS52	14
Modelling	1- Decision Model, 2- Modelling by Using Software, 3- Computer Aided Design, 4- 3S Planning Technique.	PS31, PS6, PS4, PS38, PS26	5
Civil Engineering	1- Structural Engineering, 2- Hydraulic Engineering, 3- Transportation infrastructure engineering, 4- Transportation System Engineer.	PS2, PS40, PS16, PS20, PS3, PS49, PS14, PS18, PS23, PS32, PS36, PS41, PS43, PS51	14

Social & Economics (Social & Eco.):

Those multi-disciplinary studies which are based on economic, social, political, and cultural related studies [33].

The mapping study, we came to know some researchers have proposed social & economic studies for post-disaster reconstruction planning. The goal of all these types of studies is to overcome the post-disaster situation by considering social and economic factors. However, it's really difficult to handle such circumstances in this way but even though according to Table 3.8 we have found 19 studies that provide social & economic solutions for post-earthquake reconstruction planning.

Data Sciences:

These studies handle the post-disaster situation by applying tools and techniques on a vast volume of data to find meaningful information for decision-making [111].
In this regard we have found 14 articles that use algorithmic techniques like genetic algorithms to handle post-earthquake reconstruction planning problems but the overall percentage of these types of articles is 26.9% from selected studies.

Modelling:

To solve the challenging problem sometimes it's really difficult for researchers to use advanced algorithms or to provide a mathematical solution then authors use modeling techniques for solution implementation. That's why we have observed during the mapping study few authors have proposed simulation solutions but the overall percentage of these kinds of articles is very less which is 9.6% from selected studies.

Civil Engineering:

All these primary studies are based on professional designing and development of the infrastructure or experience papers [113]. The percentage of these kinds of articles is similar to algorithms type solutions which are (29.9%).

3.2.4 Classification of Studies According to the Information Learned

According to the results, we have extracted information from different primary studies like solution proposals, empirical studies, evaluation research, philosophical papers, survey papers, opinion papers. However, during information extraction [115] we have considered key attributes like damage level in the area, required time for reconstruction of properties, cost/budget required to reconstruct properties, and the number of people who got affected by the disaster in the damaged area. Out of 52 studies 19 studies have shown information on abstract level for instance, graphs or graphical representations which are: PS28, PS46, PS33, PS31, PS26, PS1, PS31, PS38, PS4, PS48, PS15, PS39, PS25, PS27, PS44, PS46, PS30, PS21, PS42.

In this mapping we have also found empirical research articles like: PS24, PS50, PS8, PS12, PS22, PS534, PS17, PS43, PS11, PS18, PS7, PS19, PS41, PS47, PS29, PS1, PS50, PS52.
The rest of the primary studies are considered as a general category because every article contains some key attributes.

3.2.5 Classification of Studies According to IT Solution and Civil Engineering Field

As we go further in-depth for mapping study analysis we have analyzed 23 papers based on IT solutions and 29 papers suggesting solutions from the civil engineering field from a total of 52 studies. Additionally, the proportion of civil engineering solutions is more than IT because post-earth reconstruction problem is more oriented to the civil engineering field.

3.2.6 Most Fertile Researchers in Area

On behalf of primary studies, we have analyzed publications trends as well as the number of published articles by each author to check research impacts in this particular area. We have found few active researchers those have published few papers in last two decades like : Opricovic et al. PS9 [98], Tavakkol et al. PS25 [123], Ghannad et al. PS46 [45] Rodriguez et al. PS47 [114] and Ghulam et al. PS52 [92]. Although the rate of papers publication increased in 2007,2015, 2018, and then in 2019 according to Fig.3.6. But according to results and thorough analysis, we came to know that no research group dealing with this critical problem using cutting-edge technologies like machine learning.

3.3 Potential Research Areas

On behalf of mapping study results, we can say that few people have tried to work but a not fair amount of research has been carried out in this domain. Most of the studies are based on a graphical representation of the damaged area instead of empirical research. That's why we can say that most research efforts are not methodologically sound and some issues remain unexplored. In this section, we have explained various kinds of potential research directions, especially the use of cutting-edge technologies in this critical domain of reconstruction planning in a post-earthquake situation.

Applying cutting-edge technologies like machine learning algorithms in this area could be very useful because according to our mapping study results we have found only one article PS52 [92] that have used DDQN reinforcement learning algorithm apart from that no one has used. To make a reconstruction plan manually is really challenging for decision-makers. Because it is really hard for them to maintain balance in all formal and informal requirements including a guarantee to repopulate the damaged area. Secondly, it is compulsory to consider the benefits of affected people that come from optimizing some values, e.g., the vulnerability of buildings, the budget and time required to accomplish the building plan. Development plans must be implemented in accordance with the new strategies devised to drive future development including taking into account the sustainability factor.

Additionally, another unconsidered aspect by public decision-makers is the societal impact and relative benefits that citizens experience from the implementation of a certain recovery plan. Indeed, the societal impact and benefits are different in every plan, but these are the key features that should be considered in all post-disaster phases.

For the aforementioned complexities, machine learning algorithms are the best solution that can provide a mechanism to public decision-makers, servants, and citizens that can help effectively to define and evaluate rebuilding plans.

Thus, more empirical and detailed research is required to analyze how machine learning algorithms can be used to define reconstruction plans in a post-earthquake situation.

3.4 Threat to Validity

There are many aspects that need to be considered when assessing systematic mapping study which can potentially limit the validity of the findings but in this section, we have discussed possible validity threats to our systematic mapping study regarding analysis, conduct, design, and clarifications. We have considered threats like bias in the selection of digital libraries, inaccuracy in data extraction, bias in the time frame for primary studies, bias in the definition of search strings, and publication bias.

Bias selection of digital libraries means we might have a distortion in statistical analysis in the selection of all those libraries which contain or do not contain too many related studies. We handled this threat (to at least some extent) by defining comprehensive inclusion and exclusion criteria for post-disaster situation-related studies.

Secondly, *inaccuracy of data extraction* and misclassification can occur during information extraction which is done by reviewing it in different ways. To minimize these kinds of discrepancies (to at least some extent) were solved by consensus by all reviewers.

Thirdly *bias in the time frame for primary studies* for this purpose we have considered articles from 2000 to 2021 range to mitigate chances not to miss any recent relevant study.

Fourthly to tackle *bias in search string* we have used all techniques like tabs, quotes, hyphens to exclude words and asterisk wildcard tips (at least some extent) to make a comprehensive string.

Lastly, *publication bias* refers sometimes positive problems published more as compared to negative and also negative results take longer time to be published and usually cited fewer [69]. To tackle this threat (to some extent) we have scanned all related journals and conferences apart from grey literature like reports or Ph.D. thesis and unpublished results because all these kinds of things may affect the validity of our results.

Additionally , in this section we have also used classification schemes of Petersen et al.[104], Campbell et al.[16] and [133]. According to these schemes following types of validity threats have been taken into account which is: descriptive validity, theoretical validity, internal validity, external validity, and conclusion validity. All these have explained the following.

3.4.1 Descriptive validity

Descriptive validity is about the accuracy and objectivity of collected information. Usually, threats of descriptive validity exist more in qualitative studies as compared to quantitative studies. For this purpose, we have designed a data collection form to record the data related to post-earthquake situations and also describe the process of data extraction in Table 3.5 and reviewed many times to not miss any related article. Additionally, this form can be revisited whenever required for primary studies. So this threat is handled very effectively.

3.4.2 Theoretical validity

Theoretical validity is about to determine collected data about post-earthquake situation fits into intended what we have required without any bias selection. Because there is always a chance to miss some relevant studies e.g Wohlin et al. [134] did work on two mapping studies on the same topic and ended up with different articles. We have used PRISMA [119] and backward snowball sampling techniques [60] to handle this threat in subsection 3.1.2.

3.4.3 Internal Validity

Internal validity is based on two main threats which are missing relevant studies and bias in paper selection by researchers. By the way, mapping studies consider a wide range of related articles from different databases [70]. So in our mapping study, we have considered the seven most widely used digital libraries to minimize the chance of not missing any relevant study about the post-disaster situation. We believe most of the related primary studies are considered but still, we can't rule out the possibility that we might have missed some relevant studies during the automatic search in digital libraries. Additionally, we also used quasi-gold standard (subsection 3.1.2) to validate the completeness of automated searches strings which are based on RQs keywords.

Researchers' bias in paper selection might also lead to inaccuracy in data extraction. For this purpose, we have defined data inclusion (DI's) criteria in Table. 3.5 for data extraction, where all researchers were agreed, and if there was any conflict in data extraction we settled by mutual consensus.

3.4.4 External Validity

According to Petersen et al. [104] external validity of systematic mapping study is about how many findings are generalizable and useful for other population interests. So the major threat is whether considered primary studies are representing the subject area or not. For this purpose, we have followed the standard research process and considered all relevant studies apart from those which were not in English.

Additionally, some primary studies do not provide full information for extraction form, in that case, we have assumed some information on behalf of DIs during data synthesis. Similarly, some approaches did not describe drawbacks.

3.4.5 Conclusion Validity

Conclusion validity is about up to how much we reached on reasonable conclusion as well as the relationship between selected studies and current research trends in the considered field. To handle the first threat we have answered all defined RQs on behalf of selected primary studies. Regarding the second threat about data extraction, classification and synthesis were performed as a team. However, still, there is a chance to miss any relevant study because qualitative-based mapping study is really difficult and can be missed in any article.

3.5 Discussion and Conclusion

This mapping study has identified related literature and evaluated with respect to topics, frequency of publications in the last two decades, publication venues, and type of disaster.

We believe our mapping study is based on a comprehensive and state-of-the-art overview in post-earthquake reconstruction planning studies which is quite useful for young researchers and practitioners to get an idea about this challenging field and make a contribution by using cutting-edge technologies.

We have answered all defined research questions (RQs) with the help of analysis and results on behalf of our systematic mapping study.

RQ1: *What kind of problems have been addressed in our research domain?*

According to our primary studies, we have considered only earthquake-related studies which are published in the last two decades (from 2000 to 2021). After thoroughly studying we have found twenty types of problems are addressed in all these articles which have been classified in the Table. 3.9.

RQ2: *What approaches are used to address these problems?*

The approaches which we have found in primary studies to solve post-earthquake reconstruction problems are categorized into four types which are: Optimization Model (mathematical model), Decision frameworks (implemented algorithms which can manage resources, cost, time, etc. in the post-disaster situation), Visualization model (undirected graph or maps of the damaged area),

Table 3.9: Problems addressed in primary studies

Problems	**Primary Studies**
Reconstruction criteria definition	PS1, PS8, PS12, PS15, PS16, PS23, PS30, PS28, PS48
Resources management	PS3, PS14 ,PS21
Socio-economic policy definition	PS19, PS36, PS39, PS46, PS49
Stakeholders involvement	PS9, PS17, PS20, PS26
Data collection	PS5, PS7, PS27, PS29, PS33, PS35, PS44, PS51
Data visualization	PS4, PS40
Reconstruction planning with social aspects	PS10, PS13, PS34
Resource management	PS3, PS14, PS21
Agent-based reconstruction mechanism	PS37
Cost estimation	PS43
Data modelling	PS24
Decision making	PS25
Index-based reconstruction mechanism	PS45
Master planning	PS11
Metrics definition	PS31
Reconstruction criteria for damage roads	PS47
Reconstruction plan generation	PS52
Sustainable recovery	PS2
Temporary housing	PS22

Fine-grained analysis model (studies which describe the practical implementation of reconstruction plan), Machine learning and Geographical Information Systems (GIS) as shown in Table 3.10.

RQ3: *Which parameters are used in proposed approaches?*

In selected studies, we had the analysis of all those attributes/ input parameters which are used in proposed methodologies. We have categorised these parameters into three different tables on behalf of methodologies (algorithmic and mathematical models, visualization models, and real experience reports). Overall 16 attributes have been noticed which are: time, cost, political priority (PP), damage level (DL), resident numbers (RN),city data (CD), physical dependencies (PD) people opinion (PO), gross domestic production (GDP), sustainability (Sustainbi.), state disaster recovery coordinator (SDRC), 3D, seismic strength (SS), stiffness, historical and cultural (H & C) and social benefits (Sb.). Details of each primary study with respect to parameter/attributes is mentioned in Table 3.12, 3.13, and 3.14. Reference *(Ref)* column contains related to paper and in *input parameters* column contain parameters which are mentioned by "x" if it exists in the corresponding paper and blank space vice versa.

RQ4: *What kind of limitations (i.e., threats to validity and limits) have been observed in our research domain?*

Table 3.10: Papers grouped based on approaches

Approaches	**Primary Studies**
Optimization model	PS1, PS24, PS20, PS17, PS12, PS13, PS15, PS21, PS27, PS28, PS29, PS34, PS35, PS39, PS7, PS44, PS46, PS47
Decision framework	PS2, PS25, PS9, PS10, PS19, PS18, PS16, PS14, PS26, PS48, PS31, PS50, PS32, PS33,PS51, PS36, PS37, PS38, PS41, PS43, PS45, PS49, PS22, PS30
Machine learning	PS52
Geographical Information System	PS5, PS11, PS6
Visualization model	PS4, PS40
Real experience reports	PS3, PS8, PS23, PS42

Table 3.11: Papers grouped based on limitations

Limitations	**Primary Studies**
Availability of updated data	PS4, PS14, PS6, PS18, PS49, PS13, PS30, PS48, PS37, PS23, PS26, PS33, PS8, PS11, PS38, PS45, PS47, PS19, PS39, PS50, PS51
Computational resources	PS1, PS12, PS42, PS34, PS16, PS2, PS29, PS9, PS5, PS46, PS31, PS40, PS35, PS24, PS43, PS20, PS27, PS17, PS32, PS41, PS22, PS44, PS28, PS36, PS52
Model efficiency (not validated on real case studies)	PS3, PS10, PS21, PS7, PS15, PS25

According to primary studies our focus is on reconstruction planning of infrastructure in the post-earthquake situation. After deep analysis, we have observed three types of limitations in available articles which are: Availability of updated data, Computational resources, and Model efficiency (not validated on real case studies). All primary studies have been categorized with respect to their limitations in Table. 3.11.

RQ5: *What is the publication trends for the considered research domain ? Further, it is divided into sub-questions:?*

During the search of primary studies, we have found 11 venues that contain most of the primary studies related to the post-earthquake reconstruction domain. All those venues including research trends and expertise required are explained in the following sub-questions.

- **RQ5.1:** *What are the top published venues?*

  In total, we have found selected primary studies are from 46 different venues. Among those only 11 conferences/journals (venues) are the most popular which contain more than one pri-

Table 3.12: Algorithmic and Mathematical models common parameters

Ref	**Input Parameters**															
PS[Ref]	**Time**	**Cost**	**PP**	**DL**	**RN**	**CD**	**PD**	**PO**	**GDP**	**Sustb.**	**SDRC**	**3D**	**SS**	**Stiff.**	**H&C**	**Sb.**
PS1[99]	X	X	X			X			X	X	X					
PS2[34]		X		X		X			X		X					
PS5[146]		X						X								
PS6[7]		X		X	X							X				
PS7[120]		X		X												
PS9[55]			X		X	X							X			
PS10[76]	X	X														
PS11[84]			X	X		X			X							
PS12[48]		X	X		X											
PS13[35]	X		X		X			X								
PS14[9]				X	X	X										
PS15[49]	X	X	X	X		X										
PS16[31]		X	X	X							X					
PS17[27]	X		X			X										
PS18[75]		X		X											X	
PS19[56]				X	X	X										
PS20[96]	X	X	X			X		X								
PS21[18]		X														
PS22[62]				X	X										X	
PS24[128]		X						X								
PS25[123]				X		X					X					
PS26[52]	X	X						X					X			
PS27[108]	X			X		X								X		
PS28[144]		X		X	X										X	
PS29[145]		X	X	X	X					X						
PS30[2]			X		X	X										
PS31[80]	X	X	X	X		X			X			X	X			
PS32[86]	X		X			X					X					
PS33[10]		X		X		X									X	
P34[77]				X	X	X					X					
PS35[136]	X	X	X			X					X					
PS36[101]		X						X						X		
PS37[141]				X	X			X					X			
PS38[37]		X		X					X						X	
PS39[74]		X							X					X		
PS41[121]	X	X								X						
PS43[142]		X	X	X	X						X					
PS44[81]		X	X		X											
PS45[17]			X		X	X									X	
PS46[45]		X	X		X						X					
PS47[114]		X	X	X	X		X									
PS48[85]			X	X	X	X							X			
PS49[44]		X	X	X	X										X	
PS50[83]		X		X	X				X							
PS51[125]		X	X		X								X			
PS52[92]	X	X	X	X	X	X	X									X

Table 3.13: Visualization Models common parameters

Ref	**Input Parameters**															
PS[Ref]	**Time**	**Cost**	**PP**	**DL**	**RN**	**CD**	**PD**	**PO**	**GDP**	**Sustb.**	**SDRC**	**3D**	**SS**	**Stiff.**	**H&C**	**Sb.**
PS4[28]	X	X	X			X		X				X				
PS40[29]				X		X										

Table 3.14: Real experience reports common parameters

Ref	**Input Parameters**															
PS[Ref]	**Time**	**Cost**	**PP**	**DL**	**RN**	**CD**	**PD**	**PO**	**GDP**	**Sustb.**	**SDRC**	**3D**	**SS**	**Stiff.**	**H&C**	**Sb.**
PS3[42]				X	X	X				X						
PS8[100]	X			X		X										
PS23[112]		X		X							X					
PS42[43]	X			X				X								

mary study. These popular venues are ISCRAM, CACIE, disasters, ICT-DM, RCIS, Journal of Big Data, decision Support Systems, Advance Engineering Informatics, ICAIS, Expert Systems with Applications, and Big Data and Society as shown in Table 3.3.

- **RQ5.2:** *What are the research trends in a time span of the last two decades?*

  According to Fig. 3.6 primary studies research trends vary from 2000 to 2021. In 2000 only a few people were working then this ratio goes down in 2003, again in 2007 research trend is on peak then we can see slight fall in 2008. Later again we can see the variation in different years but in 2014, 2017 and 2020 research demonstrate an increasing trend.
  But all these studies have tried to solve the post-earthquake situation by using different techniques.

- **RQ5.3:** *What is the expertise required in this research domain??*

  From primary studies, we came to know that reconstruction planning is related to civil engineering but during reconstruction, we need to consider the social aspect of affect communities. For this purpose, the researcher needs expertise in social sciences, data sciences, and technical skills of computer science.

RQ6: *What are the main research gaps (i.e., open issues) in the research domain?*

On behalf of results, we have observed not too many researchers are working in this area, especially with respect to cutting-edge technologies. In that aspect, we have found numerous directions which can be carried out for research because the empirical research which already been done to handle the post-disaster situation is not sufficient. Most of the proposed solutions in the considered studies are based on visual simulations like undirected graphs instead of empirical solutions.

We can claim it's a great opportunity for young researchers to explore these unexplored important research area with respect to cutting-edge technologies like artificial intelligence and machine learning.

Primary Studies Explanations

Here following we have explained all 52 primary studies (PS) in which they have proposed solutions to overcome post-disaster situations.

PS 1: Opricovic et al. [98] developed multi-criteria model (MCDM) for analysis of post-disaster planning. MCDM select the best alternative reconstruction plan on behalf of defined parameters like reconstruction cost, gross domestic production, destroyed houses and parameters, restoration ability, sustainability, acceptability by the local public, government preferences and plans have to be evaluated on the behalf of all these criteria's. And they have used fuzzy multi-criteria optimization (FUMCO) which has two phases CFU phase (converting fuzzy data into crisp scores) and the MCO phase (multicriteria optimization using compromise ranking method).

PS 2: Eid et al. [34] develop an innovative decision framework by adopting an agent-based approach for short-term redevelopment objectives and also for balancing long term goals by reducing three-dimensional vulnerabilities of communities like social, economic, and environmental ones. For this purpose, they have used residential agents, economic agents, and state disaster recovery agents (SDRC). SDRC's main purpose is to evaluate the recovery plan and prioritize the objective after every simulation through aggregated equations. The proposed approach is composed of five steps: *(i)* Implementation of an assessment tool to measure the three considered dimensional vulnerabilities; *(ii)* Modeling of stakeholders objectives, strategies, and behaviors; *(iii)* Data gathering to extract the information about the damage of the disaster; *(iv)* Simulation of the impact of the disaster event and of the interaction the stakeholders have during the post-disaster recovery phase; *(v)* Analysis of the simulation results. The utmost purpose of this research methodology is to provide optimal recovery strategies after disaster and policies at the community level.

PS 3: Ge et al. [42] reviewed disaster management practices in China with an interdisciplinary analysis to check how disaster planning and management can be used efficiently in a top-down government administration system during the 2008 Wenchuan Earthquake. Basically, two national-level plans were drawn, one is the Overall Plan for Post-Wenchuan Earthquake Recovery and Reconstruction, and the other is the City Town System Plan for Post-Wenchuan Earthquake Recovery and Reconstruction, and the evaluation of plans contents are very helpful for policymakers to build a sustainable infrastructure.

PS 4: A.Doi et al. [28] proposed a solution for reconstruction after Great East Japan Earthquake (March 11, 2011). According to this solution they proposed two policies to accelerate the reconstruction plan (i) Build 3D models for public shapes using CAD (Computer-Aided Design) and private shapes using CG (Computer Graphics) for better visualization and then they are integrated into the database (ii) Train human resources that can build for 3D models from 2D drawings of roads, river, rail and so on. As a case study in this article, they considered the "Kuwagasaki" district of Miyako city.

PS 5: W. Zhou et al. [146] have proposed a framework by using 3S (Special data Acquisition, Spatial Data Management, and Special Data Management) and remote sensing (RS provide different resolution remote sensing data before and after the earthquake) techniques for post-disaster reconstruction planning system (PRPSS) after Sichuan Wenchuan earthquake (China) in 2008. Both 3S[9] and RS (remote sensing) techniques belong to Global Information System (GIS). Overall proposed framework (PRPSS) consisted of three layers Data Source Layer (uses spatial databases technology for the management of disaster areas spatial data), Functional Service Layer (provide primary service function related system construction), and System Application Layer (Set of planning support Analysis, provide effective support for reconstruction planning). Additionally PRPSS framework

[9]geographic information system (GIS), the remote sensing (RS) and the global positioning system (GPS)

also contain seven types of databases for disaster area data. Proposed framework validated by Tsinghua University on Aba Tibetan earthquake dataset.

PS 6: L. An et al. [7] have proposed enriched algorithm that allows to combine GIS data (Geographic Information System which is taken by detailed survey results from Institute of Engineering Mechanics (IEM) and China Earthquake Administration (CEA)) and SAR (Synthetic-Aperture Radar) images to estimate damage assessment after any disaster. The method was applied to PALSAR images taken over both areas Wenchuan (China) and Yushu (China) affected by the earthquake in 2008 and 2010 respectively. According to this method, the GIS layer is not only applied for scale restriction but also as ancillary (non-video information such as audio data) data of structure vulnerability. As a case study author has considered the city of Dujiangyan, Sichuan, China affected by the earthquake on May 12, 2008.

