TERRITORI APERTI

Università degli Studi dell’Aquila

Department of Information Engineering, Computer Science and Mathematics

PhD in Information and Communication Technologies

Social-based city Reconstruction Planning in case of natural disasters: a Reinforcement Learning Approach

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XXXIV Doctoral Cycle

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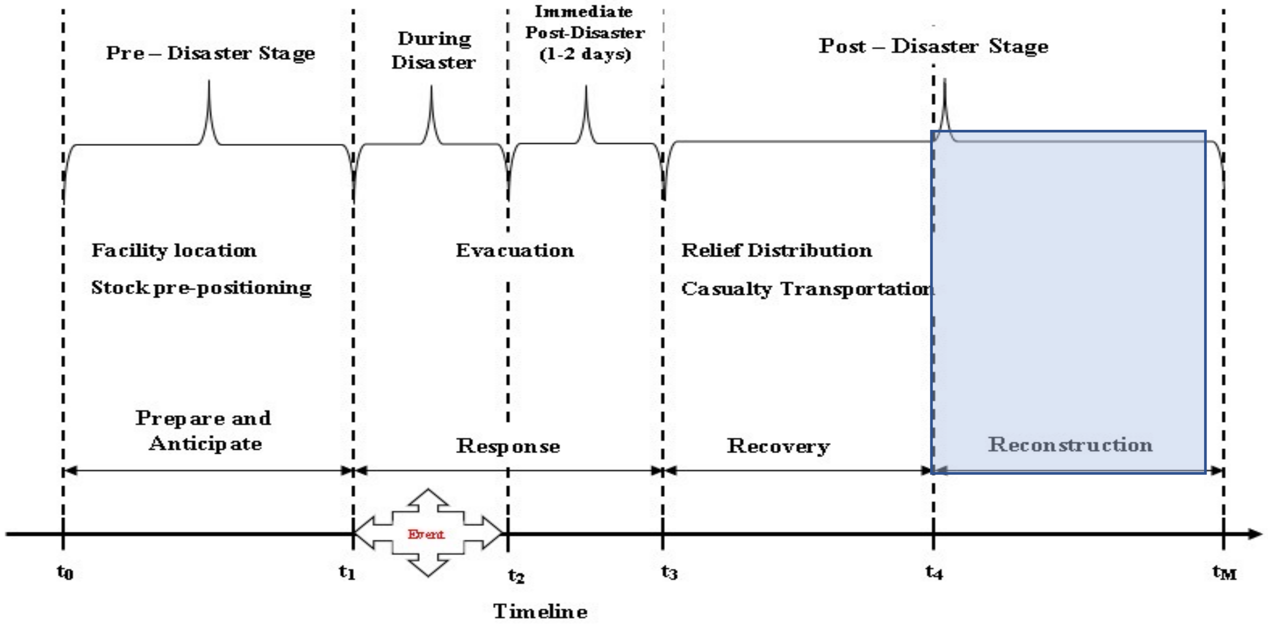
Activities Outlines