PS 7: In this paper [120] author's have evaluated the restoration situation of a damaged building in the earthquake of 2016 (Kumamoto) in which almost 3000 buildings were completely destroyed, and it was not possible to grasp damage situation information without satellite remote sensing. Furthermore, they have used object-based and pixel-based methods for extracting detailed damage of the building and other dwellings as well as to improve the resolution of a satellite image. Generally, a lot of parameters are required for image segmentation and classification by the object-based method but here damage is evaluated by the optical and SAR images observed immediately after the disaster investigated and a lot of damage features of the building were investigated by the field surveying. In this paper they have taken Mashiki town as a case study (severe damage in Kumamoto earthquake) for evaluation of proposed methodology, using high-resolution satellite data one year after the earthquake.

PS 8: In this paper [100] author's have discussed the reconstruction approach after the Wenchuan County earthquake in 2008 of Sichuan Province. According to this model they have used regional advantages, improved infrastructure, explore tourism resources, changed the economic growth mode, and focused on the protection of historical and cultural. Basically, for the whole construction, they have adopted the "Partner Assistance" approach. And they have adopted the following strategies (i) They have repaired old buildings according to their old style, size, and features so they can revive the old style and strengthen the modern technology of resisting the earthquake. (ii) Some buildings which didn't collapse in a disaster such as old houses or shops, left their appearance from outside as it is but inner side structure equipped with modern structure equipment to resist the earthquake up to 9.0 magnitude. (iii) Some buildings did not collapse but their location hampered the design of the city, so they decided to push them down and reconstruct. (iv) Keeping original structure as it is but they brought some other styles of architecture to diversify Qiang Zhai tourism product.

PS 9: Hidyat et al.[55] describe the role of key stakeholders in project management during post-disaster reconstruction like project financing and design to start the reconstruction. Additionally, they have identified key challenges during post-disaster reconstruction like policies, construction budget/cost, labor cost, coordination, communication, and political environment. In the end, they have explained 10 critical success factors that must be taken into account during post-disaster reconstruction which are: effective institutional arrangement, coordination and collaboration, supportive laws and regulations, effective information management system, competencies of managers and team members, effective consultation with key stakeholders and target beneficiaries, effective communication mechanism, clearly defined goals and commitments by key stakeholders, effective logistic management and sufficient mobilization and disbursement of a resource.

PS 10: In this paper authors [76] Z.Li et al. have proposed a mechanism for the post-earthquake reconstruction of the building to take care of the environment (like the natural environment, social environment, economic and cultural environment) and fulfill basic requirements like reconstruction of sites, the planning system, local culture, building, and environment design, physiological reconstructions and establish a good social and cultural environment to improve peoples quality of life. At last, the authors have validated the approach to the Wenchuan earthquake reconstruction planning.

PS 11: In this paper [84] Shaker Mahmood et al. proposed an approach called 'Intelligent Master Planning for Disaster Afflicted Area' that's heavily relied on state-of-the-art remote sensing and GIS technologies, including the use of computer-based data sheets and analytical tools such as MS Excel and SPSS. They have used 14 different assessment criteria (Time Saving, Effective in disaster afflicted difficult areas, Resource mobilization at the start of a project, Involvement of manpower resources, Maps updating and reproduction, Statistical and analytically choices and opportunities, Spatial data analysis, and thematic maps production, Graphics, and illustrative capabilities, Data transfer-ability, Periodic revision of plan and updating facility, Quick and rational decision-making abilities, Degree of public participation, Spatial and statistical data coverage, Conformity and adaptability with the cutting-edge technologies) on the behalf of all those criteria IMP proved more advantages then CMP. Therefore the study proposed the adoption of IMP as a modular approach, time-efficient, intelligent, detailed, and disaster sensitive.

PS 12: In this paper [48] Benedict et al. propose a generic decision support model dealing with various sectors (education, housing, and health) that could need after disaster applied through software module to automatically assign a priority value to sets of reconstruction projects in a post-disaster phase. The objective is to support the decision-makers that are not experts in post-disaster management and that have to take complex decisions related to many parameters: evolution of the disaster effects, population needs in different vital sectors, etc. The Multi-Criteria Decision Making process is basically decomposed into Modeling Phase and Exploitation Phase. They have developed a tool by using Myriad which is based on post-disaster methodologies characteristics and consider only high priority sectors like housings, health, education, transportation, energy, water, food, and entertainment. This approach is implemented in the Destriero project demonstrator to support the prioritization of the reconstruction project after a combination of disasters near Madrid.

PS 13: In this paper authors [35] have presented an agent-based model approach that aims to meet the objectives of stakeholders while decreasing the community's economic vulnerability. Agent behavior considers three assumptions which are (i) Agents are interdependent, (ii) Agents follow simple rules, (iii) Agents are adaptive. In addition, the model presents Local Disaster Recovery Management (LDRM), State Disaster Recovery Coordinator (SDRC), and Federal Disaster Recovery Coordinator (FDRC). Accordingly, the proposed model adopts a five-step research methodology: (1) implementing a comprehensive economic vulnerability assessment tool; (2) developing the objective functions and learning algorithms of the associated stakeholders; (3) modeling the different attributes and potential strategies of the various stakeholders; (4) creating an interdependent agent-based model that simulates the aforementioned information; and (5) interpreting and analyzing the results generated from the developed model. The model is developed and tested on the post-Katrina (storm inside the see) residential housing and economic-financial recovery in three Mississippi coastal counties.

PS 14: Bailu et al. [9] proposes theoretical model for post-disaster planning using regional and local level plans. The suggested model consists of three phases which are enabling phase, reconstruction planning phase, and reconstruction implementation phase. The main focus of this proposed framework is to make effective management during post-disaster housing reconstruction.

PS 15: Bénédicte et al. [49] proposed a multi-criteria decision model to take a complex decision in a post-disaster situation to reconstruct the damaged area by considering several parameters like damage level in the affected area (number of damaged houses, schools, hospitals, and transportation), the interconnection between damage buildings and to prioritize reconstruction projects. They have validated this model on fictive examples but later they will do it evaluation on real data.

PS 16: Michael et al. [31] describe the overall government reconstruction plan after a massive earthquake in Wenchuan in western China. In this reconstruction strategy's poverty of affected people is the main attribute due to this they have given priority to settling rural areas first to facilitate poor people. According to research although some resources were not used for the poor population because resources were allocated on behalf of damage assessment.

PS 17: Colin et al. [27] have described about community participation in reconstruction planning. According to this approach "where", "why" and "how" users can be involved in the technical design process and decision making where their contribution leads to positive results and outcomes. Colin et al. [27] have validated this approach on four different post-disaster housing reconstruction projects: one in Colombia, one in El Salvador, and two in Turkey.

PS 18: Qiushan et al. [75] describes post-disaster housing reconstruction mechanism and policy implementation in Dujiangyan central city. In this model, multiple entities (like market and social institutions) played a vital role in the economic and early completion of buildings reconstruction. But this paper is just elaborating on conventional methods not taking into account cutting-edge technologies to handle the post-disaster situation.

PS 19: Yosuke et al. [56] describe socio-economic and spatial polarisation framework which is used to recover damaged houses including reconstruction policy which has been defined after Great Hanshin Earthquake in Japan. In this framework, the two-tier policy is introduced one is a self-help group where people can reconstruct their own houses at market price and the second one is public housing or residential welfare housing directly provided to poor and needy people after reconstruction.

PS 20: Yuko et al. [96] present social capital role in post-disaster rehabilitation and reconstruction. According to this model people actively participate and are deeply involved in reconstruction programs to make a successful and speedy recovery. Additionally, in this reconstruction model, people have the highest satisfaction rate as well rehabilitation speed. This model is successfully validated in Kobe (Japan) and Gujarat (India) earthquakes.

PS 21: Yan et al. [18] proposed a framework for managing resources during post-disaster situations including stakeholders' needs, legislation, and policy for reconstruction, the capacity of the construction industry to rebuild the buildings, enhance the capacity of a transportation network, and incorporate environmental considerations to reconstruct damaged infrastructure and buildings. According to authors [18] the main motivation behind this framework is the post-Wenchuan earthquake reconstruction process because they have faced a bottleneck to manage resources.

PS 22: Cassidy et al. [62] proposes a framework for strategic planning to make temporary houses in a post-disaster situation by considering physical, social, economic, and organizational aspects.

For analysis of this framework, six case studies have been considered for temporary housing which is Greece in 1986, Turkey and Colombia in 1999, Japan in 1995, Mexico in 1985, and Italy in 1976.

PS 23: Muhammad et al. [112] describes owner-driven reconstruction approach after 2005 Kashmir and 2013 Awaran earthquakes in Pakistan. This approach is based on private housing and become very successful for safe housing and to complete reconstruction in time. But still, there was a delay in some buildings because of the participation of different agencies and took time in decision-making and coordination about the reconstruction process.

PS 24: Styliani et al. [128] proposed a methodology by using Unmanned Aerial Vehicles (UAV) for 3D modeling of damage or collapsed buildings for reconstruction. In this method, they have used commercial and open-source tools for 3D modeling and computational time is very fast depending upon the number of damaged infrastructure.

PS 25: Tavakkol et al. [123] have used the entropy method for posy-disaster decision making in the proposed framework to define prioritization strategy about damaged bridges or buildings on behalf of available data. They applied the proposed framework to the Nisqually earthquake.

PS 26: According to Min et al. [52] post-disaster reconstruction process after the 5.12 Wenchuan earthquake was really difficult, complex, and time taking. In their research, they took public opinions during the reconstruction process to consider their social benefits.

PS 27: Camilla et al. [108] introduced a framework where they have proposed the use of collaborative photogrammetry to involve disaster-affected people during the planning and reconstruction process. They have validated this approach in sample small data set by a group of citizen-scientists after the 2016 Central Italy earthquake.

PS 28: Xiaoming et al. [144] have proposed an optimization model by using Bean Optimization Algorithm (BOA) based on fuzzy preference relation. According to this model in a post-disaster situation reconstruction of public services will get priority. The proposed model is validated post-earthquake reconstruction in China.

PS 29: Wensheng et al. [145] proposed framework called post-disaster reconstruction planning supporting system (PRPSS) to reconstruct damaged buildings supporting system by using 3S technique planning for information extraction of the damaged area, assessment of damage cost, reconstruction planning, and so on.

PS 30: Vahid et al. [2] proposed an innovative polynomial-time online algorithm for road reconstruction in a post-disaster situation because roads play a vital role to evacuate people and reconstructing damaged buildings. Additionally, they [2] have checked the performance of the proposed algorithm with others on the Istanbul road network and show its performance is much superior to others.

PS 31: Chengqing et al. [80] have proposed reinforcement measures and suggestions during post-disaster reconstruction after the M8.1 earthquake happened near Pokhara, Nepal. They have used finite element software for reconstruction modeling. Additionally, they have considered the transmission path of structure, stiffness, consistency of structure, and site selection.

PS 32: Mouloud et al. [86] proposed a BIM-based post-disaster reconstruction framework called Virtual Permitting Framework (VPF) to improve the quality and to recover damage assets. VPF consisted of five components which are: (i) Buildings inspection and damage assessment (ii) classification of damages into different groups (iii) database of damaged buildings (storage) (iv) reconstruction type with local state regulation (v) virtual permitting (vi) decision about approval/rejection of construction unit. The proposed framework was successfully validated on the city of Gainesville data set.

PS 33: Abdulquadri et al. [10] present a methodical framework for effective management and for reconstruction of buildings in post-disaster situation. Key attributes in the proposed framework are effective management during reconstruction, consideration of affected communities, and involvement of all key stakeholders to take input for the reconstruction plan.

PS 34: Zhen et al. [77] present an approach for residential environment planning by considering reconstruction site, planning of the system, maintaining local culture, building design, psychological reconstruction, and keeping intact social and cultural environment for establishing a good quality of life of local residents.

PS 35: Ren et al. [136] present an approach that is based on a collection of information like the design before reconstruction, required stiffness of walls which is increased by using cement, technical regulation for reconstruction are considered.

PS 36: Pan et al. [101] have described the "hematopoietic type" post-disaster reconstruction model which is used in Wenchuan County in Longmen mountain of Sichuan province. In this model, key attributes are infrastructure improvement, education, environment. economic growth, and protection of historical and cultural aspects.

PS 37: Yin et al. [141] present CM-agent model approach that is used to solve construction management problem in post-disaster situation. Additionally, this model has the capability to work on "sound and rapid" (without any influence of other stakeholders) construction requirements, can solve public project management problems, and ensures the execution of public projects successfully in post-disaster reconstruction.

PS 38: The approach proposed by Feng et al. [37] for post-disaster reconstruction in Lueyang county based on analyses of rebuilding houses layout and reconstructing low-cost and affordable houses on a priority basis.

PS 39: Li et al. [74] present an approach that gives the accurate design of rural housing reconstruction with respect to the lifestyle of residential users. Additionally, housing reconstruction becomes a source of economic revelry including ecological and energy-saving technique for making an economical residence.

PS 40: Akio et al. [29] proposed an approach to speed up reconstruction in at Sanriku coast areas that were affected by Great East Japan Earthquake. They have followed two policies in this model, first one is a 3D model to visualize reconstruction plans and the second one is to train the local people that can build 3D models for reconstruction plans by considering all basic entities s like roads, bridges, railways, and buildings.

PS 41: Masashi et al. [121] have proposed an approach to reconstruct damaged buildings after one year of the 2016 Kumamoto earthquake after gathering information with the help of high-resolution satellite data of Worldview-3. They have used Gray-Level Co-occurrence Matrix (GLCM) for calculation of texture index, and analysis shows there is too much difference with respect to building damage level and recovery situation.

PS 42: Yue et al. [43] reviews post-disaster management strategies for the analysis and management by using a top-down approach after the 2008 Wenchuan Earthquake. For this purpose, they have used two different plans which are "Overall Plan for Post-Wenchuan Earthquake Recovery" and "Reconstruction and the City/I-own System Plan for Post-Wenchuan Earthquake Recovery and Reconstruction" by considering different strategies to make reconstruction plan on behalf of available resources and funds.

PS 43: Milad et al. [142] proposed an approach for reconstruction of roads including estimation of repairing cost on behalf of total damage area in a post-disaster situation. In this approach, they also consider bridges, tunnels, and pavements as a part of roads reconstruction. Additionally, they [142] also describe rehabilitation duration for reconstruction with cost.

PS 44: Lixiong [81] proposed framework for post-earthquake reconstruction which claims proper institutional arrangements can make reconstruction and recovery process fast. They justified their claim with Weizhou Town reconstruction which is consisted of both long-term and short-term reconstruction of a public building with public facilities. Additionally, this approach is a much better top-down approach and rapid reconstruction process.

PS 45: Wei et al. [17] proposed a mechanism for post-disaster reconstruction based on an index system to restore the living and to reconstruct damaged buildings and other facilities. They [17] have used the quintile grading method to improve the accuracy of the model by using the DIDF method. Validation of this approach is done by empirical analysis of China's 31 provinces.

PS 46: Ghannad et al. [45] proposed a post-disaster recovery model to define the priority of reconstruction plans of damage projects/facilities on behalf of socioeconomic factors of affected communities with minimum time and cost. They have used AHP(Analytical Hierarchy Process) for decision making, and an optimization model for resource allocation. For evaluation, they have applied this model on counties (called parishes) data. In [45] they didn't consider damage physical dependencies among reconstruction units and their priority to reconstruct but our model explicitly considering.

PS 47: Rodriguez et al. in [114] proposed a model for the reconstruction of roads and removing debris in a post-disaster situation. They have used the two-stage methodology Steiner Tree Model (to check roads that need to be reconstructed first) and Scheduling Algorithm (Scheduling for restoring roads and crews assignment). For verification, they applied this technique on 1994 Northridge California Earthquake data.

PS 48: Mejri et al. [85] proposed an innovative approach for the dynamic evolution of disasters to assess post-damage facilities to help planners for making the right decision on behalf of available information. They have used web-based technologies for the collection and analysis of damage territory data. For validation of this approach, they have used Tacloban city data in the Philippines which was affected by Super Typhoon Haiyan in November 2013.

PS 49: Ghannad et al. [44] present an approach to prioritize damage facilities on behalf of social and economic benefits including resource allocation for reconstruction in a post-disaster situation. They have validated this model with the help of different tools like the Federal Emergency Management Agency and GIS.

PS 50: Lyons et al. [83] proposed a framework for post-disaster reconstruction called "Building Back Better" which considers five different attributes before starting reconstruction of any damaged unit. Those attributes are financial/economic, social, organizational, and environmental.

PS 51: Vahanvati et al. [125] proposed an approach for reconstruction planning which consists of four steps: (i) use 'agile approach for planning and implementation (ii) specific time for gaining community trust (iii) usage of technologies, expert labor and quality material for hazard-safety housing (iv) capacity building of community until reconstruction work complete. Authors have validated this approach [125] on four different case studies.

PS 52: Ghulam et al. [92] proposed an approach for post-earthquake reconstruction planning by using the DDQN reinforcement learning algorithm. In this approach, they have considered all compulsory attributes like social benefits of affected people, political priority, time, and cost to reconstruct damaged buildings and roads. They have validated the approach by applying it to L'Aquila city which was affected by the earthquake in 2009.

Chapter 4

REPAIR Methodology

For post-disaster reconstruction activities, we developed *REPAIR* approach that considers damaged infrastructures to reconstruct such as buildings, roads, and bridges. Our approach is new and innovative by using reinforcement learning algorithm (DDQN) which considers all key attributes required for the reconstruction process/plans like time, cost, social benefits of affected people, physical dependencies, and political priority of each unit.

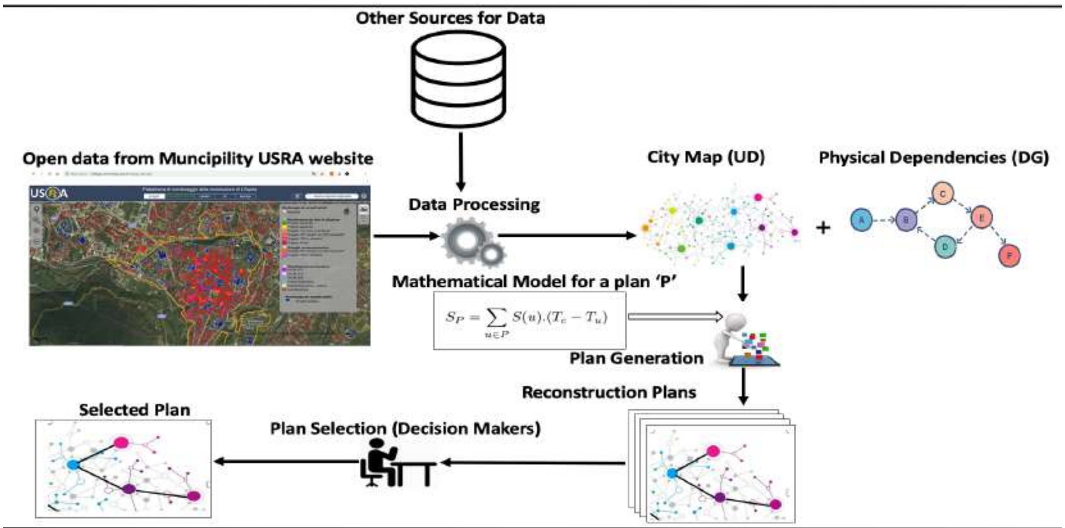


Figure 4.1: Proposed methodology

If we make analysis of these generated plans with *REPAIR* approach and manual recovery plan. We come to know that manual recovery plan always challenging for public decision makers to keep balances all the involved formal and informal requirements that guarantees the repopulating of the damaged area. Additionally, another unconsidered aspect in manual recovery plan , that instead should be taken into account by the public decision makers, is the societal impact and relative benefits that citizens experience from the implementation of a certain recovery plan. Indeed, the societal impact and benefits are different from one plan to another, and they should be key feature to consider in all post-disaster phases. And *REPAIR* approach generated plans covering all these aspects successfully.

REPAIR methodology is sketched in fig.4.1. It consists of three key steps: *i)* `Data extraction and processing` (detailed in section 4.2) whose aim is to generate an undirected graph to represent the area to reconstruct and its physical dependencies. In this step, data from Web Geographic Information System and from other sources are used; *ii)* `Plans generation` that, using deep reinforcement learning (namely, double deep Q-Learning), generates multiple reconstruction plans. The generation step leverages on an optimization model that maximizes the social benefit metric (details on the optimization model are provided in section 4.3). In last step, namely *iii)* `Plan selection` step (discussed in section 4.4), generated plans are proposed to the decision-makers for the selection of the plan to actuate.

The REPAIR approach is novel for two main reasons: firstly it uses reinforcement learning to determine reconstruction plans and secondly because it considers in the plan generation novel key concepts, namely social benefits, physical dependencies and political priority that we define in details in section 4.1.

4.1 Definitions of Key Concepts

Here following we have defined the key concepts our approach leverage on, that are *Physical Dependencies*, *Political Strategies* and *Social Benefits*.

4.1.1 Physical Dependencies

Physical Dependencies enable to specify reconstruction order among reconstruction units (such as buildings, roads, bridges, etc.). For example, if a bridge is damaged by a natural disaster, it is compulsory to reconstruct it first to access other destroyed buildings [14]. Again, if the disaster damages the historical center of a small village, there could be some physical dependencies among ancient houses that in general are very close to each other, hence a reconstruction order should be mandatory. To model all such situations, we introduce Physical Dependencies that are modeled as a directed graph. Fig. 4.2 shows a simple example of one of such situations. On the left side of the figure, it is reported a map where there is a bridge through which it is possible to access a hospital, a university, and a supermarket (i.s., CONAD). The map is enriched with information on the status of the city buildings and infrastructure (such as the bridge). In particular, the bridge, the hospital, and the university buildings have been destroyed by the disaster (as indicated by *status=0* label), whereas the CONAD supermarket does not need to be reconstructed (indicated by *status=1* label). In a post-disaster situation, the reconstruction of a hospital or university is not convenient because the bridge, that is the main access to these buildings, is damaged, hence bridge comes first in reconstruction.

4.1.2 Political Priority

Political Priority models the political strategy to follow. It associates with all reconstruction units and represents the political importance of every unit for the specific strategy. It is modeled as an attribute whose value is an integer in the range $[1, 10]$. By giving different political priority values to buildings we are able to represent different political strategies. Let us make an example of political priority: the decision-makers together with policy actors decide that the reconstruction must give priority to public services such as health and educational services, and then to private residences and finally to private and commercial services. This strategy is implemented by giving different

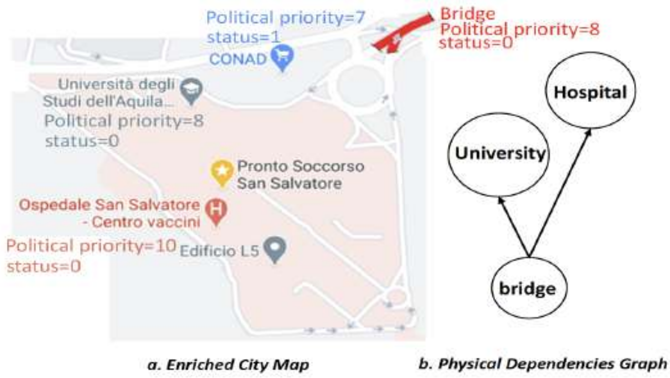


Figure 4.2: Physical dependencies modeling

values to the priority attribute of reconstruction units and imposing a constraint on the political priority of the whole plan (let's say that the acceptable plans are the ones whose political priority is higher than 80%). Referring to Fig. 4.2, here political strategy is modeled by giving 10 political priority to the Hospital, 8 to the Bridge and to the University of L'Aquila, and 7 to the CONAD supermarket (if it is damaged).