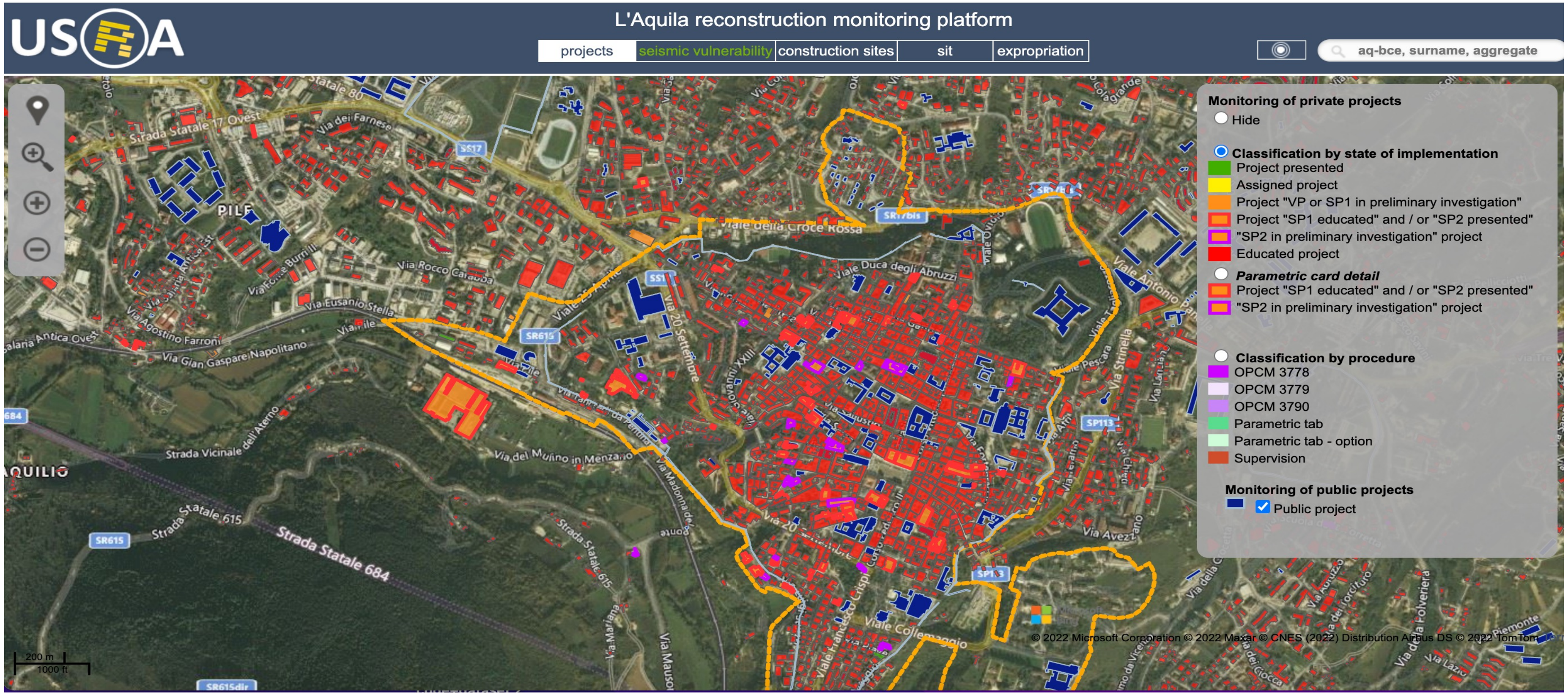
- Motivating Scenario
- Main Challenges
- State of the Art and Systematic Mapping Study
- Research Problems
- Proposed Methodology
- Evaluation and Results
- Conclusion and Future work
- List of Publications
- Courses and Seminars

Motivating Scenario

- Natural Disaster
- Post-Disaster
  - ✓ Relief
  - ✓ Recovery
  - ✓ Development (Reconstruction Plan)
    - ❖ Reconstruction of city (buildings, roads/bridges..)
    - ❖ Reconstruction constraints (budget, time, city topology, political priority, etc)
    - ❖ Social benefits of effected community



Motivating Scenario



Research Goals

- To develop an approach for the purpose of city reconstruction planning taking into account the social benefits of affected people, political strategies *(represents the political importance of every unit),* physical dependencies, time *(specify reconstruction order among reconstruction units like damage roads/bridge)* and cost for reconstruction;
- The approach generates a set of plans *(specifying reconstruction order among reconstruction units like damaged roads/bridges)* that satisfies constraints and maximize social benefits

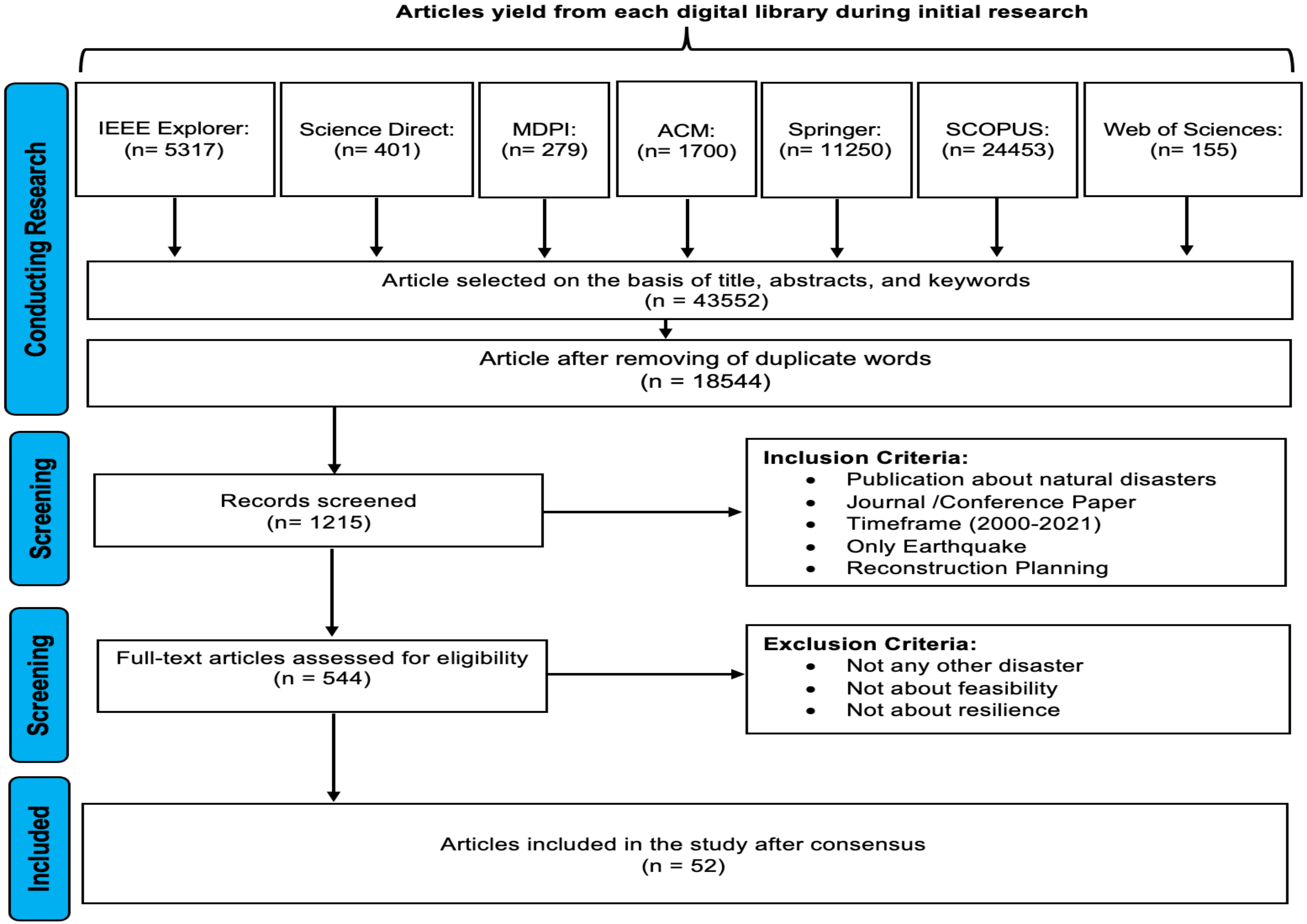
Systematic Mapping Study

We conducted a Systematic Mapping Study using the Goal-Question-Metric approach.