4.1.3 Social Benefits

Social Benefits is defined as "*the total benefit to society from producing or consuming a good/service. It includes all the private benefits plus any external benefits of production/consumption.[...]*[1]." In our work, Social Benefits is a metric that quantifies the benefits gained by the affected community from a reconfiguration plan. It is defined as the average number of citizens per day that will benefit directly and indirectly from the plan. For example, when we rebuild a school, the number of people that gain benefits from this reconstruction is related primarily to the school staff and students, then to the students' parents and relatives, and finally to the shops and services near the school, including citizens living in the neighborhood.

The social benefit $S(u)$ of the u reconstruction unit starts to accrue benefits at time T_u when the reconstruction of unit u is finished. Whereas, the social benefit of a plan is a cumulative function (as defined in equation 4.1) depending on the order of the reconstruction of the selected units.

Fig.4.3 shows the social benefits of two reconstruction plans that contain the same set of reconstruction units (hospital(h), school(s), and cinema(c)) rebuilt following a different temporary order. In the figure, the x-axis shows the reconstruction time of the units, in terms of years. 0 indicates the starting of the *recovery* phases. T_e is the time we have to complete the reconstruction plan. T_h, T_s and T_c represent the time needed to reconstruct the hospital, school, and cinema, respectively. For the sake of example, we fix $T_e = 6$ years, $T_h = 2$ years, $T_s = 1.5$ years and $T_c = 1$ year. In the figure, the y-axis shows the social benefit of reconstruction units. For the sake of example, we fix $S(h) = 2000$, $S(s) = 1000$ and $S(c) = 600$ people.

No social benefit is awarded until a unit is reconstructed. In plan P_1 the first unit reconstructed is the 'Hospital' completed in $T_h = 2$ years. After the completion of 'Hospital', we start getting $S(h) = 2000$ social benefits until the end. The completion of following units (school and cinema) will amplify the total benefit after $T_s = 1.5$ and $T_c = 1$ time. In this case, the social benefit of the

[1]https://www.economicshelp.org/blog/glossary/social-benefit/

plan is determined by the area dashed in Fig. 4.3.a that in our example is equal to 11400. In plan P_2, we have the same units but different reconstruction order: first, it is reconstructed the 'School', then the 'Cinema' and finally the 'Hospital'. In this case, the social benefit of P_2 is equal to 9600. Hence, in our example, the most beneficial plan is P_1.

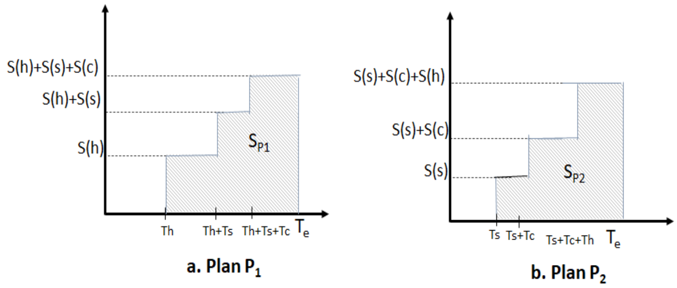


Figure 4.3: Social benefits of plan P_1 and plan P_2

4.2 Data Extraction and Processing

Data extraction and processing consist on three steps which are: (i) Generation of graph from GIS data (GisToGraph, in section 4.2.1) and (ii) Cleaning and add missing data from other sources data (as described in section 4.2.2). In section 4.2.3, we formally define the graph used as input data model in our approach. Because initial map doesn't contain all the required information's that's why we need to pass through data extraction process.

4.2.1 GisToGraph

The available information in the form of GIS data relating to a damaged city needs to be transformed into a network structure that incorporates useful information for subsequent phases of evacuation and reconstruction. The resulting network, called *Enriched Undirected Graph* (EUG), helps the effective manipulation of information in all such phases.

The EUG of the damaged area is built in two steps [58]: (i) collection of the required information of the city that is needed for reconstruction (such data could come from shapefiles or other city's data repositories); (ii) by using the *GisToGraph* algorithm we transform these input data into the nodes, edges, and other attributes of the EUG.

The generated EUG is really helpful for the decision support system in finding out damaged buildings/units and roads during the recovery and reconstruction phase. Additionally, the EUG is enriched with other information like the damage level of buildings and roads that are useful for reconstruction planning including the number of affected people.

Geographical data which describes a city is mostly available in some specific spatial data format (e.g. shapefiles). All geographical features inside spatial data are described as geometric elements (Points, Linestrings, and Polygons), flanked by textual attributes. The object-oriented modeling approach is used to organize collections of simple features: the crossroads as points, the streets as lines, the sets of points of interest as points or polygons, and the sets of census areas as polygons, respectively.

Additionally, besides this main data, it is necessary to add other textual information which is required for disaster management to start reconstruction planning in an emergency situation, in particular we added following:

- road length and width: are useful to understand how many people a road can contain at a given time;
- people in buildings: to estimate the number of people in any particular building during a disaster;
- time of reconstruction: time to reconstruct any building after a disaster occurred;
- building state: state of a building under reconstruction;
- state of reconstruction;
- the required amount for reconstructing the building and the amount actually granted;
- practicability of the building such as hospital, schools, banks and offices;
- type of the buildings: useful to give priority to the buildings in the reconstruction phase.

4.2.2 Cleaning and add Missing data

In second step we have cleaned the extracted information's from GisToGraph algorithm data like damage units, physical dependencies and other unit attributes (number of people, cost and time for reconstruction) which is downloadable online as shapefiles[2], enriched by additional shapefiles provided by urban planners. In this step, we have also used an adapted version of the work published in [58]. The extracted information's are saved in .CSV and .XLSX files.

During the data extraction process, all the information related to the disaster (such as unit status, reconstruction cost and time, and physical dependencies graph) might not be extracted from the shapefiles. For this purpose, we have also used data from other sources which is not available in shapefiles. All the required information needed for the reconstruction planning model is not directly available as external data. For this reason, we implemented a script in the second step to completes the input data with the following information:

- it determines the unit status s_v on behalf of vulnerability index of a building v. The script assigns status equal to 0, to all units having vulnerability index between 0 and 3, and 1 otherwise.
- reconstruction of *cost* and *time* of a node v is determined by following the approach described by M. Polese et al. in [109];
- *politically priority* is integrated into the dataset according to the type of the buildings [30];
- on the basis of the obtained units' status, we are able to generate the physical dependencies graph G'.

[2]http://opendata.regione.abruzzo.it/catalog

4.2.3 Undirected Graph as representation of the damaged area

The proposed approach requires an undirected graph G representing the city, physical dependencies graph G' (directed graph) between damaged units, and the units' attributes. We have considered nodes as a units and edge as road. Each node contain five attributes and edge contain four attributes as shown in Table. 4.1. Additionally, we have used different color specifications to identify damage units and physical dependencies (roads or bridges). For this purpose red color nodes represent damaged units/buildings and green shows fine/reconstructed ones. Similarly, red dotted edges represent damaged roads/dependencies including length, and dark black shows fine/reconstructed ones (detail explanation in Chapter 5 subsection 5.3.1).

Table 4.1: Undirected graph attributes detail

Graph Element	Attribute	Attribute Description
Node	Damage Level	Vulnerability level from 0 to 5
	Political Priority	Value is set 1 to 10 for each unit
	Number of People Living	Number of residents
	Cost for reconstruction of units	Required budget to reconstruct
	Time for reconstruction of units	Required time to reconstruct
Edge	Damage Level	Slightly, partially or fully damage
	Distance between between units	Buildings distance between each other
	Cost to reconstruct physical dependency	Cost of reconstruction
	Time to reconstruct physical dependency	Required time to reconstruct

4.3 Plan Generation: the used Mathematical Model

In the `Plan generation` step, REPAIR approach, leveraging on an optimization model, generates several reconstruction plans that satisfy all the constraints and maintain high social benefits. In the following sections, we provide details of the optimization model while the approach we implemented to solve it is deeply described in Chapter 5. We used a reinforcement learning algorithm (DDQN) that allowed us to generates many plans that are sub-optimal, i.e., that satisfy all the posed constraints and show high social benefit.

4.3.1 Optimization Model Formulation

The model we propose is based on a undirected graphs $G(V, E)$ representing the damaged area where nodes $v \in V$ indicate reconstruction units (such as buildings, roads, bridges, etc.) and edges $e \in E$ represent connections among them. Table 4.2 reports all variables and attributes we use in the following mathematical modeling.

We formulate our problem as an optimization model that determines a plan P satisfying all the constraints (related to time, budget, physical dependencies, etc.) and maximizing its social benefits S_P.

Table 4.2: Mathematical notations

Notation	Definition
V	Set of vertices v, that represent reconstruction units (e.g, building, hospital, bridge).
E	Set of edge e=(v_1, v_2), that represents connections between two reconstruction units, namely v_1 and v_2.
s_v	$s_v \in \{0, 1\}$ represents the status of v, if $s_v = 1$ then v is a not damaged or its reconstruction is completed.
T_v	the time needed to reconstruct v. If $s_v = 1$, T_v is zero.
c_v	Established cost for the reconstruction of v. $s_v = 1$, c_v is zero.
p_v	political priority of v: $p_v \in \{1, 2 \cdots 10\}$ where 1 represents *Low Priority* and 10 represents *Highest Priority*.
b_v	Number of people that take direct advantage of $v, b_v \in N$. If v is a residence building, b_v represents the number of people having the residence in v.
$S(v)$	Number of people that take directly and indirectly advantage after the reconstruction of $v, S(v) \in N$.
$d(v_1, v_2)$	Function returning the distance between v_1 and v_2 reconstruction units, v_1 and $v_2 \in V$xV. Such distance is calculated considering the minimum path connecting v_1 and v_2.
P	P represents the generated plan specified as an ordered list of reconstruction units $[v_1, v_2, ..., V_n]$
S_p	Social benefits of a plan P
T_e	Ending time of the reconstruction plan
G'	G'=(V', E') is the physical dependencies graph where $V' \subseteq V$ and E' is a set of edge $e' = (v'_1, v'_2)$ representing that v'_1 cannot be reconstructed before v'_2, as described in Section 4.1. Differently from G, G' is a direct graph.

Objective function

The social benefit of a plan P is defined as:

$$S_P = \sum_{v \in P} S(v).(T_e - T_v) \tag{4.1}$$

where:

- $S(v) = S_v$ if v has not been damaged by the natural disaster; otherwise
  $S(v) = S_r(v)$ defined in equation 4.2, if v has been damaged by the natural disaster. $S_r(v)$ (see Eq. 4.2) combines the number of people taking benefits directly from the unit v (i.e. S_v) with the ones taking benefits indirectly from it. The people taking benefits indirectly are those people living/working in the neighborhood normalized by the distance. In equation 4.2, α and β are constants that determine the weights of the two social benefit components S_v and the neighborhood function.

- $(T_e - T_v)$ represents the time where the social benefit of reconstructed unit v is awarded to the population.

$$S_r(v) = \left[\alpha.b_v + \beta \left(\sum_{u \in V | s_u = 1} \frac{S(u)}{d(u,v)} \right) \right] \tag{4.2}$$

where:

$$\alpha, \beta \in [0,1],\ \alpha + \beta = 1$$

4.3.2 Model Constraints

The proposed approach has several constraints which must be satisfied in every reconstruction plan. They are as follows:

- **Cost:** it refers to the *Budget* limit, determined by the government's annual financial statements, set aside for the reconstruction of the territories affected by the natural disaster. The total cost of the plan (or a set of plans) must be less than or equal to defined *Budget*. Such constraint is expresses as follows:

$$\sum_{v \in P} C_v \leq Budget \tag{4.3}$$

- **Plan duration:** to accelerate the reconstruction, governments can set constraints on the plan(s) duration. This constraint is represented as:

$$\sum_{v \in P} T_v \leq T_e \tag{4.4}$$

- **Political strategy:** as we discusses in Section 4.1, our approach enables to model political strategies. To this aim, each unit v is associated with political priority p_v and each plan must satisfy the following constraint:

$$\frac{\sum_{v \in P} P_v}{|P|} \geq Th_p \tag{4.5}$$

  where Th_p is a threshold forcing the desired political strategy. In evaluation (Chapter 6), we fix Th_p to 8. This guarantees that the 80% political strategy must be satisfied in every plan.

- **Physical dependencies:** if any street has width less than 3 meters and there are many buildings to be reconstructed, in this case all the damaged buildings are supposed to be constructed in a specific order that will be decided based on the actual condition of the road. We cannot start from the building in the middle of the street because the next damaged buildings will not be accessible. Additionally, political priority of all buildings in that street will be same. According to this, every plan must respect the dependencies represented by the graph $G' = (V', E')$. This constraint is modelled as:

$$\begin{gathered} \forall\ v \in P,\ \nexists\ e \in E'\ such\ that \\ e = (v, \overline{v}),\ s_{\overline{v}=0\ and\ \overline{v} \notin P} \end{gathered} \tag{4.6}$$

4.4 Plans Selection

In the plan generation step, we get multiple alternative reconstruction plans on behalf of mathematical model and DDQN algorithm. Then, all these plans are handed over to decision-makers (politicians and citizens) to select the best one to execute which considers more social benefits of affected community.

REPAIR approach provides more than one plan to the decision makers because boundary constraints (such as, geological information of the territories or unevenness of the land) could not be modelled in the mathematical model. Moreover, all the generated plans consider buildings as separate block while one can decide to give priority to a specific area considering groups of buildings as a whole and giving the same political priority to all reconstruction units belonging to that group. Additionally, in the current version of the approach, plans include every kind of buildings such as public or private buildings and infrastructure elements destroyed by the natural disaster.

Hence we decide to device an approach that provides a set of plans guaranteeing the satisfaction of posed constraints including a high benefits for the community, but at the end we leave to humans to select the final plan to execute.

Chapter 5

REPAIR Plan Generation: a Reinforcement Learning Implementation

In this chapter, we present the reinforcement learning algorithm (double deep Q-Learning Network) which is used to generates the plans starting from the optimization model we formulate in Chapter 4 (see section 4.3.1). Here following first we have described the brief concept of DDQN.

5.1 Double Deep Q-Learning Network (DDQN)

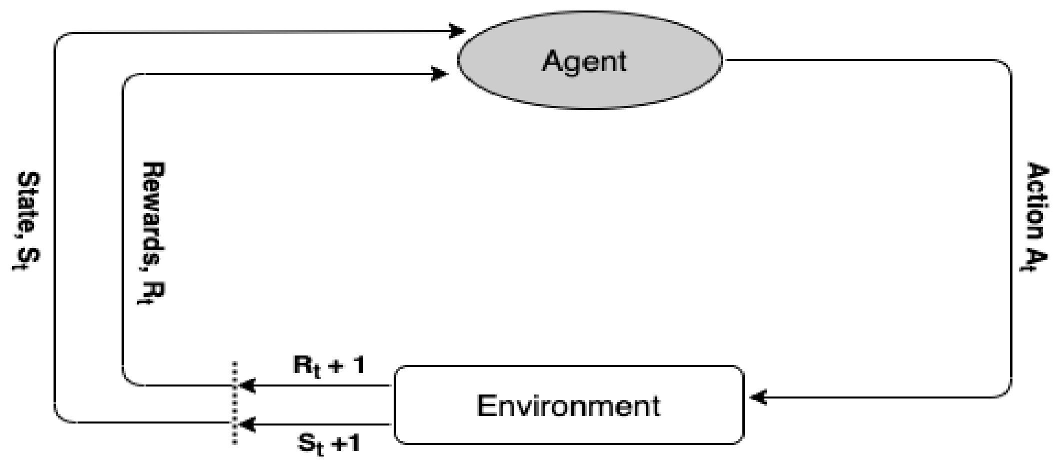


Figure 5.1: Reinforcement learning process

Double Deep Q-Learning (DDQN) also known as Dueling Deep Q-Learning is the class of reinforcement learning as mentioned in subsection 2.2.2. It is a model-free or off-policy reinforcement learning algorithm. Because it doesn't need any prior model for learning, in fact, it learns through actions feedback which is performed by an agent.

Figure 5.1 represents the general framework of the reinforcement learning process. In this framework, *Agent* is the main entity in any reinforcement learning algorithm which shows the process needs to learn. *Environment* is the *agent* space or system with which it interacts. According to Figure 5.1 when an agent performs an action within an environment then get *Reward* as a result of that action. In each action, agents move from one step to another. The most critical thing in reinforcement learning algorithms is to find out the appropriate states, actions, and rewards in any problem.

For example, consider we train robot (agent) to reach a particular destination in a room environment by avoiding all kinds of hurdles. *Action* in this scenario are moving left, right, front or back and *Environment* is the room space. On every action, the agent will get a high reward if it moves in the right direction by avoiding obstacles. On the other hand, when the agent/robot moves in the wrong direction or is hit with obstacles, it gets less reward as a penalty. With the help of feedback in the form of rewards, the agent/robot gets expertise and at each point, it tries to select the best action for the maximum reward to achieve the destination.

In the case of DDQN agent also don't have any model of the environment and learns through actions. We remind the reader that there are some types of reinforcement learning algorithms which are model-based means model of the environment is exclusively available for the agent [122] e.g TD learning. If we consider again previous example, the robot will not have any information about room shape and obstacles but the agent gets expertise as action goes on.

Before to provide details on the algorithm implemented in the REPAIR approach, we report on the experimental study we made in order to select the most suitable reinforcement learning algorithm to embed in REPAIR methodology. The comparison is made by considering four aspects which are: *number of iterations, reward, execution time and limitations.* The study highlighted DDQN as the best algorithm, among the considered ones, that we decided to embed in REPAIR methodology. Indeed, it showed better performance with respect to obtained reward which is higher than rest of all algorithms, execution time and not found any limitation under specified environment. Such a comparison is detailed in section 5.2.

The implementation of double deep Q-Learning Network (DDQN) is described in section 5.3 .

5.2 Comparison of reinforcement learning (RL) algorithms

In reinforcement learning (RL) various kinds of algorithms are used to solve decision-making and planning problems (like budget planning, business planning, and strategy planning). Fundamentally all these algorithms combine deep neural networks with control engineering practices to achieve decision-making power like humans or better than human decision-making power. Real-life planning and combinatorial problems are handled by using reinforcement learning algorithms with the help of maximizing or minimizing value function by taking the best possible action/decision. Typically Q-Learning, SARSA, Deep SARSA, and Double Deep Q-Networks (DDQN) are considered to solve planning and combinatorial problems by interacting with the environment by using loss function evaluation [8]. Additionally, reinforcement learning also allows online learning policy by directly interacting with environment[89]. Furthermore, various reinforcement learning methodologies have been developed which can be used to solve these kinds of problems like planning and combinatorial [127]. But here following we have explained the concept and made a performance comparison of four major algorithms including the random agent (for the verification of trained agent).

5.2.1 Considered Algorithms

In this section we briefly describe the approach we considered in the comparison study. They are:

- **Q-Learning** - Q-learning is a model-free values-based reinforcement learning algorithm that updates value function with the help of the Bellman equation. Agents keep learning and continuously improve the selection with the help of exploration and exploitation strategies.

- **DDQN** Double Deep Q-learning is the class of reinforcement learning. It is also a model-free or off-policy reinforcement learning algorithm. Already explained in subsection 5.1.
- **SARSA (State-Action-Reward-State-Action)** - SARSA is an on-policy reinforcement learning algorithm that updates Q-table value on single step reward $r + 1$ which is obtained by taking an action a on state s. It's also called single-step SARSA.
- **Deep SARSA** - Deep SARSA is also an on-policy reinforcement learning algorithm that calculates state action values with the help of a multi-layer neural network in order to build an optimal policy for a given agent.
- **Random Agent** - The random agent starts training from any random unit. We have used it as baseline in the comparison.

5.2.2 Experimental specification and setting

For the experimentation we have specified following settings to evaluate and analyze the performance of all these algorithms.

Experiment Specification: We have implemented reinforcement learning algorithms by using Python (Keras framework with Tensor flow backend) on a small dataset of L'Aquila (included 70 damaged buildings and 27 damaged roads because heavy dataset is not compatible with some of algorithms e.g Q-Learning).

Experimental Setup: The computational platform is Google Collab and MacBook Pro with quad-core intel core i5 processor and Intel Iris Plus Graphics 645 graphics. We trained the agent of each algorithm on behalf of the specified dataset.

5.2.3 Experiment results

The obtained experimental results from defined experimental specification and setting are shown in figure 5.2. Where, performance comparison of each algorithm is performed by training on 5000 episodes in the form of bar charts. According to *Q-Learning*, the bar chart maximum social reward goes up to 40 on the specified dataset. If we increase the size of the dataset then the size of states and actions will also be increased accordingly. Due to this, the Q-Table becomes really complex and memory would be overloaded. *Q-Learning* is not recommended for complex environment problems. On the other hand, SARSA's social reward is 35 which is less than *Q-Learning* under the same environment because SARSA follows near-optimal policy whilst exploring, and also complexity gets increased in complicated problems.

In the meanwhile, the Deep SARSA social reward chart is slightly higher than SARSA and Q-Learning because neural networks are used to store the Q-value of each action instead of Q-Table still social reward results are not that much satisfactory which is 42.

Additionally, we have also shown random agent social reward in performance comparison because we did verification of trained agent with the help of the random agent. As shown, the social reward of the random agent is also less as compared to others which are around 25 as shown in the bar chart.

In performance comparison we can see only DDQN algorithm have highest social reward which is 80 on specified dataset. That's why we have used it in our proposed *REPAIR* research model.

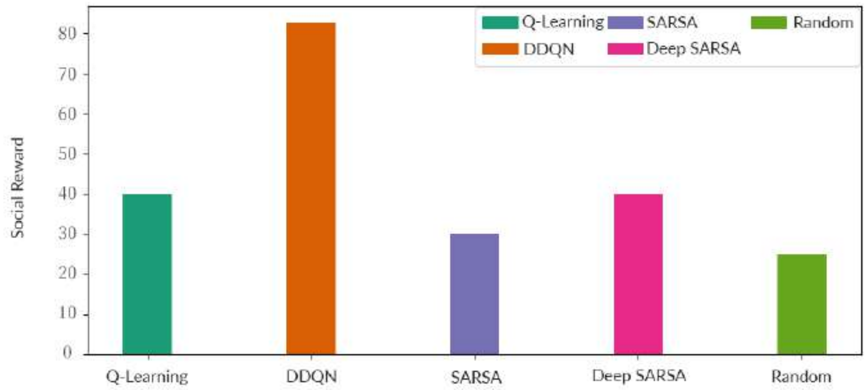


Figure 5.2: Performance comparison of RL algorithms

Table 5.1 explains the performance summary of four considered algorithms including random agent on behalf of four aspects which are *iterations, reward, time and limitations*. *Q-Learning* takes 4 hours to complete 5K iterations and at the same time memory gets overloaded in a complex environment. Similarly, *SARSA* and *Deep SARSA* training completed in 5.5 and 3.2 hours respectively, and both algorithms have computational complexity of resources and computationally expensive as well. *Random Agent* takes 3 hours to complete 5K iterations but it's time-consuming. Apart from all these DDQN results are much better because we achieved a maximum reward of 80 and takes a minimum time of 2.5 hours to complete the training process. Additionally, we also did not find any limitation with respect to our research problem.