Analyze the state-of-the-art post-earthquake approaches **for the purpose of** city reconstruction planning aiming to:

- Identify kind of problems have been addressed
- identify the developed approaches and evaluate them in terms of used parameters, limitations and on what extent they have been experimented and used,
- Identify publication venue, trend over the time; the expertise required and latest active research in our domain from the point of view of researchers and practitioners
- The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) technique is applied

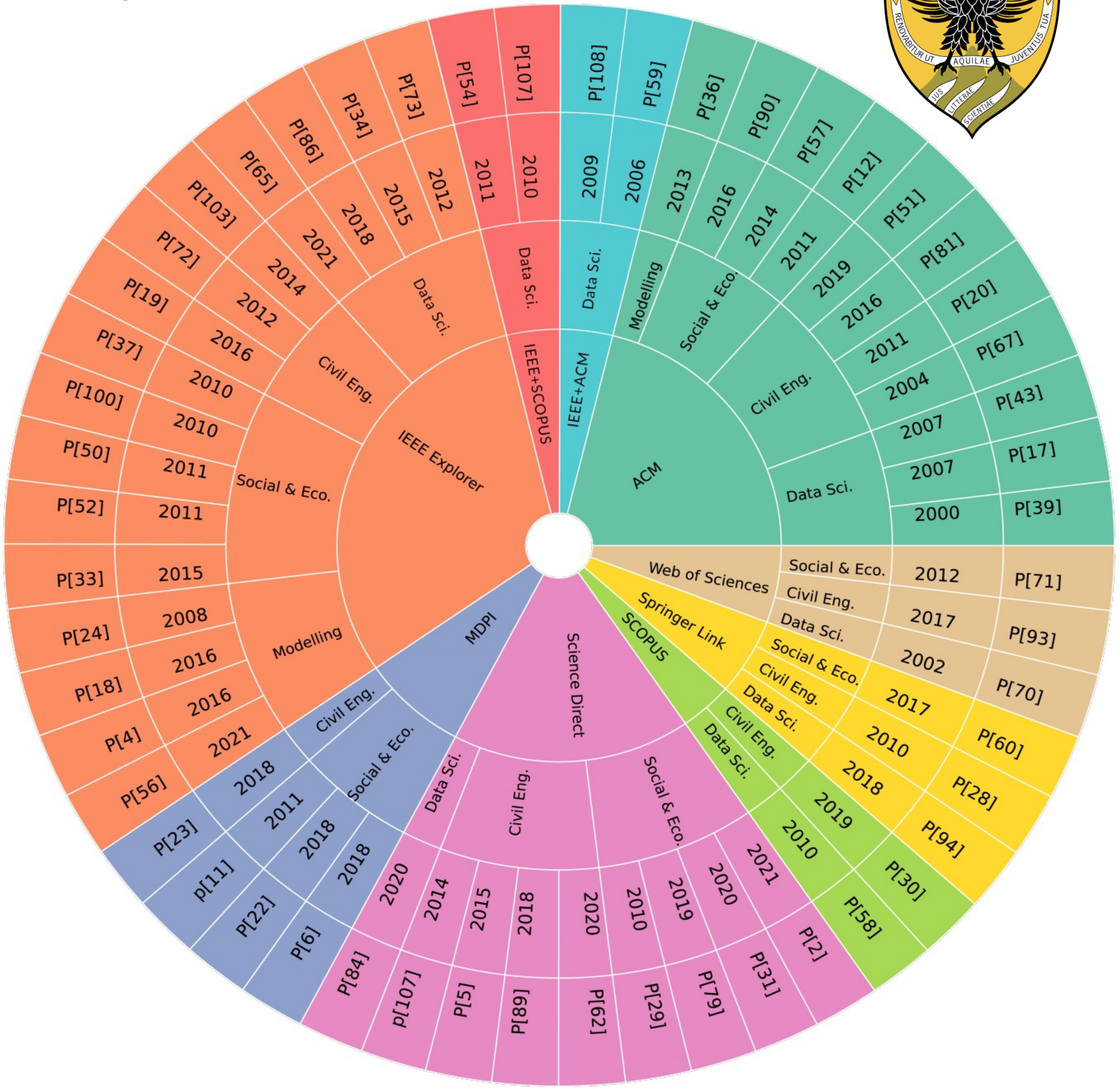
Results obtaining by means of PRISMA



Selected Primary Studies

Classification Framework:

- Digital Libraries (7)
- Thematic Areas (4)
- Year of Publication (*from 2000 to 2021*)
- References of the primary studies (52)



Key Attributes of Primary Studies

- Time
- Cost
- Political Priority
- Damage Level
- Residents Number
- City Data
- Physical Dependencies
- People Opinion
- Gross Domestic Production
- Sustainability of the reconstruction
- State Disaster Recovery Coordinator
- 3D Models
- Seismic Strength
- Stiffness
- Historical and Cultural
- Social Benefits

Key Attributes in the Primary Studies

None of the primary study addresses (or deals with) social benefits, only one of them (PS47) considers Physical Dependency (PD)

Ref	Input Parameters																
PS[Ref]	Time	Cost	PP	DL	RN	CD	PD	PO	GDP	Sustainbi.	SDRC	3D	SS	Stiffness	H&C	Env.	SB
PS1	X	X	X			X			X	X	X						
PS2		X		X		X			X		X						
PS5		X						X									
PS6		X		X	X							X					
PS7		X		X													
PS9			X		X	X							X				
PS10	X	X															
PS11			X	X		X			X								
PS12		X	X		X												
PS13	X		X		X			X									
PS14				X	X	X											
PS15	X	X	X	X		X											
PS16		X	X	X							X						
PS17	X		X			X											
PS18		X		X											X		
PS19				X	X	X											
PS20	X	X	X			X		X									
PS21		X															
PS22				X	X										X		
PS24		X						X									
PS25				X		X					X						
PS26	X	X						X					X				
PS27	X			X		X								X			
PS28		X		X	X										X		
PS29		X	X	X	X					X							
PS30			X		X	X											
PS31	X	X	X	X		X			X			X	X				
PS32	X		X			X					X						
PS33		X		X		X									X		
P34				X	X	X					X						
PS35	X	X	X			X					X						
PS36		X						X						X			
PS37				X	X			X					X				
PS38		X		X					X						X		
PS39		X							X					X			
PS41	X	X								X							
PS43		X	X	X	X						X						
PS44		X	X		X											X	
PS45			X		X	X									X		
PS46		X	X		X						X						
PS47		X	X	X	X		X									X	
PS48			X	X	X	X							X				
PS49		X	X	X	X										X		
PS50		X		X	X				X							X	
PS51		X	X		X								X				

Main Challenges

- ➢ Manual rebuilding plan is error prone
- ➢ Existing approaches do not consider key attributes we want to target:
  - ✓ Social benefits
  - ✓ Political Priorities
  - ✓ Physical Dependencies
- ➢ And automatic technique ✓ Reinforcement Learning