Table 5.1: Performance comparison table

Sr.No	Algorithms	Iterations	Reward	Time(hr)	Limitations
1	Q-Learning	5000	40	4	Memory overload
2	DDQN	5000	80	2.5	Not found w.r.t *REPAIR* model
3	SARSA	5000	35	5.5	Computational Complexity
4	Deep SARSA	5000	42	3.2	Computationally Expensive
5	Random Agent	5000	25	3	Time Consuming

5.2.4 Further consideration

Additionally, since our research problem is based on a dynamic environment, DDQN is the most appropriate and suitable algorithm for the implementation of our proposed approach because we can handle dynamic and critical issue comprehensively.

5.3 Reconstruction planning by Double Deep Q-learning Network (DDQN)

We have divided reconstruction planning by Double Deep Q-learning Network (DDQN) into two subsections 5.3.1 and 5.3.2. Because visualization of the damaged area is a pre-step of reconstruction after that we define a reconstruction plan for damage units.

5.3.1 Visualization of damage area with undirected graph

After extraction of required information's from shapefiles we convert it into .XLSX and .CSV formats. We visualized damage units ID/roads on behalf of extracted information with the help of an undirected graph (see Fig. 5.3). Red color nodes represent damaged units/buildings and green shows fine/reconstructed ones. Similarly, red dotted edges represent damaged roads/dependencies including length, and dark black shows fine/reconstructed ones. Graph will update the colors on successful completion of every plan.
Here following `Algorithm 1` reports the pseudocode for visualisation of damage units in post-disaster situation.

Algorithm 1 Visualization of Damage Buildings/Roads Identification

Require: Dataset D, Constructed/Damage Building B, Constructed/Damage Roads R
Ensure:

1. Extract data from shapefiles
2. Convert extracted data into .CSV and .XLSX format

for B in G **do**
  if B(status) =0 **then**
    Damage building node will be shown in red color
  else
    Fine/reconstructed building node will be shown in green
  end if
end for
for *R in G* **do**
  if R(status) =0 **then**
    Damage road will be shown with red dotted edge;
  else
    Fine/reconstructed roads will be shown with dark black edge
  end if
end for

5.3.2 Model implementation by DDQN

Double deep Q-learning algorithm is used in our proposed approach for defining alternative reconstruction plans. In DDQN, convolutional neural networks (CNNs) are used to approximate action-value non-linear functions called Q-function [116], with the help of state, action and reward which are defined following according to our approach:
State: is a tuple depicted as `(current location, remaining budget, remaining time)`
Action: represents all possible agent moves in the action space, which is composed by `reconstruction`

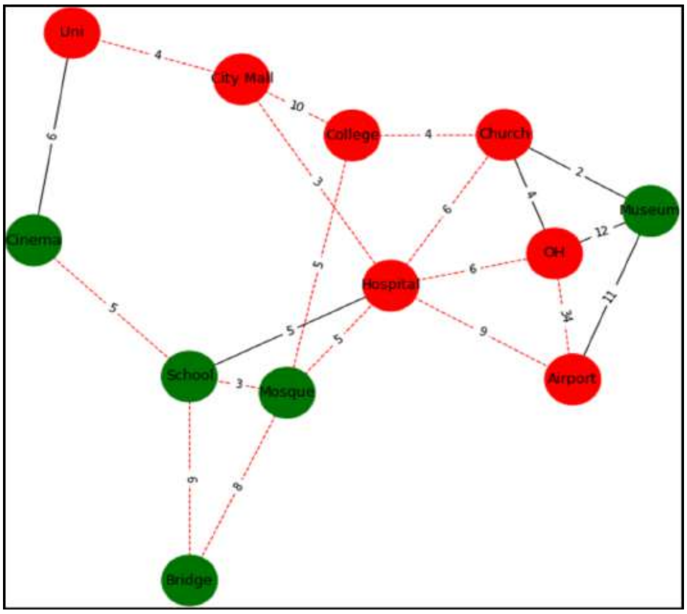


Figure 5.3: Physical dependencies modeling

`units ID`.

Reward: is the social benefit as defined in Eq. 4.2.

Agent keeps learning (one node to another) from action reward function by iteratively updating Q-value with the help of equation (5.1) which is fundamentally known as Bellman equation.

$$Q(s, a; \theta) = S_r(v) + \gamma \max_{a' \in A_v} Q'(s', a'; \theta_i^-) \tag{5.1}$$

where $a' \in \mathrm{A}_v$ and a' represents agent action to next node v which has maximum Q value. $Q(s, a; \theta)$ defines Q value of state s which is a tuple depicted as *(current location and action, remaining budget, remaining time)*, action a is *(units/roads ID)*, θ is neural network parameter, $S_r(v)$ is the immediate social reward achieved by optimal action a on behalf of current state s, γ is the discount factor that trades off the importance of immediate and later rewards, $s^{'}$ is followed by s after taking action a, and θ_i^- is the network parameter used to compute the target network. According to generic approach of reinforcement learning [89], network is trained by minimizing a sequence of loss function ($L_i(\theta_i)$) that changes at each iteration i. Loss function in DQN is the squared difference between Q-target and Q-network.

$$L_i(\theta_i) = E[(\overbrace{S_r(v) + \gamma \max_{a' \in A_v} Q'(s', a'; \theta_i^-)}^{\text{Q-target}}) - \overbrace{Q(s, a; \theta_i)}^{\text{Q-network}})]^2 \tag{5.2}$$

Here, θ_i is used to compute Q-network and θ_i^- is used for Q-target computation.

5.3.3 Customized Immediate Social Reward Function (S$_r(v)$)

The baseline of the agent in the proposed approach is random action from any damaged unit on behalf of input parameters (i.e., budget and time (Te)) and the posed constraints (such as political priority and physical dependencies). After the reconstruction of unit u, the agent searches in the neighborhood of u for the next unit 'v' to reconstruct which contains the highest social benefits.

Additionally, when the agent selects any unit 'v', it checks if the physical dependencies are satisfied, otherwise, the agent adds in the reconstruction plan and consider as a unit. The social benefit of the reconstructed dependency (bridge/road) will be added in the following (next reconstructed) unit.

Agent action space is dynamic and when an agent performs an action, the environment evaluates it according to unit attributes and returns reward to the agent itself.

5.3.4 Constraints check

The listing described in `Algorithm 2 (Part 1)` implements the constraints check. It requires input parameters which are total *'Budget'* and 'T_e', which is the maximum duration of a plan. Verification of constraints is executed when the agent selects a new node v and generates a plan. In every cycle[1], agent checks all constraints including budget and time. If conditions hold, agents continuously add to the plan damaged units until budget and time are not saturated. During the cycle, the agent also checks if there exists any *Physical dependency* among the damaged reconstruction units and determines a plan that is consistent with them. *Political priority* is another constraint which must be satisfied in every reconstruction plan ($P_v \geq 8$) [30] and each building has specific *political priority*. According to this concept, at least 80% of overall set political strategies (Th_p) should be covered in every cycle with the help of the following formula.

$$Th_p \ = (MaxP_v - TrainingCycle + 1) \times \frac{80}{100} \tag{5.3}$$

```
#USER INPUT
budget = 1000000
total_time = 500

n = 10
training_number = 1
OVERALL_PRIORITY_THRESHOLD = (n-training_number+1)*(80/100)
print(OVERALL_PRIORITY_THRESHOLD)
```

```
8.0
```

Figure 5.4: Political priority

Here $MaxP_v$ is the set maximum political priority of 'v' and $TrainingCycle$ is the round of agent training. The overall threshold of political priority is getting decreased because less beneficial buildings are considered in later cycles.

5.3.5 Post-disaster Rebuilding Planning implementation

`Algorithm 2 (Part 2)` reports the pseudo-code for rebuilding planning by using Double Deep Q-learning (DDQN) technique. During the training process replay, memory, and deep Q-networks are initialized. Post-disaster rebuilding planning agent start action from any random damage unit 'v' by considering *(part 1)* constraints. On every action Q-value (see in Eq. 5.1) gets updated on behalf of immediate social reward ($S_r(v)$) and stored in deep neural networks (DNNs) that's called *Training*. In the training process ϵ-greedy random action a selection policy is used, and on every action social reward $S_r(v)$ is calculated, and the agent moves to the next state s'.

[1]Trained agent returns alternative reconstruction plans. On successful implementation of the selected plan, the data set will be updated and the agent will be trained again to determine new reconstruction plans for the remaining damaged units. A cycle is composed of agent training and reconstruction plan successful implementation.

Additionally, approximation of Q-value is calculated by non-linear function and it is very unstable [89] due to this DNNs can be overfitted very easily. To solve this problem experience replay technique is used, it stores all the experience set $< s, a, S_r(v), s' >$ during forward pass. After that, random mini-batches will be taken from the replay store to update parameter θ by minimizing the loss function (defined in Eq. 5.2) whose aim is to handle imbalance data issue [129] and a large amount of complex data. The training process will go on until defined iterations are executed. Subsequently, *Training verification* of the trained agent is done through a random agent by running an equal number of iterations of the trained agent. Once training will be completed we get every time different *alternative reconstruction plan* (see in Eq. 4.1) from the trained dataset (called agent testing) by satisfying all the basic constraints. Furthermore, multiple sub-lists are created from the generated plan of those units which can be constructed in parallel. All those units which are part of the plan their status will get changed from '0' to '1' (in data set) after successful reconstruction, an updated data set will be created and saved in .XLSX and .CSV format. Again, the agent will be trained on the updated dataset for the remaining damaged units, and this process will go on until all units and roads/dependencies will be reconstructed.

Algorithm 2 (Part 1) Constraints computation during agent training *(REPAIR) Constraints*

Require: 'Budget' for reconstruction, Time for reconstruction 'T_e'

1. Initialize $C_v = 0$ and $T_v = 0$
2. Array List<Boolean> flag= Array List <Boolean>()

while ($C_v \leq Budget$ and $T_v \leq T_e$) **do**

Keep reconstructing units until '*Budget*' is not finished ($Budget = Budget - C_v$)

Keep reconstructing units until time 'T_e' doesn't end ($T_e = T_e - T_v$)

Political strategies must be satisfied in every reconstruction plan ($P_v \geq 8$)

Damage *physical dependencies* consider as a unit in reconstruction plan

flag.add (true)

end while

return flag

Ensure: All those units/buildings 'v' will be considered to reconstruct which satisfy constraints.

Algorithm 2 (Part 2) Post-disaster Reconstruction Planning *(REPAIR)*

Training

1. Initialise replay memory
2. Initialise Double Deep-Q Network with weights θ
3. Find **B**: set of unconstructed buildings in G and **R**: set of unconstructed roads in G

for episode =1, N **do**

Observe random initial state s

while (algorithm 2 (Part 1).size()>0) **do**

with probability ϵ select random action a

otherwise

Select $a = arg\max_{a \in A_v} Q(s, a; \theta)$

Carry out action a

Observe reward $S_r(v)$ and new state s'

ϵ - greedy action

Store experience $< s, a, S_r(v), s' >$ in replay memory

Calculate target for each mini batch

$$Set\ y_k = \begin{cases} S_r(v) & \text{for terminal } s' \\ \mathrm{S}_r(v) + \gamma \max_{a' \in A_v} Q(s', a'; \theta) & \text{otherwise} \end{cases}$$

Train the Double Deep Q-learning Network by performing gradient descent using loss function $(y_k - Q(s, a; \theta))^2$

end while

end for

Experience Replay

Training verification

4. Verification of trained agent through random agent

for episode=1, N **do**

Run random agent

end for

5. Visualize plotting results

Algorithm 2 (Part 2 - Continue) Post-disaster Reconstruction Planning *(REPAIR)*

Best alternative reconstruction plans

6. Test agent on trained dataset.

for $v \in V$ **do**

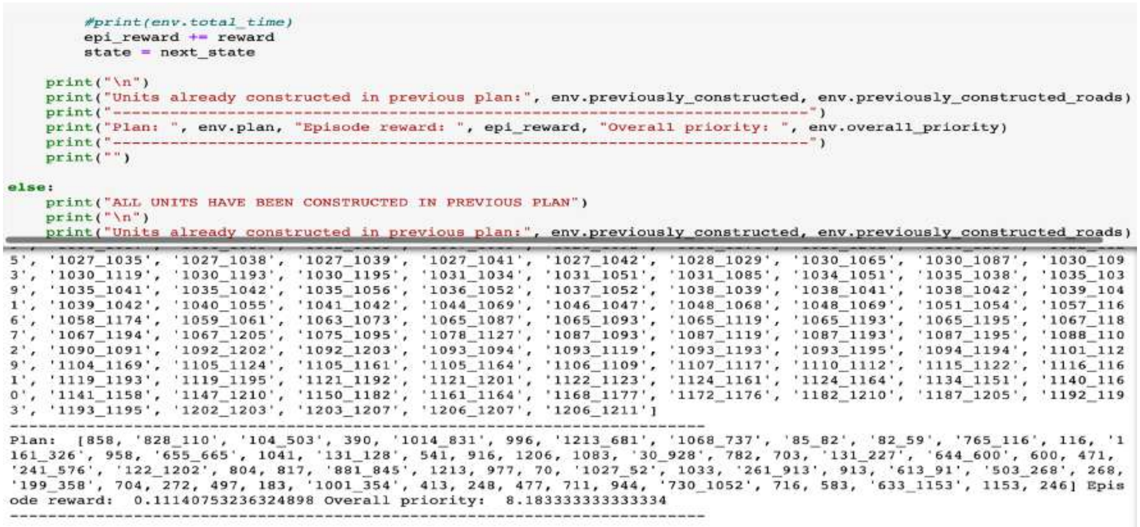
Generate reconstruction plan with maximum social benefits S_p (Eq. 4.1)

end for

7. Different alternative reconstruction plans are generated.
8. Create unit sub-lists from the generated plan which can be constructed in parallel.
9. Update dataset with newly constructed units.
10. Update undirected graph G from updated dataset D.
11. Save new updated dataset in .XLSX and .CSV file.
12. Again agent will be trained on the updated dataset to reconstruct the remaining damage units.

Here, following figure 5.5 showing the generated reconstruction plan with the help of a trained agent by satisfying all constraints including episode reward and overall political priority. The reconstruction plan always consisted of all those damaged buildings/units and physical dependencies which are highly beneficial for affected people after reconstruction. Indeed, we can also see the list of all reconstructed units and damaged roads in earlier reconstructions plans.

Additionally, if government release more budget during implementation of any reconstruction plan even though first we finish the implementation of defined plan with respect to constraint. Additional budget will be accommodated in next plan.



```
        #print(env.total_time)
        epi_reward += reward
        state = next_state

    print("\n")
    print("Units already constructed in previous plan:", env.previously_constructed, env.previously_constructed_roads)
    print("----------------------------------------------------------------------------------")
    print("Plan: ", env.plan, "Episode reward: ", epi_reward, "Overall priority: ", env.overall_priority)
    print("----------------------------------------------------------------------------------")
    print("")

else:
    print("ALL UNITS HAVE BEEN CONSTRUCTED IN PREVIOUS PLAN")
    print("\n")
    print("Units already constructed in previous plan:", env.previously_constructed, env.previously_constructed_roads)
```

```
5', '1027_1035', '1027_1038', '1027_1039', '1027_1041', '1027_1042', '1028_1029', '1030_1065', '1030_1087', '1030_109
3', '1030_1119', '1030_1193', '1030_1195', '1031_1034', '1031_1051', '1031_1085', '1034_1051', '1035_1038', '1035_103
9', '1035_1041', '1035_1042', '1035_1056', '1036_1052', '1037_1052', '1038_1039', '1038_1041', '1038_1042', '1039_104
1', '1039_1042', '1040_1055', '1041_1042', '1044_1069', '1046_1047', '1048_1068', '1048_1069', '1051_1054', '1057_116
6', '1058_1174', '1059_1061', '1063_1073', '1065_1087', '1065_1093', '1065_1119', '1065_1193', '1065_1195', '1067_118
7', '1067_1194', '1067_1205', '1075_1095', '1078_1127', '1087_1093', '1087_1119', '1087_1193', '1087_1195', '1088_110
2', '1090_1091', '1092_1202', '1092_1203', '1093_1094', '1093_1119', '1093_1193', '1093_1195', '1094_1194', '1101_112
9', '1104_1169', '1105_1124', '1105_1161', '1105_1164', '1106_1109', '1107_1117', '1110_1112', '1115_1122', '1116_116
1', '1119_1193', '1119_1195', '1121_1192', '1121_1201', '1122_1123', '1124_1161', '1124_1164', '1134_1151', '1140_116
0', '1141_1158', '1147_1210', '1150_1182', '1161_1164', '1168_1177', '1172_1176', '1182_1210', '1187_1205', '1192_119
3', '1193_1195', '1202_1203', '1203_1207', '1206_1207', '1206_1211']
---------------------------------------------------------------------------
Plan:  [858, '828_110', '104_503', 390, '1014_831', 996, '1213_681', '1068_737', '85_82', '82_59', '765_116', 116, '1
161_326', 958, '655_665', 1041, '131_128', 541, 916, 1206, 1083, '30_928', 782, 703, '131_227', '644_600', 600, 471,
'241_576', '122_1202', 804, 817, '881_845', 1213, 977, 70, '1027_52', 1033, '261_913', 913, '613_91', '503_268', 268,
'199_358', 704, 272, 497, 183, '1001_354', 413, 248, 477, 711, 944, '730_1052', 716, 583, '633_1153', 1153, 246] Epis
ode reward:  0.11140753236324898 Overall priority:  8.183333333333334
---------------------------------------------------------------------------
```

Figure 5.5: Generated reconstruction plan

Following figure.5.6 shows the lists of those units in implementation results which can be constructed in parallel to minimize the time of reconstruction process and to utilize the resources up to maximum level.

```
if len(env.plan) !=0:
    Plan_lists =[]
    list1 = []
    for ix in range(len(env.plan)):
        list1.append(env.plan[ix])
        if type(env.plan[ix])!=int:
            Plan_lists.append(list1)
            list1 = []
        elif ix == len(env.plan)-1:
            Plan_lists.append(list1)
    print("Plan Lists:",  Plan_lists)
else:
    print("ALL UNITS HAVE BEEN CONSTRUCTED IN PREVIOUS PLAN")
```

```
Plan Lists: [[858, '828_110'], ['104_503'], [390, '1014_831'], [996, '1213_681'], ['1068_737'], ['85_82'], ['82_59'],
['765_116'], [116, '1161_326'], [958, '655_665'], [1041, '131_128'], [541, 916, 1206, 1083, '30_928'], [782, 703, '13
1_227'], ['644_600'], [600, 471, '241_576'], ['122_1202'], [804, 817, '881_845'], [1213, 977, 70, '1027_52'], [1033,
'261_913'], [913, '613_91'], ['503_268'], [268, '199_358'], [704, 272, 497, 183, '1001_354'], [413, 248, 477, 711, 94
4, '730_1052'], [716, 583, '633_1153'], [1153, 246]]
```

Figure 5.6: Parallel units reconstruction

Here, following figure.5.7 shows total social benefits of the generated plan in implementation results. According to subsection 4.1.3 *social benefits* is a metric that quantifies the benefits gained by the affected community from a reconfiguration plan. It is defined as the average number of citizens per day that will benefit directly and indirectly from the plan.

```
if len(env.plan) !=0:
    plan_social_reward = social_reward[env.plan[0]]*(total_time-G.nodes[env.plan[0]]['time'])
    #print( plan_social_reward)
    for ix in range(1,len(env.plan)):
        if type(env.plan[ix])==int:
            # print("Location:", env.plan[ix],", ", "Social reward:", social_reward[env.plan[ix]])
            plan_social_reward += social_reward[env.plan[ix]]*(total_time-G.nodes[env.plan[ix]]['time'])
            # print(plan_social_reward)
    print("\n")
    print("Plan: ", env.plan )
    print("Episode reward: ", epi_reward)
    print("Overall priority: ", env.overall_priority)
    print("Complete plan Social Reward:", plan_social_reward)
else:
    print("ALL UNITS HAVE BEEN CONSTRUCTED IN PREVIOUS PLAN")
```

```
Plan:  [858, '828_110', '104_503', 390, '1014_831', 996, '1213_681', '1068_737', '85_82', '82_59', '765_116', 116, '1
161_326', 958, '655_665', 1041, '131_128', 541, 916, 1206, 1083, '30_928', 782, 703, '131_227', '644_600', 600, 471,
'241_576', '122_1202', 804, 817, '881_845', 1213, 977, 70, '1027_52', 1033, '261_913', 913, '613_91', '503_268', 268,
'199_358', 704, 272, 497, 183, '1001_354', 413, 248, 477, 711, 944, '730_1052', 716, 583, '633_1153', 1153, 246]
Episode reward:  0.11140753236324898
Overall priority:  8.183333333333334
Complete plan Social Reward: 97688.43041674324
```

Figure 5.7: Social benefits

5.3.6 Cross-check verification of reconstructed units

Here, figure.5.8 shows the successful implementation of selected plan and updated data set will be created (reconstructed units status will be change from 0 to 1) which is saved in .xlsx and .csv format. Additionally, we can do cross-check verification of latest reconstructed units with the help of undirected graph. Reconstructed damage units (red color nodes) get changed into green color and reconstructed physical dependencies (red dotted edges) get changed into dark color.

Saving new Dependencies excel sheet

```
DD = pd.read_csv('Data_set_Dependencies.csv')
for index, row in DD.iterrows():
    if index in env.constructed:
        DD.set_value(index, 'Reconstructed', 1)
DD.to_csv('Data_set_Dependencies_1.csv', sep=',', index = False)
DD.to_excel('Data_set_Dependencies_1.xlsx', index = False)
```

Saving new Attributes excel sheet

```
DD1 = pd.read_csv('Data_set_Attributes_R1.csv')
if env.number_of_roads_constructed !=0:
    for index, row in DD1.iterrows():
        b1 = row['Buildings1']
        b2 = row['Buildings2']
        if "{}_{}".format(a.index(b1),a.index(b2)) in env.plan or "{}_{}".format(a.index(b2),a.index(b1)) in env.plan:
            DD1.set_value(index, 'Dependencies (Road)', "Fine")
else:
    print("ALL UNITS HAVE BEEN CONSTRUCTED IN PREVIOUS PLAN")

DD1.to_csv('Data_set_Attributes_R2.csv', sep=',', index = False)
DD1.to_excel('Data_set_Attributes_R2.xlsx', index = False)
```

Figure 5.8: Update dataset

Chapter 6

REPAIR Experimentation and Evaluation

Data collection for experimentation and evaluation is always challenging in the post-disaster activities. However, we have extratcted required data with help of *GisToGraph* algorithm which gives us detailed information about damage infrastructure and physical dependencies including affected people due to natural disaster.
For the case studies, to evaluate *REPAIR* model we have applied on two different datasets of *Sulmona* and *L'Aquila*, which are explained following.

6.1 Sulmona Case Study

In order to explain the feasibility and applicability of our proposed framework *REPAIR*, the first step is about *data processing* which is collected from disaster areas to rebuild (such as a city) and the status of buildings and roads. We use data set of (Fig 6.1) "Sulmona" city of Abruzzo region (Italy) which is collected from municipality using the USRA (L'Ufficio Speciale per la Ricostruzione dell'Aquila) website to verify the result. The data set was not in processed form but it was in shapefiles. We have extracted information and then converted into .xlsx and .csv formats. Collected dataset attributes consist of information like the number of people living and vulnerability status. Vulnerability status is defined from '0' to '5'. '0' shows fully damage, '1' extremely damage, '2' slightly extreme, '3' is partially damaged, '4' is slightly partial, and '5' number represents very less damage. Additionally, *political priority* attributes are missing in the collected dataset, for this purpose we integrate political priority (political priority number from '1' to '10') in the collected dataset with respect to each building type [30].
In the next step, whole data is processed and visualized damage units ID and roads with the help of an undirected graph (Fig 6.2). Red color nodes represent damaged units/buildings and green shows fine/reconstructed ones. Similarly, the red dotted edge representing damaged roads/dependencies including length and dark black shows fine/reconstructed one. The graph will be updated by colors of damaged buildings/roads on every cycle after the successful completion of the considered plan. According to the health status of units, we have found 597 buildings out of 1214 are damaged and 470 roads out of 3476 are damaged. Proposed approach suggests five different cycles to reconstruct all damaged units/roads by considering maximum social benefits and others constraints.

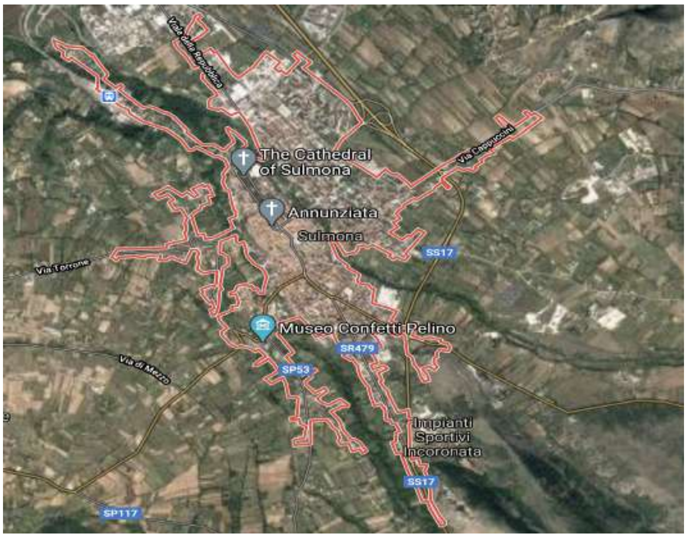


Figure 6.1: Sulmona city map

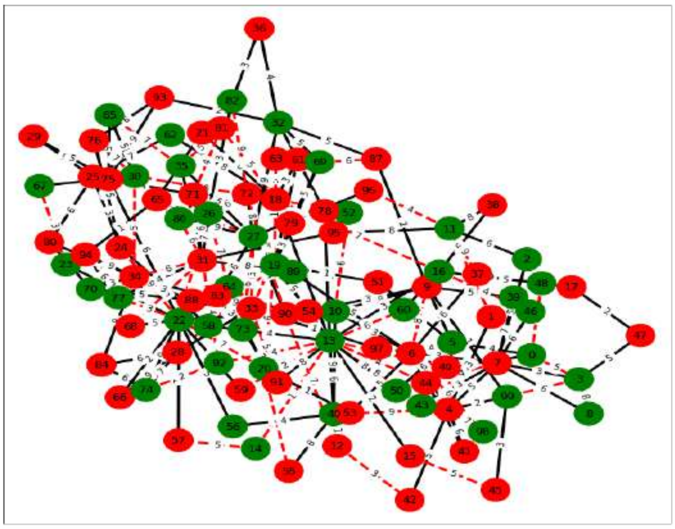


Figure 6.2: Damage buildings and roads

6.1.1 Experimental Setup

We implement this approach using Python with TensorFlow. The computational platform is MacBook pro with quad-core intel core i5 processor and Intel Iris Plus Graphics 645 graphics. We have used three fully connected hidden layers and rectified linear unit activation for each. Hidden layers contain 8,64 and 128 neurons respectively. For training we used Adam optimizer with 0.001 learning rate giving satisfactory results on the applied dataset. Mean square error have used for loss function. The rebuilding planning agent is fully trained on 15000 episodes and did verification of trained agent with the random agent by running it also for 15000 episodes. There are some other influential hyper-parameters in this approach which are mentioned in the Table 6.1 with specific details.

Table 6.1: Fixed parameters

Fixed Parameters	**Value**
Optimizer	Adam optimizer, learning rate = 0.001
Loss function	Mean squared error, Eq. 5.2
Q-Learning function	Q(s,a;θ) = $S_r(v) + \gamma \max_{a' \in A_v} Q'(s', a'; \theta_i^-)$
Batch size	32
Steps before training	15000
Maximum memory size	2000
Political Priority	Minimum=0 , Maximum =10
Exploration strategy	Epsilon greedy policy (Epsilon $\in 10^{-7}, 1$ and self.epsilon_ decay=0.0003.)
Reward discount factor	self.discount_factor = 0.95
Input Parameters	'Budget' and 'Time' (T_e)

6.1.2 Accuracy Verification and Comparison

To measure the accuracy of the trained agent in deep reinforcement learning is an open and challenging issue for researchers [126]. But still, some conventional methods are used for the verification and the random agent method is one of them. We have also adopted the random agent method in our approach for the training verification of trained agents. We have run the same number of episodes (15000) for the random agent as we have used during the training of the trained agent. Random agent verification is performed in every cycle of training. Additionally, during training verification, the maximum reward value of the trained agent is set as a threshold that's why it seems to be stagnant in every training verification plot but, in reality, it is not. Following cycles for reconstruction planning showing agent training verification and comparison respectively.

6.1.3 Experimental Results

We have reconstructed all damaged buildings and physical dependencies in five different cycles. In post-disaster situation governments always allocates budgets in different phases for rehabilitation because it's really hard to reconstruct the whole infrastructure in a single budget (however our model has the capability to reconstruct all damaged buildings in a single cycle but in practice, it's really difficult). Here following we have explained all reconstruction cycles [1] including agent training plot and verification by the random agent on behalf of specific input parameters (budget and time). Then at the end, we have responded to all defined research questions.

Cycle-1 for Agent Training:

In the first cycle of agent training, we have input budget/cost: \$1,000,000 and time: 60 months for reconstruction. Fig. 6.3 showing agent training plot in which the X-axis represents the number of episodes which we run for training and the Y-axis is the social reward. Columbia blue line represents actual reward and dodger blue line is used for mean reward value. The curve is getting steeper after 15000 episodes which shows the agent is fully trained. Similarly, in the agent verification plot

[1] Trained agent returns alternative reconstruction plans. On successful implementation of the selected plan, the data set will be updated and the agent will be trained again to determine new reconstruction plans for the remaining damaged units. A cycle is composed of agent training and reconstruction plan successful implementation.

orange line represents random agents, and the dodger line shows the learning level of the trained agent. After agent training, we got two different reconstruction plans (we can generate as many as want but here we are mentioning only two alternative reconstruction plans in each cycle) by satisfying all constraints which are in Table 6.2 and 6.3. Cycle-1:Plan 1 contains 130 buildings with 96 physical dependencies (Phys. Depend.), political priority (PP) is 8.6, and 'S_p' is 6257. Similarly, Cycle-1:Plan 2 is slightly changed because the agent starts reconstruction randomly that contains 134 buildings, 92 physical dependencies (Phys. Depend.) and political priority is 8.5 with $S_p =$ 6254. After that, we have defined the lists of all those units which can be constructed in parallel in Table 6.4 and Table A.4 of both planes.

Cycle-1 Agent Training Verification:

Figure.6.4 showing cycle-1 training verification through the random agent by running an equal number of iterations of the trained agent. In the end, we can see random agent reward remain around 100 and trained agent reward is around 500 which is five times higher than the random agent. So, the trained agent is reliable and expert enough.

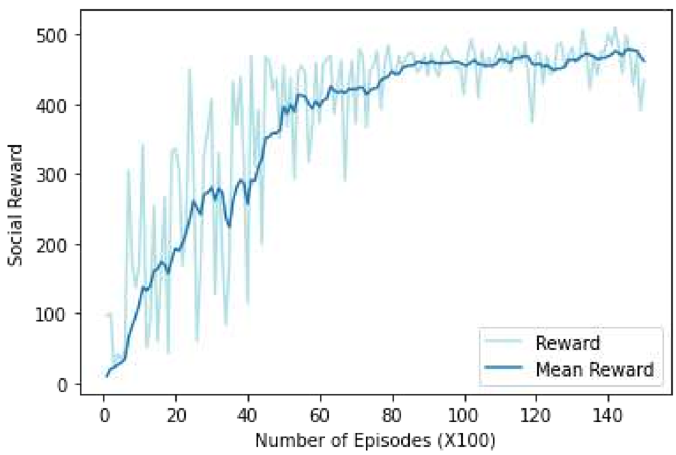


Figure 6.3: Cycle-1 training

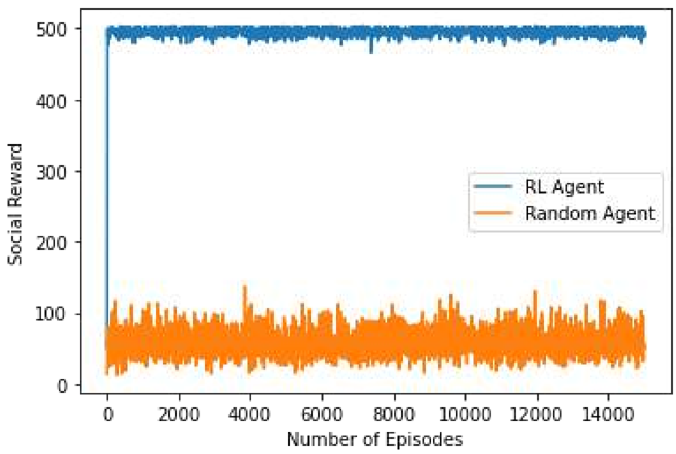


Figure 6.4: Cycle-1 training verification

Table 6.2: Cycle-1:Plan 1

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	35	Hospital	130	96	8.6	6257
2	690-783	Road				
3	732	University				
4	434	Civil Building				
5	1166	Civil Building				
6	432	Private Building				
7	911	Civil Building				
8	1213-681	Bridge				
9	582	Civil Building				
10	85-82	Road				
11	59	Civil Building				
12	765-116	Road				
13	116	Private Building				
14	1014-831	Road				
15	131-227	Road				
16	644-600	Road				
17	600-604	Road				
18	604	Private Building				
19	633-472	Road				
–	–	–				
226	131	Civil Building				

Table 6.3: Cycle-1:Plan 2

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	65	Civil Building	134	92	8.5	6254
2	516-1071	Road				
3	906-912	Road				
4	912	Civil Building				
5	1166	Civil Building				
6	432	Private Building				
7	911	Civil Building				
8	1213-681	Bridge				
9	582	Civil Building				
10	85-82	Road				
11	59	Civil Building				
12	765-116	Road				
13	16	Private Building				
14	1014-831	Road				
15	131-227	Road				
16	644-600	Road				
17	600-604	Road				
18	604	Building				
–	–	–				
226	131	Civil Building				

Table 6.4: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[35,690-783]
2	[732,434,1166,432,911,1213-681]
3	[582,85-82]
4	[59,765-116]
5	[116,1014-831]
6	[131-227]
7	[644-600]
8	[600-604]
9	[604,633-472]
10	[241,327-203]
11	[172, 168, 532-92]
12	[1133,1074,133, 677-981]
13	[36,692-784]
14	[733,436,1188,435,922,1215-683]
15	[583,584,85-86]
16	[60,63,765-118]
17	[119,1017-832]
18	[133-228]
19	[77,644-602]
20	[586, 605-607]
21	[605,609, 635-475]
22	[243,329-215]
23	[221, 96-821]
24	[1133,1073,132-135]
25	[136,680-785]
26	[732,434,1213-681]
27	[1213,582,681]
28	[87, 59, 765, 1166-432]
29	[118,1016-831]
30	[155-226]
31	[22, 645-606]
32	[607-609]
33	[756, 611, 635-480]
34	[246,329-210]
35	[336, 721-698]
36	[1131,1072,131]
37	[35,690-783]
38	[732,434-1166]
39	[590, 560, 88-90]
40	[70,770-119]
41	[118,1016-840]
42	[177-229]
43	[555, 630-621]
44	[424, 618-630]
45	[630,635-490]
46	[280,333-205]
-	-
52	[1131,1072,131]

Table 6.5: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[65,516-1071]
2	[906-912]
3	[912,1166,432,911,1213-681]
4	[582,85-82]
5	[59,765-116]
6	[116,1014-831]
7	[131-227]
8	[644-600]
9	[600-604]
10	[604,633-472]
11	[1133,1074,133, 677-981]
12	[172, 168, 532-92]
13	[583,584,85-86]
14	[36,692-784]
15	[733,436,1188,435,922,1215-683]
16	[119,1017-832]
17	[60,63,765-118]
18	[77,644-602]
19	[586, 605-607]
20	[133-228]
21	[243,329-215]
22	[221, 96-821]
23	[605,609, 635-475]
24	[136,680-785]
25	[1133,1073,132-135]
26	[1213,582,681]
27	[732,434,1213-681]
28	[118,1016-831]
29	[87, 59, 765, 1166-432]
30	[22, 645-606]
31	[155-226]
32	[756, 611, 635-480]
33	[607-609]
34	[336, 721-698]
35	[246,329-210]
36	[35,690-783]
37	[1131,1072,131]
38	[590, 560, 88-90]
39	[732,434-1166]
40	[118,1016-840]
41	[70,770-119]
42	[555, 630-621]
43	[177-229]
44	[630,635-490]
45	[280,333-205]
46	[424, 618-630]
-	-
52	[1131,1072,131]

Cycle-2 for Agent Training:

In cycle-2 we have trained the agent on the same input parameters like cycle-1 in which budget/cost: \$1,000,000 and time: 60 months for reconstruction (the resulting tables of cycle-2 are placed in Appendix "A" to make better readability of results). After agent training we have considered two different reconstruction plans which satisfied all constraints as shown in Table A.1 and A.2. Cycle-2:Plan 1 contains 127 buildings with 112 physical dependencies (Phys. Depend.), political priority (PP) is 7.9, and 'S_p' is 5237. Similarly, Cycle-2:Plan 2 is slightly changed which contains 124 are buildings, 99 physical dependencies (Phys. Depend.) and political priority is 7.6 with $S_p = 5198$. We have also shown the lists of those units which can be constructed in parallel in Table A.3 and A.4 .

Cycle-2 Agent Training Verification:

Figure.6.6 showing cycle-2 training verification through the random agent on the same number of iterations that we have used during agent training. In the end, we can see random agent reward remain around 100 and trained agent reward is around 400 which is four times higher than the random agent. So trained agent is reliable and expert enough.

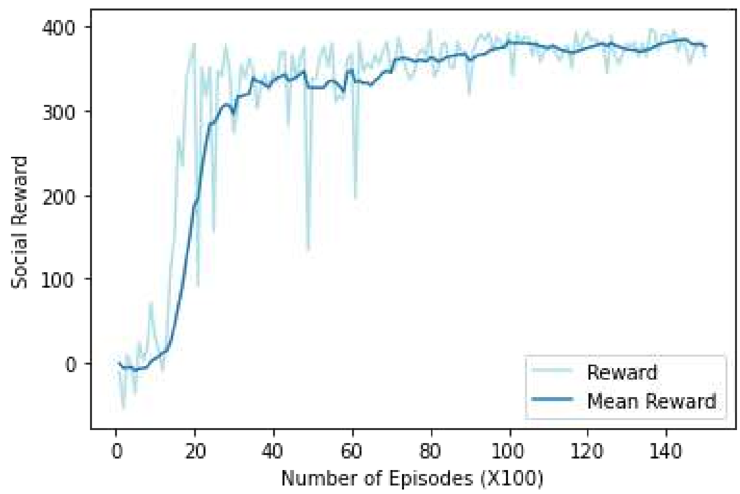


Figure 6.5: Cycle-2 training

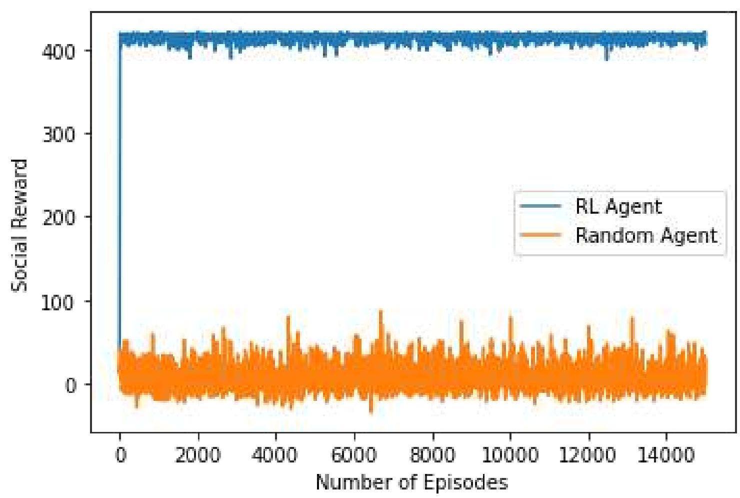


Figure 6.6: Cycle-2 training verification

Cycle-3 for Agent Training:

In cycle-3 we trained agent on same input parameters (budget/cost:$1,000,000 and time:60 months for reconstruction) and got two different reconstruction plans by satisfying all constraints which are in Table A.5 and A.6 (the resulting tables of cycle-3 are placed in Appendix "A" to make better readability of results). Cycle-3:Plan 1 contain 122 buildings with 95 physical dependencies (Phys. Depend.), political priority (PP) is 6.9 and 'S_p' is 4527. Similarly Cycle-3:Plan 2 is slightly changed because agent starts reconstruction randomly that contains 125 buildings, 98 physical dependencies (Phys. Depend.) and political priority is 7.1 with $S_p = 4590$. Furthermore, lists of all those units which can be constructed in parallel are shown in Table A.7 and Table A.8 of both planes.

Cycle-3 Agent Training Verification:

Figure.6.21 shows cycle-1 training verification through random agent by running equal number of iterations of trained agent. At the end we can see random agent reward remain around 150 and trained agent reward is around 350 which is higher than random agent. So trained agent is reliable and expert enough.

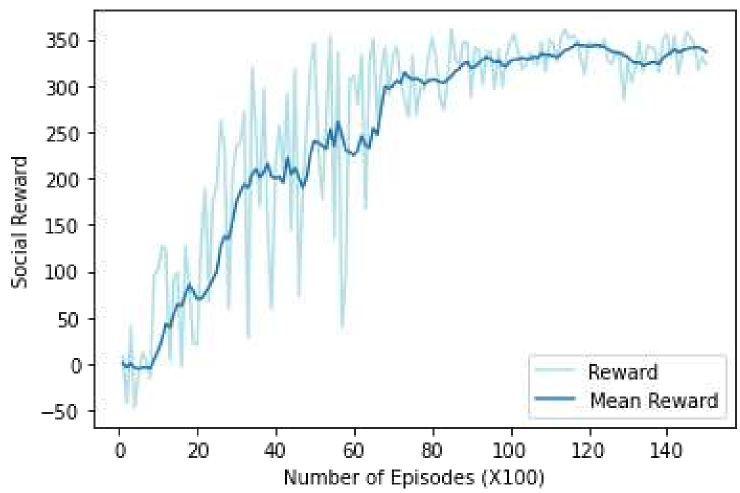


Figure 6.7: Cycle-3 training

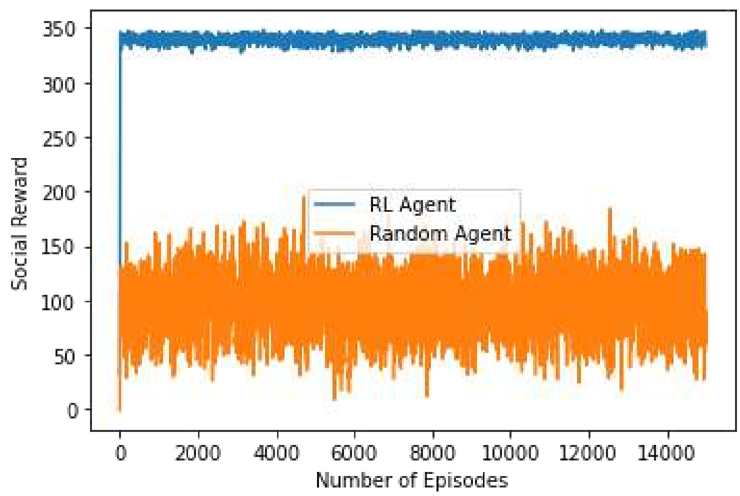


Figure 6.8: Cycle-3 training verification

Cycle-4 for Agent Training:

We have trained agent in cycle-4 on same input parameters as in previous cycles (budget/cost: $1,000,000 and time: 60 months for reconstruction) and we got two different reconstruction plans which are shown in Table A.9 and A.10 (the resulting tables of cycle-4 are placed in Appendix "A" to make better readability of results). Cycle-4:Plan 1 contains 115 buildings with 91 physical dependencies (Phys. Depend.), political priority (PP) is 6.1, and 'S_p' is 4112. Similarly, Cycle-4:Plan 2 slightly changes because the agent starts reconstruction randomly that contains 113 buildings, 95 physical dependencies (Phys. Depend.) and the political priority is 6.3 with $S_p =$ 4136. Furthermore we shown the list of units which can be constructed in parallel in Table A.11 and Table A.12.

Cycle-4 Agent Training Verification:

Figure.6.10 showing cycle-4 training verification through random agent by running it for 500 iterations. At the end we can see random agent reward remain around 100 and trained agent reward is around 300 which is three times higher than random agent. So trained agent is reliable and expert enough.

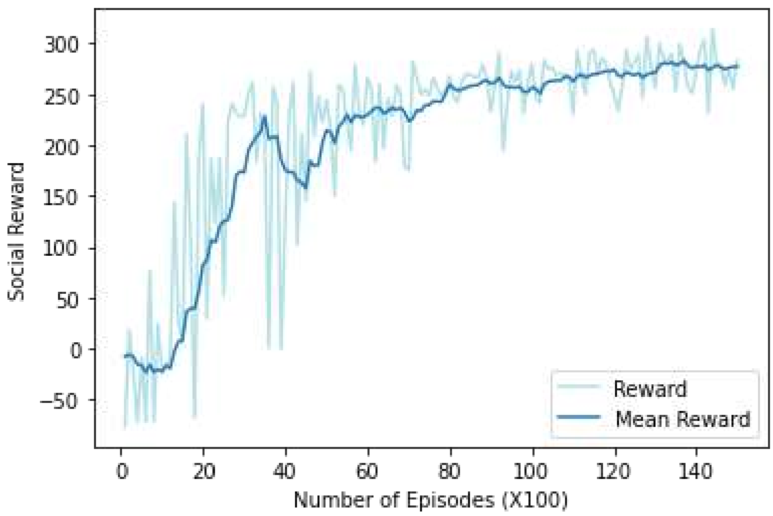


Figure 6.9: Cycle-4 training

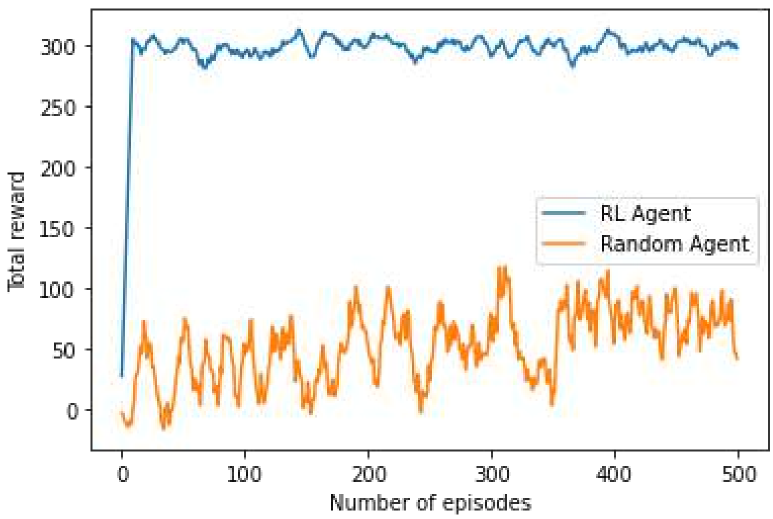


Figure 6.10: Cycle-4 training verification

Cycle-5 for Agent Training:

In cycle-5 we trained agents on the same input parameters as in previous cycles. After agent training we got two different reconstruction plans by fulfilling all constraints which are in Table A.13 and A.14 (the resulting tables of cycle-5 are placed in Appendix "A" to make better readability of results). Cycle-5:Plan 1 contains 103 buildings with 102 physical dependencies (phys. Depend.), political priority (PP) is 5.2, and 'S_p' is 3601. Similarly, Cycle-5:Plan 2 slightly changes because the agent starts reconstruction randomly that contains 101 buildings, 99 physical dependencies (phys. Depend.) and political priority is 5.0 with $S_p = 3577$. At the end we got the list of units which can be constructed in parallel as shown in Table A.15 and Table A.16.

Cycle-5 Agent Training Verification:

Figure. 6.12 showing cycle-5 training verification through random agent by running equal number of iterations of trained agent. At the end we can see random agent reward remain around 80 and trained agent reward is around 140 which is higher than random agent. So trained agent is reliable and expert enough.

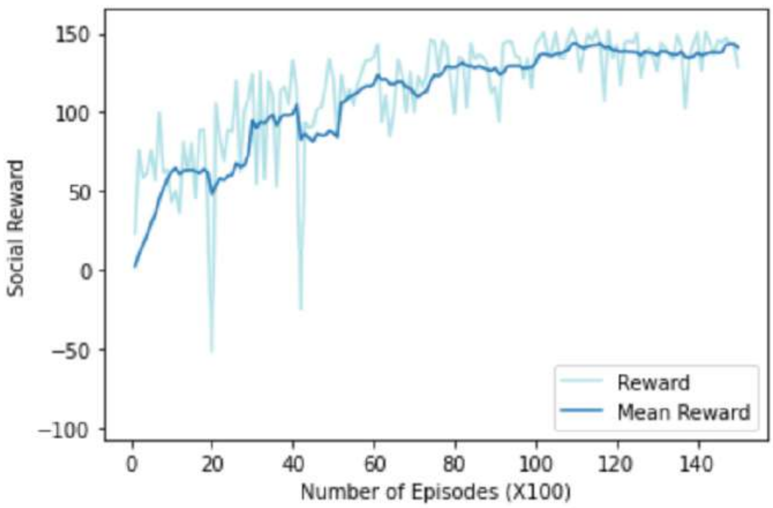


Figure 6.11: Cycle-5 training

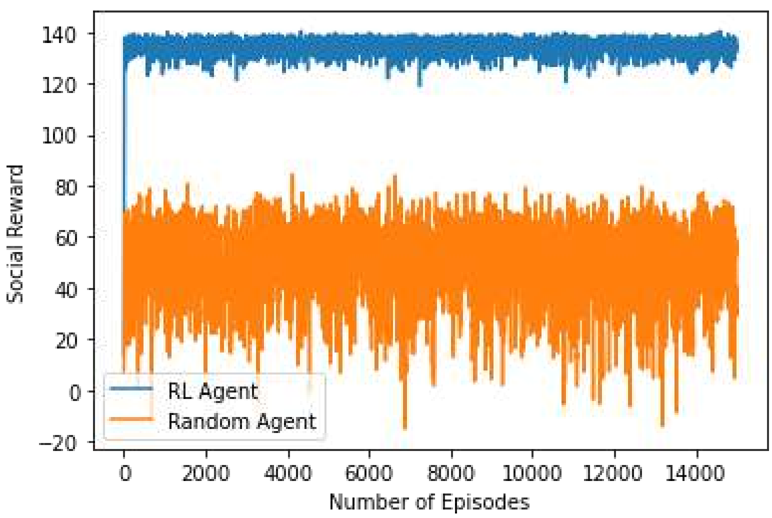


Figure 6.12: Cycle-5 training verification

6.2 L'Aquila Case Study

In this section, we did evaluation of *REPAIR* methodology on the L'Aquila city center data considering a small portion of the historic city center of L'Aquila, in the Abruzzo region (Italy) (see Fig. 6.13), which was severely affected by the 2009 earthquake. For our case study, we considered a small area extending towards the northwest of the crossing of three main streets: Corso Vittorio Emanuele (north-south axis of the city), Corso Principe Umberto, and Via San Bernardino, for a total land size of 246,684.28 m^2. The aim is to provide more details on the implementation and check the results of the reconstruction planning model described in chapter 4 and chapter 5.

In the considered area, we can find 133 buildings and 297 streets with 216 crossroads. Applying the GisToGraph algorithm, we generated the EUG shown in Fig. 6.14. It contains 349 nodes (216 nodes for crossroads and 133 nodes for buildings' entrances) and 533 edges (297 are the streets while the remaining 236 are the half-streets and the connections between a building and another node, crossroad or building, reachable from the same street).

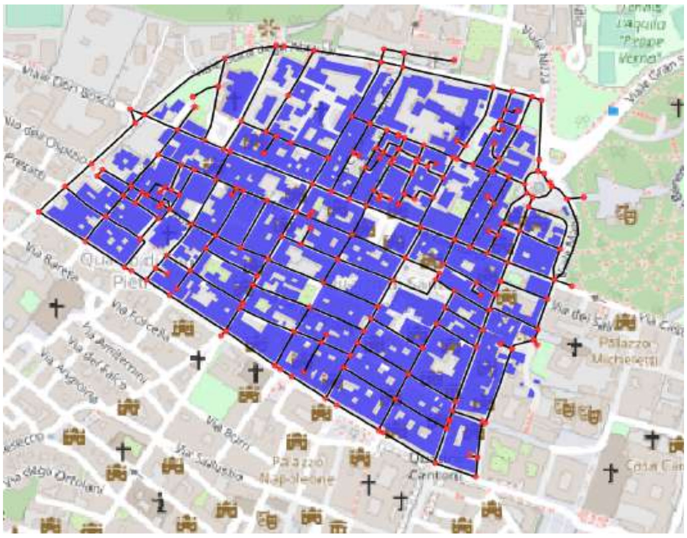


Figure 6.13: Considered area

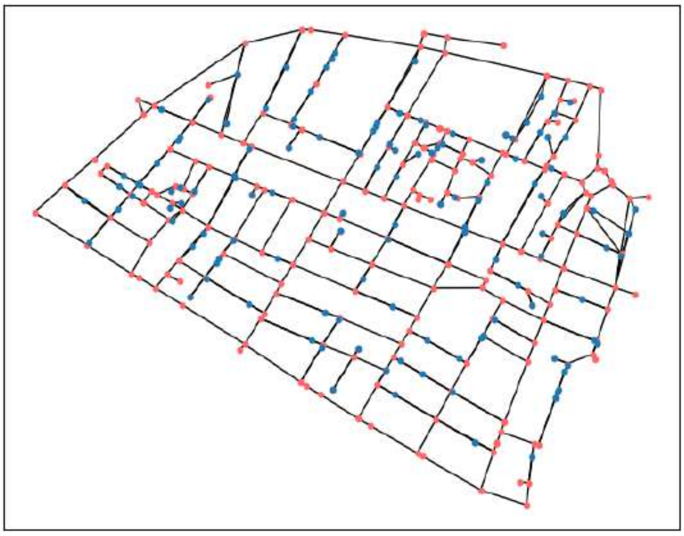


Figure 6.14: Generated graph of the considered area

The results of the evaluation of post-disaster reconstruction planning are based on the aforementioned dataset and information of the damaged area. In the graph representation (see Fig.6.15), red nodes represent damaged units and green nodes show reconstructed/usable units. Similarly, red dotted edges show damaged roads/bridges, and dark edges show reconstructed/usable roads and bridges. In the selected area, there are 37 damaged units/buildings out of 133 and 20 damaged roads/bridges out of 150 roads. Every damaged unit/building and road/bridge has a specific political priority (i.e. from 1 to 10). These priorities are reported in previous chapter 6 in Table 6.18 according to [30]. Every reconstruction plan have specific thresholds (Eq. 5.3) as reported in Table 6.19. These thresholds decrease every cycle in a way that in later cycles less beneficial buildings can be considered.

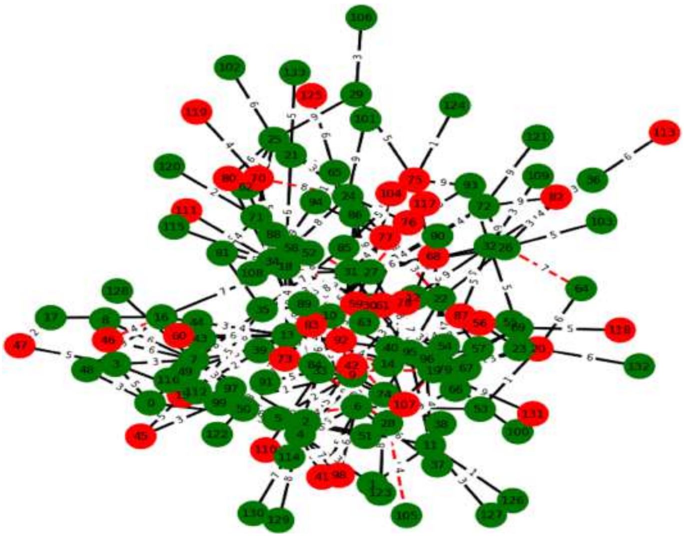


Figure 6.15: Damaged buildings and roads

6.2.1 Experimental Results

All damaged buildings and physical dependencies in the L'Aquila dataset get reconstructed in three different cycles. Here following we have explained all reconstruction cycles in which trained agent returns alternative reconstruction plans. On successful implementation of the selected plan, the data set will be updated and the agent will be trained again to determine new reconstruction plans for the remaining damaged units.

Cycle-1 for Agent Training:

In the first cycle of agent training, we have input budget/cost: $1,000,000 and time: 24 months for reconstruction.Fig.6.16 shows the agent training plot in which the X-axis represents the number of episodes that we run for training and the Y-axis is the social reward. Columbia blue line represents actual reward and dodger blue line is used for mean reward value. The curve is getting steeper after 15000 episodes which shows that the agent is fully trained. Similarly, training agent verification did with help of random agents. After agent training, we got two different reconstruction plans by satisfying all constraints which are in Table 6.6 and 6.7. Cycle-1:Plan 1 contains 11 buildings with 4 physical dependencies (Phys. Depend.), political priority (PP) is 9.4, and 'S_p' is

3132. Similarly, Cycle-1:Plan 2 is slightly different because the agent starts reconstruction randomly that also contains 11 buildings, 5 physical dependencies (Phys. Depend.) and political priority is 9.3 with $S_p = 3120$. We also have defined the lists of all those units which can be constructed in parallel in Table 6.16 and Table 6.17 of both planes.

Cycle-1 Agent Training Verification:

Figure.6.17 showing cycle-1 training verification through random agent by running it for 15000 iterations. At the end we can see random agent reward remain around 50 and trained agent reward is around 250 which is higher than random agent. So trained agent is reliable and expert enough.

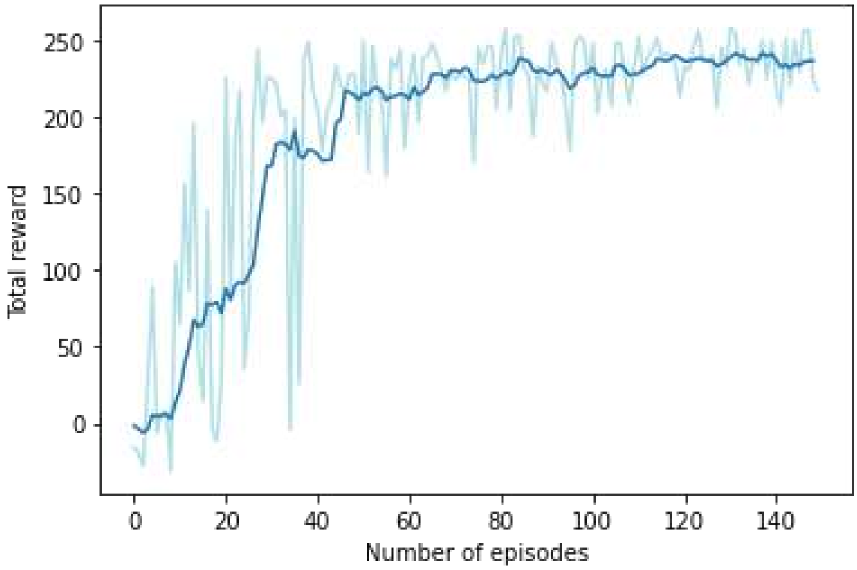


Figure 6.16: Cycle-1 training

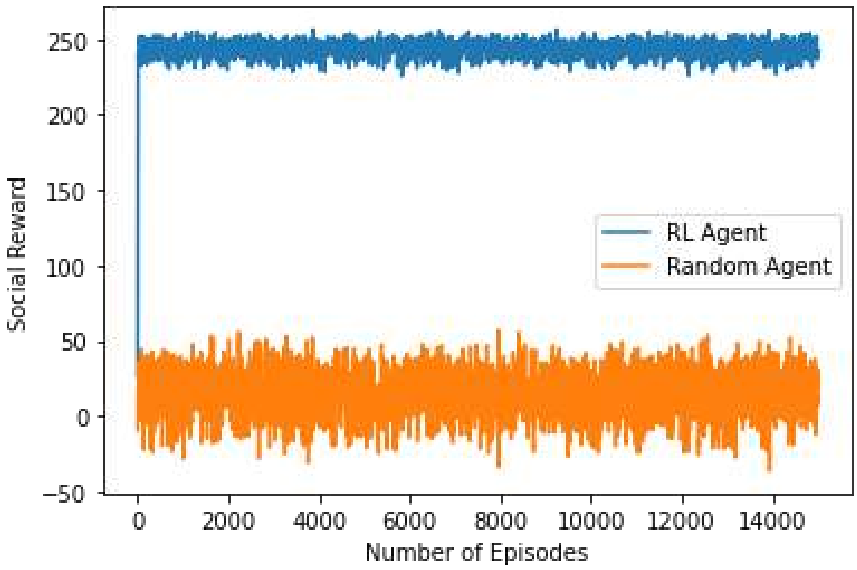


Figure 6.17: Cycle-1 training verification

Table 6.6: Cycle-1:Plan 1

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	104	Hospital	11	4	9.4	3132
2	87	Private Building				
3	87-9	Road				
4	22-77	Road				
5	77	University				
6	82	Civil Building				
7	86-65	Bridge				
8	125	Private Building				
9	15	Civil Building				
10	41	Civil Building				
11	20	Civil Building				
12	79-33	Road				
13	80	Private Building				
14	70	Civil Building				
15	83	Civil Building				

Table 6.7: Cycle-1:Plan 2

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	77	University	11	5	9.3	3120
2	77-22	Road				
3	9-87	Road				
4	87	Private Building				
5	82	Civil Building				
6	86-65	Bridge				
7	125	Private Building				
8	15	Civil Building				
9	41	Civil Building				
10	20	Civil Building				
11	79-33	Road				
12	80	Private Building				
13	70	Civil Building				
14	83	Civil Building				
15	16-46	Road				
16	46	Civil Building				

Table 6.8: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[104,87,87-9]
2	[22-77]
3	[77,82,86-65]
4	[125,15,41,20,79-33]
5	[80,70,83]

Table 6.9: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[77,77-22]
2	[9-87]
3	[87,82,86-65]
4	[125,15,41,20,79-33]
5	[80,70,83,16-46]
6	[46]

Cycle-2 for Agent Training:

Once the agents get trained in cycle-2, we got two different reconstruction plans by satisfying all constraints which are in Tables. 6.10 and 6.11. Cycle-1:Plan 1 contains 12 buildings with 7 physical dependencies (Phys. Depend.), political priority (PP) is 7.9, and 'S_p' is 2871. Similarly, Cycle-1:Plan 2 is slightly changed which contains 12 buildings, 8 physical dependencies (Phys. Depend.) and political priority is 7.6 with $S_p = 2802$. In the meanwhile, Tables. 6.12 and 6.13 showing list of units which can be constructed in parallel.

Cycle-2 Agent Training Verification:

Figure.6.19 showing cycle-1 training verification through random agent by running equal number of iterations of trained agent. Random agent reward remains around 80 and trained agent reward is around 140 which is higher than random agent. So we can say trained agent is reliable and expert enough.

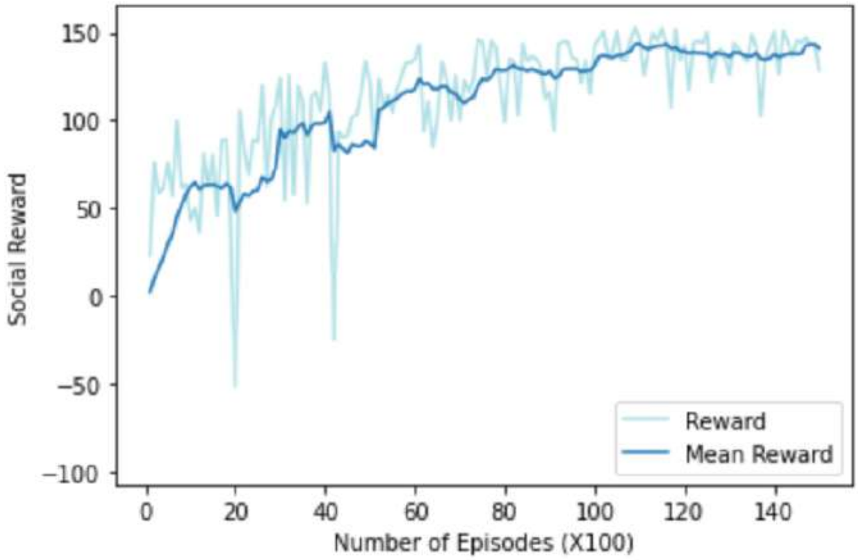


Figure 6.18: Cycle-2 training

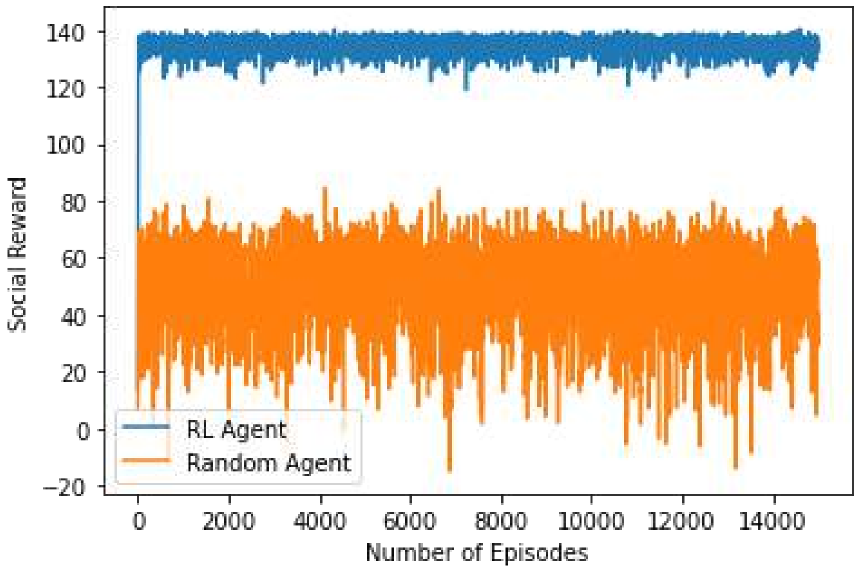


Figure 6.19: Cycle-2 training verification

Table 6.10: Cycle-2:Plan 1

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	88	University	12	7	7.9	2871
2	23	Civil Building				
3	90	Civil Building				
4	20-90	Road				
5	113	Private Building				
6	37-65	Road				
7	36	Civil Building				
8	121-90	Bridge				
9	81	Civil Building				
10	47	Private Building				
11	35-90	Road				
12	48-27	Road				
13	73	Civil Building				
-	-	-				
19	71-108	Road				

Table 6.11: Cycle-2:Plan 2

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	85	Civil Building	12	8	7.6	2802
2	41	Civil Building				
3	39-89	Road				
4	75	Civil Building				
5	29-45	Road				
6	121	Civil Building				
7	121-90	Bridge				
8	81	Civil Building				
9	47	Private Building				
10	35	Civil Building				
11	48-27	Road				
12	73	Civil Building				
-	-	-				
19	71-108	Road				

Table 6.12: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[88, 23, 90, 20-90]
2	[113, 37-65]
3	[36, 121-90]
4	[81, 47, 35-90]
5	[48-27]
6	[73, 35, 39, 85-118]
7	[51, 83, 71-108]

Table 6.13: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[85, 41, 39-89]
2	[75, 29-45]
3	[121, 121-90]
4	[81, 47, 35, 48-27]
5	[25, 35, 56-93]
6	[73, 45, 85-97]
7	[102, 112-133]
8	[38, 71-108]

Cycle-3 for Agent Training:

During the last cycle of agent training, budget/cost: \$1,000,000 is defined and time is 24 months for reconstruction. After agent training we got two different reconstruction plans by satisfying all constraints which are in Table 6.14 and 6.15. Cycle-3:Plan 1 contains 14 buildings with 8 physical dependencies (Phys. Depend.), political priority (PP) is 6.8, and 'S_p' is 2252. Similarly, Cycle-3:Plan 2 slightly changes because the agent starts reconstruction randomly that's why it contains 12 buildings, 9 physical dependencies (Phys. Depend.) and political priority is 6.7 with $S_p = 2217$. At the end lists of all those units which can be constructed in parallel are presented in Table 6.16 and Table 6.17 of both planes.

Cycle-3 Agent Training Verification:

Figure. 6.21 shows cycle-3 training verification through random agent which contains reward around 60 and trained agent reward is around 120 which is higher than random agent.

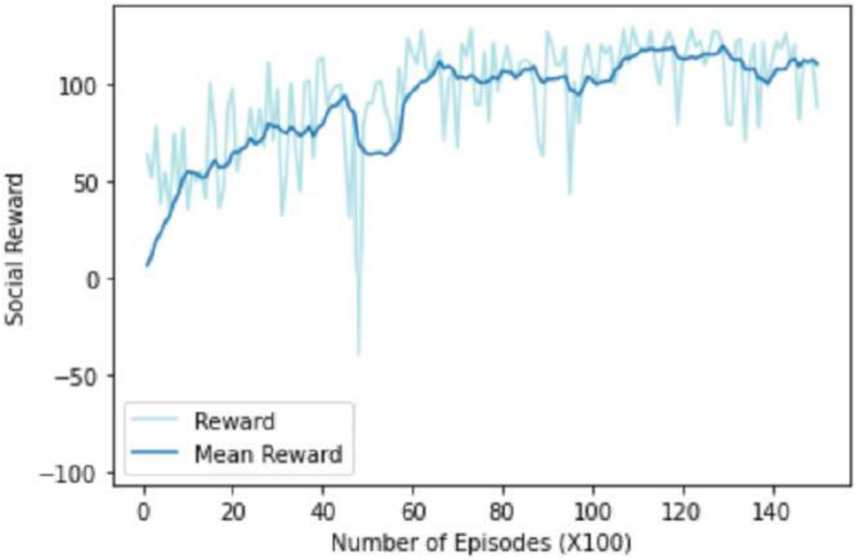


Figure 6.20: Cycle-3 training

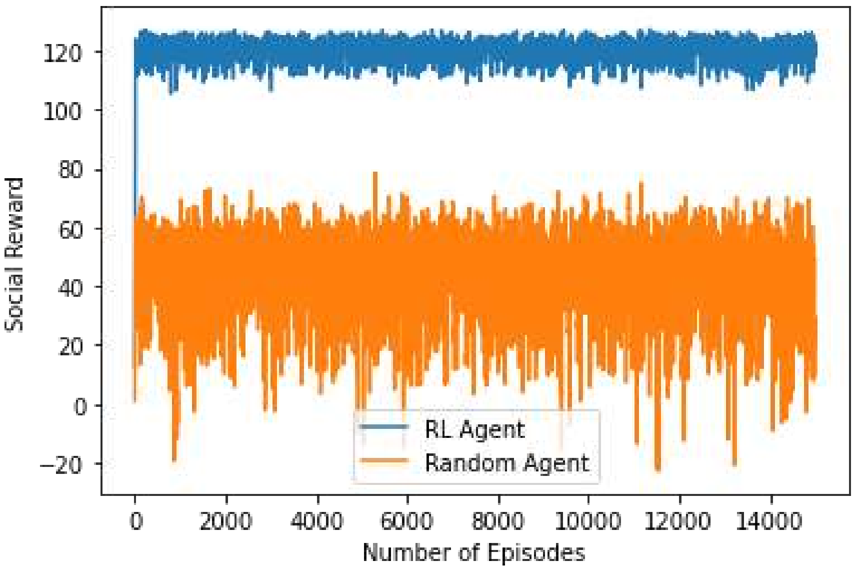


Figure 6.21: Cycle-3 training verification

Table 6.14: Cycle-3:Plan 1

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	119	Civil Building	14	8	6.8	2252
2	101	Private Building				
3	99	Civil Building				
4	47-69	Road				
5	93	Civil Building				
6	71	Private Building				
7	39-81	Road				
8	113	Civil Building				
9	103	Civil Building				
10	64	Civil Building				
11	59	Private Building				
12	59-39	Road				
13	78	Civil Building				
-	-	-				
22	128-96	Road				

Table 6.15: Cycle-3:Plan 2

Budget: $1,000,000 Time:24 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	91	Civil Building	12	9	6.7	2217
2	58-119	Bridge				
3	111	Civil Building				
4	129-79	Road				
5	131-113	Road				
6	113	Civil Building				
7	100	Civil Building				
8	28	Civil Building				
9	41-96	Road				
10	64	Civil Building				
11	59	Private Building				
12	59-39	Road				
-	-	-				
21	128-96	Road				

Table 6.16: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[119, 101, 99, 47-69]
2	[93, 71, 39-81]
3	[113, 103, 64, 59, 59-39]
4	[78, 17-22]
5	[26, 53-79]
6	[101, 16-81]
7	[39, 18-69]
8	[68, 128-96]

Table 6.17: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[91, 58-119]
2	[111, 129-79]
3	[131-113]
4	[113, 100, 28, 41-96]
5	[64, 59, 59-39]
6	[71, 95, 115-18]
7	[96, 56-77]
8	[78, 68, 12-33]
9	[128-96]

6.3 Discussion

In this section, we provide the details of the results on behalf of define research questions from the experiments and evaluations (both case studies Sulmona (SL) and L'Aquila (AQ)) with respect to post-disaster reconstruction planning.

Table 6.18: Buildings priority

Buildings	**Priority**
Hospitals	10
Colleges/School	9
Residential Area	9
Public Points	8
Religious	8
Public Buildings	7
Business Centers	6
Gym Centers	5
Banquet Halls	5
Private Buildings	4
Museums	3
Bars/Cinemas	2
Other Places	1

Table 6.19: Cycles priority

Cycles	$\mathbf{Th_p}$ **(Eq. 5.3)**
1	>= 8.0
2	>= 7.2
3	>= 6.4
4	>= 5.6
5	>= 4.8
6	>= 4.0
7	>= 3.2
8	>= 2.4
9	>= 1.6
10	>= 0.8

RQ1: *Which is the best way to embed the* ***political strategies and political priorities*** *into the rebuilding planning model?*

To embed political strategies/priorities into rebuilding planning model, for this purpose during immediate reward '$S_r(v)$' calculation political priority of every damaged building is considered according to its type as in Table 6.18 and each building has specific priority in between 1 to 10 (some buildings have the same political priority). In the end, every proposed reconstruction plan 'S_p' has an accumulative political priority (PP) that must meet the threshold of Table 6.19 according to its cycle. The table shows overall Threshold Political Priority (Th_p) is decreasing in every cycle because in later cycles less beneficial buildings are considered. Table 6.20 shows the practical implementation of our proposed approach which is satisfying defined threshold successfully in each cycle. And also overall political priority getting decreased (8.6 to 5.2) from cycles 1 to 5 respectively because less beneficial buildings are considered in later cycles.

RQ2: *How can we model local community needs (namely,* ***social benefits****) and embed them into the rebuilding planning model?*

In order to ensure local community social benefits in the rebuilding planning model, for this purpose our *REPAIR* approach is calculating social benefits of every unit which is going to be reconstructed; on behalf of the number of people 'b_v' living there plus already reconstructed units 'S_u' in the neighborhood divided by distance 'd' (see Eq. 4.2). In the end, we get accumulative special benefits of considered damaged buildings/units in every proposed reconstruction plan 'S_p' as in Table 6.21. The table shows S_p value is getting decreased gradually from C1 to C5. Because C1

Table 6.20: Political priority

Criteria	Cycles	PP(SL)	PP(AQ)	Th_P
RQ1	C 1	8.6	9.3	>= 8.0
RQ1	C 2	7.9	7.9	>= 7.2
RQ1	C 3	6.9	6.8	>= 6.4
RQ1	C 4	6.1	-	>= 5.6
RQ1	C 5	5.2	-	>= 4.8

Table 6.21: Social benefits

Criteria	Cycles	S_P(SL)	S_P(AQ)
RQ2	C 1	6257	3132
RQ2	C 2	5627	2871
RQ2	C 3	5122	2252
RQ2	C 4	4520	-
RQ2	C 5	3990	-

considers highly beneficial buildings, that's why the total value is high (6257) compared to others. As the reconstruction process goes on, less beneficial buildings are considered because highly beneficial buildings are reconstructed in earlier cycles due to this total social benefits (S_p) value is getting decreased in subsequent cycles (C2, C3, C4, and C5).

RQ3: *How can we model the* ***physical city dependencies*** *and embed them into the rebuilding planning model?*

In order to evaluate the physical dependencies/roads recoveries in our approach, for this purpose when trained agents define the reconstruction plan it checks the path to access damage units if its damage becomes of part the plan and is considered as a unit during reconstruction. Damaged road or any physical dependency is supposed to be reconstructed first because the order of reconstruction matters. Damage road (dependency) is represented by corresponding ID's of buildings through which it is connected e.g. (1-2, here it is showing damage road/dependency existed between buildings which have ID's 1 and 2). As in *Sulmona* case study (Cycle-1) Table 6.2 plan 1 contain 96 physical dependencies (PD) and in Table 6.3 plan 2 contain 92 physical dependencies (PD) (rest of all cycles have different physical dependencies (PD)). Similarly, in *L'Aquila* case study (Cycle-1) Table 6.6 plan 1 contain 4 physical dependencies (PD) and in Table 6.7 plan 2 contain 5 physical dependencies (PD) (rest of all cycles have different physical dependencies (PD)). Additionally, on behalf of these physical dependencies, we make different lists of those units from proposed plans which can be reconstructed in parallel. All units before any physical dependency can be reconstructed in parallel and all those will be in the same list. And if there would be two or more damaged physical dependencies together then each of those will have a separate list. We can't construct more than one physical dependency together. Because the only way to access the next dependency/road is if the first dependency is constructed. Here, in *Sulmona* cases study Table 6.8,6.9) contain 52 and 54 lists of parallel units reconstruction (Cycle-1))from Plan 1 and Plan 2 respectively. On the other hand *L'Aquila* dataset contain 5 and 6 lists of parallel units reconstruction (Cycle-1) in Plane 1 and Plane 2.

RQ4: *Which is the* ***most efficient approach*** *that, leveraging on the defined rebuilding planning model, provides alternative rebuilding plans on real case studies?*

RQ5: *How do we validate the proposed* ***post-disaster Rebuilding Planning*** *approach?*

(RQ4:) We have proposed the most appropriate approach *REPAIR* by using Double Deep Q-

Network and then applied on the real case studies of **(RQ5:)** *"Sulmona"* and *"L'Aquila"* datasets to validate its capability for the reconstruction of damaged buildings and roads. For this purpose, initially, we have input budget/cost: \$1,000,000 and time: 60 months for reconstruction in cycle-1. After agent training on we got two different reconstruction plans for each datasets by satisfying all constraints which are in Tables 6.2, 6.3, 6.6 and 6.7. *Sulmona* dataset Cycle-1:Plan 1 contains 130 buildings with 96 PD, political priority (PP) is 8.6, and 'S_p' is 6257. Similarly, Cycle-1:Plan 2 slightly changes because the agent starts reconstruction randomly that contains 134 buildings, 92 PD and political priority is 8.5 with $S_p = 6254$. We can see same kind of trend for *L'Aquila* dataset.

Following Tables 6.23 and 6.22 describing the summary of remaining cycles results of both case studies. Every cycle contains detailed information like the total number of units and types whether they are buildings or roads. In last two columns show political priority 'PP' and total social benefits 'S_p' as well. After responding to all these research questions we have successfully validated

Table 6.22: Summary table (Sulmona) (Budget: \$1,000,000 Time: 60)

Sr.No	Cycles	Units	Buildings	PD/Roads	PP	S_P(SL)
1	Cycle 2	239	127	112	7.9	5237
2	Cycle 3	217	122	95	6.9	4527
3	Cycle 4	206	115	91	6.1	4112
4	Cycle 5	205	103	102	5.2	3601

Table 6.23: Summary Table (L'Aquila) (Budget: \$100,000 Time: 24 Months)

Sr.No	Cycles	Units	Buildings	PD/Roads	PP	S_P(AQ)
1	Cycle 2	19	12	7	7.9	2871
2	Cycle 3	21	14	8	6.8	2252

our approach on *"Sulmona"* and *"L'Aquila"* data by considering all key attributes like cost, time, physical dependencies, social benefits of the affected community, and political priority to consider politicians' input.

RQ6: *Which learning algorithm is the most effective and efficient one for the REPAIR approach?*

We made a comparative study among Q-Learning, SARSA, Deep SARSA, and Double Deep Q-Networks (DDQN) in Chapter 5 (section 5.2) which are used to solve planning and combinatorial problems by interacting with the environment by using loss function evaluation [8]. In comparison we can see only DDQN algorithm have highest social reward which is 80 on specified small dataset of L'Aquila (included 70 damaged buildings and 27 damaged roads) as shown in fig 5.2. After comparison, we came to know DDQN is the best and most suitable algorithm for the implementation of *REPAIR* approach.

6.4 Threat to Validity

- **External Validity: Scalability of our Approach** We have evaluated our approach on two different case studies (L'Aquila and Sulmona) successfully. After this evaluation, we believe that our approach is generic and can be applied in any kind of bigger area with more resources. The reinforcement learning technique which we used in this approach can be applied easily on heavy datasets.

- **External Validity: Generality of our Approach** Our approach has been applied and validated on different case studies for reconstruction planning. This approach may also be applied to the same kind of management problems by considering all kinds of key attributes like time, cost, political priority and social benefits.

- **Internal Validity: Incorrect Forecast** Main internal validity threat in our approach is decision making on behalf of incorrect information /data of damaged areas which can lead to wrong reconstruction planning. Due to data uncertainty, post-disaster reconstruction can be started in the least affected area. This thing will negate the basic soul of the *REPAIR* approach. We understand this issue and have observed it on two different real datasets during evaluation (by giving incorrect information).

Chapter 7

Conclusion, Discussion and Future Work

“We can only see a short distance ahead, but we can see plenty there that needs to be done" (Alan Turing)

Public decision-makers face many issues to define post-disaster recovery plans like maintaining a balance between involved formal and informal requirements, that can guarantee the re-population of the damaged area. They should consider benefits rising from automatizing the planning of the city reconstruction. In fact, automatic approaches allow them to satisfy constraints (e.g., time and costs), to consider specific aspects of the area (building vulnerabilities and physical dependencies), maximize advantages (e.g., social benefit), reduce human evaluation errors (since the automatic approach can combine several elements and can consider wider areas), and provide several alternative solutions in short time.

In this thesis, we have considered the challenges of post-disaster reconstruction planning by proposing REPAIR, an automatic approach that, starting from enriched GIS data, generates alternatives reconstruction plans that satisfy constraints and maximizes benefits. Meanwhile, REPAIR considers critical damaged units such as roads and bridges, that are necessary to access specific damaged areas.

Additionally, until now, public decision-makers ignore social benefits, that the local community can get after implementation of a certain recovery plan. Of course, the societal impact and benefits are different for a different plan, and this feature must be considered because it plays a vital role in all post-disaster phases. To address these challenges, we came up with an innovative and generic “Reinforcement learning and Social based approach to Post-disaster Reconstruction Planning *(REPAIR)*” approach which helps public decision-makers, servants, and citizens to effectively define and evaluate alternative rebuilding plans as well as to solve the aforementioned complexities.

REPAIR is defined to achieve the goals of reconstruction of city after an earthquake however REPAIR is generic and it can be applied in any situation where the REPAIR’s assumptions are satisfied. Let make us an example: a municipality need to plan the maintenance of its buildings. It (REPAIR approach) can apply by changing the status of the building marking as "to be reconstructed", so running the approach and obtaining several plans that satisfies the constraints and maximize the social benefits of the maintenance action.

Additionally, the presented approach (REPAIR) is innovative and core decision-support system. It takes into account the *Physical* features of the city, *time*, *budget*, *physical dependencies(road/bridges)* and embeds *Social* needs and benefits in accordance with *Political* priorities. The treatment of such aspects as well as the implementation of a solution algorithm that can be accurate and efficient in real situations was very challenging. To handle all these aspects we have used machine learning techniques called Double Deep Q-learning (DDQN) algorithm for defining different kinds of post-disaster reconstruction plans in our proposed methodology. Furthermore, the overall goal was further split into the following six main research questions:

RQ1: *Which is the best way to embed the political strategies and political priority into the rebuilding planning model?*

We have answered this question by considering the political priority of each damaged unit adding a specific attribute for the buildings and specifying in the optimization model (formalized in Chapter 6.2) as a constraint that requires that cumulative political priority (PP) must meet a fixed threshold in every training cycle of *REPAIR* with the help of Eq. 5.3 (Chapter 5).

RQ2: *How can we model local community needs (namely, social benefits) and embed them into the rebuilding planning model?*

To address this question we have specified an attribute, namely, (*social benefits*) that allow to add in the model the benefits gained by the citizens if the building is reconstructed. In our implementation we considered as social benefit attribute the number of people that will benefit directly (i.e., citizens living in the building) from the building reconstruction (in Chapter 5). The benefit of a plan is then calculated by means of a more complex function that considers, not only the people living in the buildings composing the plan, but also the number of citizens that indirectly gain benefits from it, that is all the people attending the neighbouring area (see function defined by the Eq. 4.2 in Chapter 4). The reinforcement learning algorithm tends to maximize such accumulative benefits while constructing the plan.

RQ3: *How can we model the physical dependencies and embed them into the rebuilding planning model?*

Basically in our proposed *REPAIR* model, the trained agent always checks the path (road/bridge) to access damaged units, if it's damaged then it becomes part of the reconstruction plan and considered as a unit during reconstruction. That damage road/physical dependency suppose to reconstruct before damage buildings (Chapter 4). Moreover, the physical dependencies can also impose temporal order in the reconstruction of two or more buildings. Let assume to have a narrow dead end street where more buildings must be rebuilt. In this case, two situations can apply: the building further inside, or further, in the street must be rebuilt first. This constraint is formalized by the physical constraint (see function defined by the Eq.4.6 in Chapter 4).

RQ4: *Which is the most efficient approach that, leveraging on the defined rebuilding planning model,* *provides alternative rebuilding plans on real case studies?*

As an answer to this question we proposed *REPAIR* an efficient and innovative approach for defining alternative rebuilding planning in the post-disaster situation (formalized in Chapter 4 and whose implementation is presented in Chapter 5). It leverages on a mathematical model that considers *time, cost, social benefits, political priority, and physical dependencies* and returns alternative reconstruction plans that respects the posed constraints. REPAIR properly works on real case studies (see Chapter 6).

RQ5: *How do we validate the proposed post-disaster rebuilding planning approach?*

We have successfully validated *REPAIR* approach on two real medium size cities: Sulmona and L'Aquila. On the basis of results, we can assert that our approach guarantees all damaged units and roads get reconstructed by considering all key factors and constraints (Chapter 6). The implementation returns several plans and takes reasonable execution time that goes between 7 to 5 hours depending on the size of the damaged area and on the numerosity of the building to reconstruct The runs have been executed by using a common laptop (see section 6.1.1) but using more performing computer, it would take less time.

RQ6: *Which learning algorithm is the most effective and efficient one for the REPAIR approach?*

For the selection of most effective and efficient reinforcement learning algorithm to implement in *REPAIR*, we made a comparative study among four reinforcement learning algorithms, i.e, DDQN, Q-Learning, SARSA, and Deep SARSA. We considered as baseline the random agent. Results in Chapter 5 shows DDQN is the best algorithm for our proposed research. On behalf of these results we have decided to implement it in *REPAIR* approach.

Basically, *REPAIR* is multi-disciplinary approach which covers all the major aspects and involved requirements that guarantees the repopulating of the damaged area to define post-disaster reconstruction plan. Because manual reconstruction planning is very challenging for decision makers to optimize the budget and time required to accomplish the building plan and to manage societal impact and relative benefits that citizens experience from the implementation of a certain recovery plan. All these complexities effectively handled in *REPAIR* approach.

Additionally, *REPAIR* approach is novel and unique (see Table. 3.12) because we are explicitly considering social benefits of affected people which no one else did in the past studies. This thesis is a first attempt to solve real problems in post-reconstruction of damaged area. Due to its multi-disciplinary nature, some considered aspects can be improved involving domain experts. For example Social Scientists can be involved to design different types of social benefit functions that consider other societal factors, or geologists that help us to add more soil aspects to consider for a more robust and sustainable reconstruction.

7.1 Future Work

We are pretty sure what we have presented in this research is just a starting point in the direction of post-disaster reconstruction planning. The research topic is multi-disciplinary and can improve in several directions.

More accurate social benefit function can be defined that consider wider social aspects. A close collaboration with social scientists is necessary in this respect,

Moreover, the approach can be made more robust adding more information to the dataset *REPAIR* takes as input. One example is related to geological information of the soil under the damaged areas. In L'Aquila city, after the 2009 earthquake, the municipality made the micro-zoning of the area providing detail information on the geological composition of the soil. This information would help to take aware and safe decision in the reconstruction. For example, *REPAIR* can exclude from the plan buildings that are located on soils that are not geologically adequate, highlighting them to experts for broader technical considerations that are not subject to *REPAIR*. In such a way, *REPAIR* would provide a more resilient reconstruction strategies.

The current implementation of *REPAIR* is made up of a series of components that are not integrated into a service that can be easily used by decision makers. Hence, another future direction of this research is to create a service for end users with high usability and with user-friendly graphical interface. Such a service should also seamlessly integrated with external systems (such as local GIS systems or the IT systems of institutions) feeding it with necessary data.

To be more specific our future directions could finally be but not limited:

- to consider the 'DiReCT' approach [94] which mainly focus on evacuation and reconstruction plans altogether. It would be consisted on three main parts: i) the construction of a network (or graph) based on the GIS data (GisToGraph algorithm) (section 4.2.1), ii) the dynamic flow modeling, and the solution to evacuation planning (determination of safe areas, determination of paths and ramification of people [59]), and iii) the modeling of the reconstruction planning and its solution built by employing double deep Q-learning network (DDQN) approach (chapter 4 and chapter 5). 'DiReCT' loop shows feedback to GisToGraph algorithm after evacuation and reconstruction. The proposed methodology is overall illustrated in Fig. 4.1, where the rounded rectangles represent the processes, i.e, the set of operations for the different algorithms, and the rectangles represent the outputs of the various operations.

- to consider the assessment and rehabilitation of basic facilities of life like water and gas pipelines including street walk-ability based on more specific attributes than the mere number of residents living in an area before reconstruction.

- quantitative research to assess damage level accurately by using cutting-edge technologies. This would be really helpful to estimate the damaged infrastructure and to estimate the reconstruction budget accurately.

7.2 Research Publications

The research presented in this thesis is based on the following peer-reviewed publications:

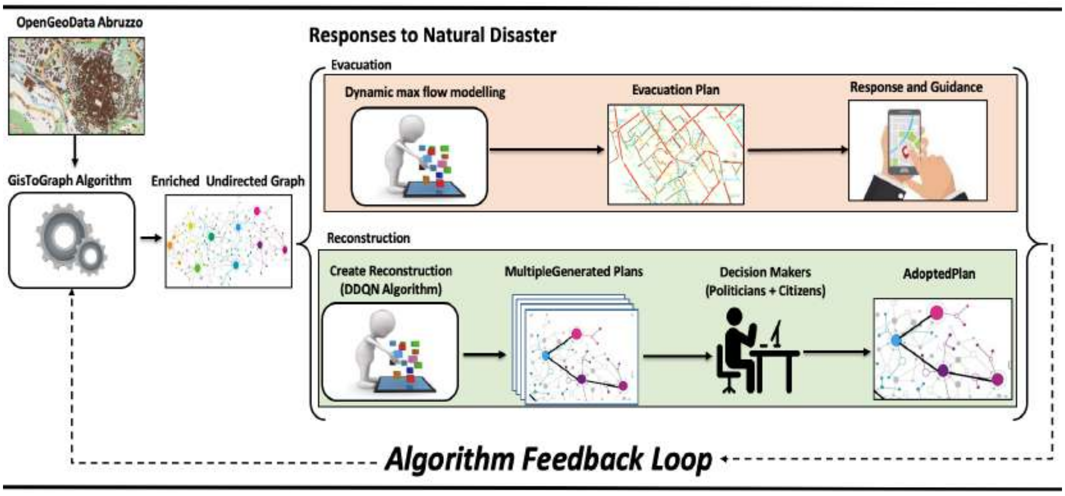


Figure 7.1: DiReCT approach

- Ghulam Mudassir "Social-based physical reconstruction planning in case of natural disaster: A machine learning approach" In 2019 International Conference on Research Challenges in Information Science (RCIS) pp. 604- 612. (*Thesis author contribution:* Overall idea of approach and writing under the guidelines of the supervisor).
- Ghulam Mudassir, Antinisca Di Marco "Social-based City Reconstruction Planning in case of natural disasters: a Reinforcement Learning Approach" In Proceedings of the 2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC) pp.493-503 (*Thesis author contribution:* Mathematical modeling, implementation, experiment setup. evaluation and writing under the guidance of the supervisor).
- Ghulam Mudassir, Evans Etrue Howard, Lorenza Pasquini, Claudio Arbib, Antinisca Di Marco, and Giovanni Stilo "Toward Effective Response to Natural Disasters: a Data Science Approach" In IEEE Access 2021, volume 9, pp.167827-167844 (*Thesis author contribution:* Overall idea, implementation, experiment setup. evaluation and writing under the guidance of the supervisor and other team members).
- Ghulam Mudassir, Antinisca Di Marco and Lorenza Pasquini "City Reconstruction Planner with Social Perspective" In Proceedings of i-cities conference 2021. (*Thesis author contribution:* Overall idea along with other authors, Implementation, experiment setup. evaluation and equally contributed in writing under the guidance of the supervisor and others team members).

The following papers are under internal-review:

- Ghulam Mudassir and Antinisca Di Marco "Reconstruction Planning approaches in case of natural disasters: A Systematic Mapping Study" DISIM, University of L'Aquila, L'Aquila, Italy. Venue: ACM Computing Surveys. (*Thesis author contribution:* Overall search of a literature review from seven different digital libraries, mapping of all those related articles, and writing under the guidance of the supervisor).

- Ghulam Mudassir and Antinisca Di Marco "REPAIR: REinforcement learning and Social based aPproAch to Post-dIsaster Reconstruction Planning" DISIM, University of L'Aquila, L'Aquila, Italy. Venue: International Journal of Data Science and Analytics (IJDSA) (*Thesis author contribution:* This paper is the extension of COMPSAC paper and did work implementation, experiment setup. evaluation, and writing under the guidance of the supervisor).

Appendix A

Results Tables

Here following, we have shown the results of *Sulmona* case study of cycle-2, cycle-3, cycle-4 and cycle-5.

Table A.1: Cycle-2:Plan 1

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	40	Civil Building	127	112	7.9	5237
2	36	Civil Building				
3	691-785	Road				
4	437	Private Building				
5	1160-1005	Road				
6	332	Civil Building				
7	813	Civil Building				
8	1120-670	Road				
9	580-112	Bridge				
10	87	Civil Building				
11	60-526	Road				
12	870	Private Building				
13	120	Civil Building				
14	1020	Civil Building				
15	135-240	Road				
16	544-720	Road				
17	720-630	Road				
18	532-476	Road				
–	–	–				
239	147	Private Building				

Table A.2: Cycle-2:Plan 2

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	71	University	124	99	7.6	5198
2	92	Civil Building				
3	912	Hospital				
4	806-578	Road				
5	1271	Civil Building				
6	439-122	Road				
7	960	Civil Building				
8	668	Civil Building				
9	583-621	Road				
10	87	Civil Building				
11	60-526	Road				
12	870	Private Building				
13	120	Civil Building				
14	1020	Civil Building				
15	135-240	Road				
16	544-720	Road				
17	720-630	Road				
18	610-532	Road				
–	–	–				
239	147	Private Building				

Table A.3: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[40,36, 691-785]
2	[437, 1160-1005]
3	[332, 813, 1120-670]
4	[580-112]
5	[87, 60-526]
6	[870, 120, 1020, 135-240]
7	[544-720]
8	[720-630]
9	[610-532]
10	[532-476]
11	[181, 178, 621, 732-116]
12	[1136,1084,678-985]
13	[46,53, 1151-385]
14	[831,137,1192,666,824,1314-686]
15	[590,338,188-80]
16	[62,64,770-120]
17	[120,222,106-840]
18	[16, 21, 130-220]
19	[78, 629-611]
20	[590, 123, 666-697]
21	[705, 435-476]
22	[247,331-216]
23	[221, 109-821]
24	[1188,1080,131-140]
25	[140,690-761]
26	[742,431,1214-689]
27	[1166,590-701]
28	[87, 59, 765, 1166-432]
29	[118,1016-831]
30	[17, 33, 121-216]
31	[28, 844-790]
32	[133-610]
33	[956, 612, 535-410]
34	[255,219-271]
35	[340, 749-599]
36	[1121, 972-121]
37	[39, 586-991]
38	[840, 331-1150]
39	[697, 580, 778, 365-1181]
40	[91,694-116]
41	[319, 1090-637]
42	[456, 178-221]
43	[595, 835-611]
44	[324, 336, 641-719]
45	[641, 638-410]
46	[299, 322, 326-269]
-	-
55	[1360,147]

Table A.4: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[71, 92, 912, 806-578]
2	[1271, 439-122]
3	[960, 668, 583-621]
4	[87, 60-526]
5	[870, 120, 1020, 135-240]
6	[544-720]
7	[720-630]
8	[610-532]
9	[532-476]
10	[476, 521-639]
11	[181, [1136,1084,678-985]
12	178, 621, 732-116]
13	[831,137,1192,666,824,1314-686]
14	[46,53, 1151-385]
15	[62,64,770-120]
16	[590,338,188-80]
17	[16, 21, 130-220]
18	[120,222,106-840]
19	[590, 123, 666-697]
20	[78, 629-611]
21	[247,331-216]
22	[705, 435-476]
23	[1188,1080,131-140]
24	[221, 109-821]
25	[742,431,1214-689]
26	[140,690-761]
27	[87, 59, 765, 1166-432]
28	[1166,590-701]
29	[17, 33, 121-216]
30	[118,1016-831]
31	[133-610]
32	[28, 844-790]
33	[255,219-271]
34	[956, 612, 535-410]
35	[1121, 972-121]
36	[340, 749-599]
37	[840, 331-1150]
38	[39, 586-991]
39	[91,694-116]
40	[697, 580, 778, 365-1181]
41	[456, 178-221]
42	[319, 1090-637]
43	[324, 336, 641-719]
44	[595, 835-611]
45	[641, 638-410]
46	[299, 322, 326-269]
-	-
55	[1360,147]

Table A.5: Cycle-3:Plan 1

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	51	Civil Building	122	95	6.9	4527
2	591	Civil Building				
3	640	Private Building				
4	782	Private Building				
5	1187-785	Road				
6	449	Civil Building				
7	949	Civil Building				
8	1203	Private Building				
9	594-720	Bridge				
10	91	Civil Building				
11	75	Civil Building				
12	815-246	Road				
13	137-213	Road				
14	916	Civil Building				
15	149-759	Road				
16	344	Civil Building				
17	444-507	Road				
18	537	Private Building				
19	483-312	Road				
–	–	–				
217	161-289	Road				

Table A.6: Cycle-3:Plan 2

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	72	Hospital	125	98	7.1	4590
2	520	Civil Building				
3	915	Civil Building				
4	669-839	Road				
5	786	Civil Building				
6	320-199	Road				
7	878	Private Building				
8	1201-571	Road				
9	594-720	Road				
10	91	Civil Building				
11	75	Civil Building				
12	815-246	Road				
13	137-213	Road				
14	916	Civil Building				
15	149-759	Road				
16	344	Civil Building				
17	444-507	Road				
18	537	Private Building				
19	483-312	Road				
–	–	–				
217	161-289	Road				

Table A.7: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[51, 591, 640, 782, 1187-785]
2	[449,949,1203,594-720]
3	[91, 75, 815-246]
4	[137-213]
5	[916,149-759]
6	[344, 444-507]
7	[537, 483-312]
8	[507-104]
9	[173, 234-456]
10	[544, 245, 358-274]
11	[188, 178, 544-115]
12	[1177,1172,449, 123-788]
13	[83,631-661]
14	[742,617,721,199,255,1115-783]
15	[918,88,87-95]
16	[601,630,770-128]
17	[145,190-132]
18	[145-211]
19	[768,535-694]
20	[487, 301-108]
21	[501,810, 811-875]
22	[389-250]
23	[325, 101-421]
24	[114,173,134-156]
25	[158,585-698]
26	[123,534,799, 121-585]
27	[1117,397-588]
28	[100, 133, 466, 1120-332]
29	[130,1120-631]
30	[191-228]
31	[25, 549-508]
32	[31, 409-817]
33	[660, 517, 888-375]
34	[246,329-210]
35	[39, 983-599]
36	[136,174-179]
37	[351,780-927]
38	[73,134-1056]
39	[69, 160, 231-821]
40	[677-140]
41	[158,113-835]
42	[391, 17-211]
43	[450, 458-537]
44	[549, 721-729]
45	[410,537-567]
46	[390,322-290]
-	-
54	[1198,1001,161-289]

Table A.8: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[72, 520, 915, 669-839]
2	[786, 320-199]
3	[878, 1201-571]
4	[594-720]
5	[91, 75, 815-246]
6	[137-213]
7	[916, 149-759]
8	[344, 444-507]
9	[537, 483-312]
10	[188, 178, 544-115]
11	[544, 245, 358-274]
12	[83,631-661]
13	[1177,1172,449, 123-788]
14	[918,88,87-95]
15	[742,617,721,199,255,1115-783]
16	[145,190-132]
17	[601,630,770-128]
18	[768,535-694]
19	[145-211]
20	[501,810, 811-875]
21	[487, 301-108]
22	[325, 101-421]
23	[389-250]
24	[158,585-698]
25	[114,173,134-156]
26	[1117,397-588]
27	[123,534,799, 121-585]
28	[130,1120-631]
29	[100, 133, 466, 1120-332]
30	[25, 549-508]
31	[191-228]
32	[660, 517, 888-375]
33	[31, 409-817]
34	[39, 983-599]
35	[246,329-210]
36	[351,780-927]
37	[136,174-179]
38	[69, 160, 231-821]
39	[73,134-1056]
40	[158,113-835]
41	[677-140]
42	[450, 458-537]
43	[391, 17-211]
44	[549, 721-729]
45	[390,322-290]
46	[410,537-567]
-	-
54	[1198,1001,161-289]

Table A.9: Cycle-4:Plan 1

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	63	University	115	91	6.1	4112
2	235	Civil Building				
3	645	Civil Building				
4	335	Civil Building				
5	966	Private Building				
6	635-758	Road				
7	813	Civil Building				
8	1178	Civil Building				
9	683-772	Road				
10	195-214	Bridge				
11	98	Private Building				
12	570-616	Road				
13	120	Civil Building				
14	859	Civil Building				
15	1209	Civil Building				
16	589-613	Road				
17	1009	Private Building				
18	898	Civil Building				
19	537-762	Road				
–	–	–				
206	696	Civil Building				

Table A.10: Cycle-4:Plan 2

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	75	Civil Building	113	95	6.3	4136
2	418-171	Road				
3	983	Civil Building				
4	1012	Civil Building				
5	1091-1071	Bridge				
6	745	Civil Building				
7	893	Private Building				
8	1178	Civil Building				
9	683-772	Road				
10	195-214	Bridge				
11	98	Private Building				
12	570-616	Road				
13	120	Civil Building				
14	859	Civil Building				
15	1209	Civil Building				
16	589-613	Road				
17	1009	Private Building				
18	898	Civil Building				
19	537-762	Road				
–	–	–				
206	696	Civil Building				

Table A.11: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[63, 235, 645, 335, 996, 635-758]
2	[813, 1178, 683-772]
3	[195-214]
4	[98,570-616]
5	[120, 859, 1209, 589-613]
6	[1009, 898, 537-762]
7	[715, 868, 749-807]
8	[25, 539-671]
9	[611,412-621]
10	[559,129-457]
11	[178, 278, 79-115]
12	[890,1123, 140, 590-891]
13	[438,197, 587-894]
14	[739, 516, 188, 845, 1168-683]
15	[782,495,133-891]
16	[259,175,889-918]
17	[106, 220,217-762]
18	[142-149]
19	[851,538-588]
20	[588, 517-718]
21	[88, 255, 195-289]
22	[37, 719-527]
23	[395, 477-783]
24	[491, 991, 1050, 255-476]
25	[548, 222, 492-669]
26	[659, 525, 991-792]
27	[1005, 673-592]
28	[113, 783, 696, 889-365]
29	[382, 489, 996-723]
30	[678, 468-583]
31	[342, 756-717]
32	[559, 425-521]
33	[867, 732, 546-191]
34	[373,421-121]
35	[467, 589, 812-799]
36	[223, 275-531]
37	[845, 693, 735-892]
38	[629, 521-987]
39	[603, 673, 88-90]
40	[185, 745, 673-129]
41	[221, 812, 197-201]
42	[374, 178-19]
43	[459, 340-421]
44	[570, 443, 897-749]
45	[655, 456-510]
46	[371, 311-176]
-	-
56	[971, 872, 696]

Table A.12: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[75,418-171]
2	[983, 1012, 1091-1071]
3	[745, 893, 1178, 683-772]
4	[195-214]
5	[98, 570-616]
6	[120, 859, 1209, 589-613]
7	[1009, 898, 537-762]
8	[611,412-621]
9	[25, 539-671]
10	[178, 278, 79-115]
11	[559,129-457]
12	[438,197, 587-894]
13	[890,1123, 140, 590-891]
14	[782,495,133-891]
15	[739, 516, 188, 845, 1168-683]
16	[106, 220,217-762]
17	[259,175,889-918]
18	[851,538-588]
19	[142-149]
20	[88, 255, 195-289]
21	[588, 517-718]
22	[395, 477-783]
23	[37, 719-527]
24	[548, 222, 492-669]
25	[491, 991, 1050, 255-476]
26	[1005, 673-592]
27	[659, 525, 991-792]
28	[382, 489, 996-723]
29	[113, 783, 696, 889-365]
30	[342, 756-717]
31	[678, 468-583]
32	[867, 732, 546-191]
33	[559, 425-521]
34	[467, 589, 812-799]
35	[373,421-121]
36	[845, 693, 735-892]
37	[223, 275-531]
38	[603, 673, 88-90]
39	[629, 521-987]
40	[221, 812, 197-201]
41	[185, 745, 673-129]
42	[459, 340-421]
43	[374, 178-19]
44	[655, 456-510]
45	[570, 443, 897-749]
46	[371, 311-176]
-	-
56	[971, 872, 696]

Table A.13: Cycle-5:Plan 1

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	23	Civil Building	103	102	5.2	3601
2	195	Civil Building				
3	539-679	Road				
4	781	Civil Building				
5	546	civil Building				
6	939	Civil Building				
7	281	Civil Building				
8	779-889	Road				
9	485	Civil Building				
10	90-133	Road				
11	70	Civil Building				
12	780-146	Road				
13	29	Private Building				
14	119-241	Road				
15	161	Civil Building				
16	389-923	Road				
17	790-832	Road				
18	754	Civil Building				
–	–	–				
205	635	Civil Building				

Table A.14: Cycle-5:Plan 2

Budget: $1,000,000 Time:60 Months						
Sr. No	**Units ID**	**Type**	**Buildings**	**Phys. Depend.**	**Political Priority**	**S_P**
1	17	Civil Building	101	99	5.0	3577
2	417	Civil Building				
3	387	Civil Building				
4	149-449	Road				
5	1089	Civil Building				
6	329	Civil Building				
7	815	Civil Building				
8	779-889	Road				
9	485	Civil Building				
10	90-133	Road				
11	70	Civil Building				
12	780-146	Road				
13	29	Private Building				
14	119-241	Road				
15	161	Civil Building				
16	389-923	Road				
17	790-832	Road				
18	754	Civil Building				
–	–	–				
205	635	Civil Building				

Table A.15: Plan 1- List of parallel units

Sr.No	Parallel Units
1	[23, 195, 539-679]
2	[781, 546, 939, 281, 779-889]
3	[485, 90-133]
4	[70,780-146]
5	[29,119-241]
6	[161, 389-923]
7	[790-832]
8	[754, 221, 456-791]
9	[129, 528-162]
10	[331, 39, 671-111]
11	[456-577]
12	[213, 374, 57-61]
13	[41, 49, 553-794]
14	[495, 370, 128, 437, 625-728]
15	[178, 585, 109-217]
16	[518, 414, 870-210]
17	[120-832]
18	[889, 129-446]
19	[1202,748-107]
20	[78, 897, 307-413]
21	[313, 618, 188, 741-679]
22	[268, 477, 231-427]
23	[351, 172-391]
24	[153, 190, 192-185]
25	[136,680-785]
26	[839, 622, 770-811]
27	[1207,721-931]
28	[296, 189, 737, 626-581]
29	[198, 126-875]
30	[177, 254, 129-296]
31	[328, 557-617]
32	[1179, 1025, 971-1007]
33	[890, 1075, 226-495]
34	[413, 375, 441-720]
35	[517, 611, 1031-1192]
36	[1191, 175-277]
37	[165, 391, 624-790]
38	[698, 571-824]
39	[681, 840, 354-832]
40	[178, 886, 285-369]
41	[246, 1160-939]
42	[365, 1199-739]
43	[634, 790-898]
44	[273, 119-391]
45	[879, 778-610]
46	[459, 327-415]
-	-
53	[1090,898,635]

Table A.16: Plan 2- List of parallel units

Sr.No	Parallel Units
1	[17, 417, 387, 149-449]
2	[1089, 329, 815, 779-889]
3	[485, 90-133]
4	[70, 780-146]
5	[29, 119-241]
6	[161, 389-923]
7	[790-832]
8	[129, 528-162]
9	[754, 221, 456-791]
10	[456-577]
11	[331, 39, 671-111]
12	[41, 49, 553-794]
13	[213, 374, 57-61]
14	[178, 585, 109-217]
15	[495, 370, 128, 437, 625-728]
16	[120-832]
17	[518, 414, 870-210]
18	[1202,748-107]
19	[889, 129-446]
20	[313, 618, 188, 741-679]
21	[78, 897, 307-413]
22	[351, 172-391]
23	[268, 477, 231-427]
24	[136,680-785]
25	[153, 190, 192-185]
26	[1207,721-931]
27	[839, 622, 770-811]
28	[198, 126-875]
29	[296, 189, 737, 626-581]
30	[328, 557-617]
31	[177, 254, 129-296]
32	[890, 1075, 226-495]
33	[1179, 1025, 971-1007]
34	[517, 611, 1031-1192]
35	[413, 375, 441-720]
36	[165, 391, 624-790]
37	[1191, 175-277]
38	[681, 840, 354-832]
39	[698, 571-824]
40	[246, 1160-939]
41	[178, 886, 285-369]
42	[634, 790-898]
43	[365, 1199-739]
44	[879, 778-610]
45	[459, 327-415]
46	[273, 119-391]
-	-
53	[1090,898,635]

Appendix B

Technology Stack

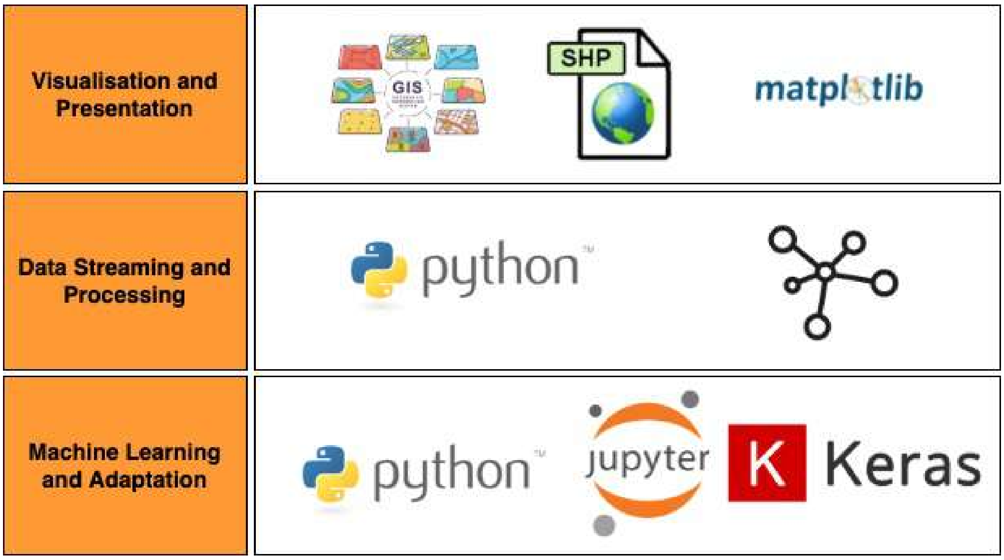


Figure B.1: Overview of technology stack

In this section we have provided the details of technologies that we have used for the different parts of the *REPAIR* approach throughout this thesis. According to fig B.1 we have categorized all technologies into three parts with respect to the implementation in various parts of the approach presented in this thesis. Here following we have explained all the categories:

Visualisation and Presentation

Basically, we have extracted shapefiles [1] from GIS data because it contains all information related to a damaged city. Later we transformed all useful information into a network structure with the help of *matplotlib* that are used for reconstruction planning.

Data Streaming and Processing

In this category we write a Python script to covert network structure into .XLSX and .CSV form to create an undirected graph. With the help of this graph, we can identify damaged buildings/units

[1] http://opendata.regione.abruzzo.it/catalog

and roads/bridges in the affected area.

Machine Learning and Adaptation

After data processing and visualization we have implemented reinforcement learning (DDQN algorithm) in python by using *Jupyter Notebook*. Additionally, we have imported *Keras* library during the implementation of the *REPAIR* model.

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