Research Problems

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

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

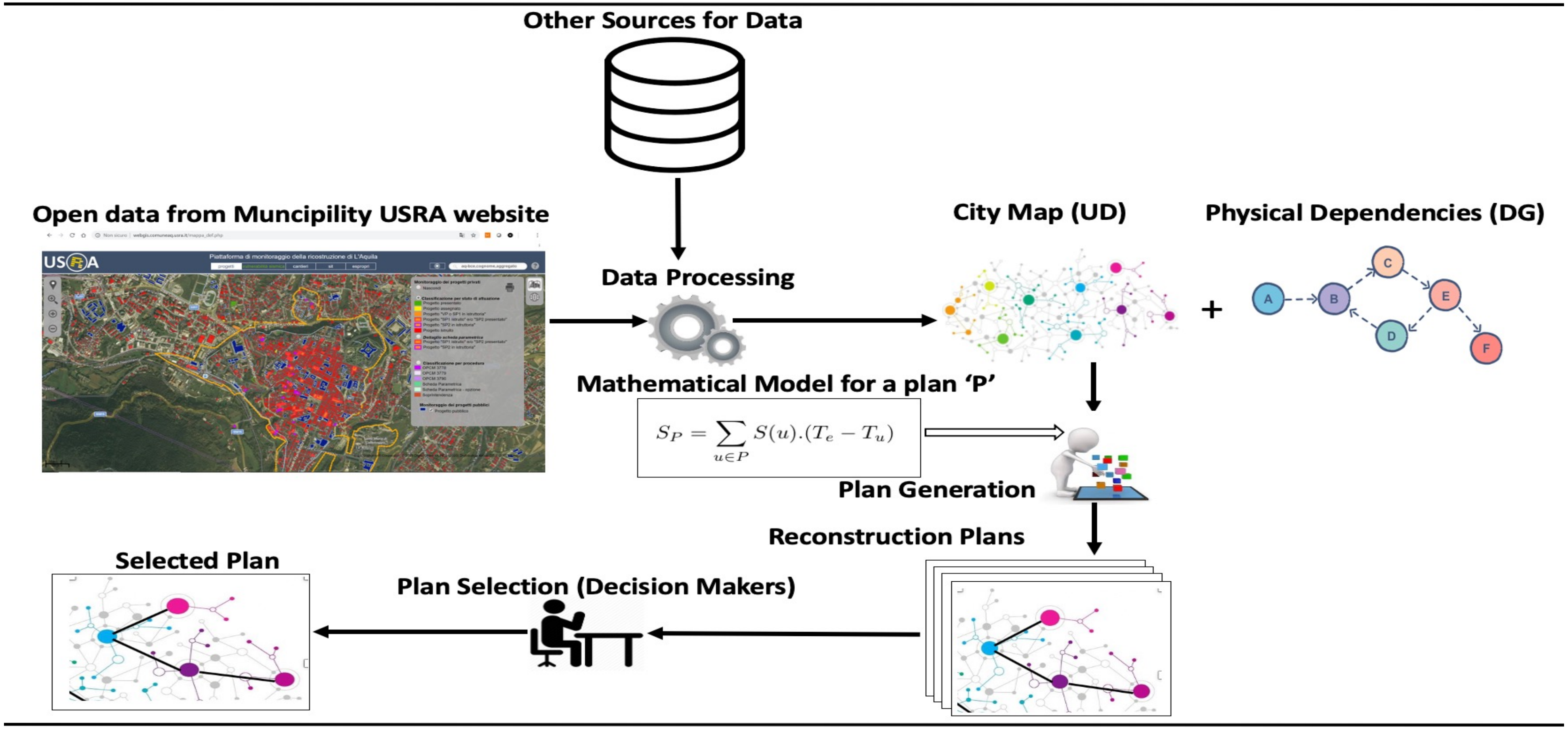
RQ3: How can we model the **physical dependencies** and embed them into rebuilding planning model?

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?

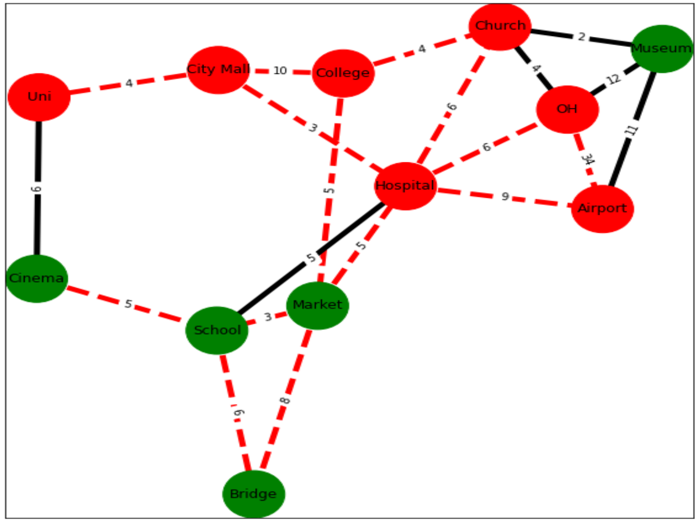
RQ6: Which reinforcement learning algorithm is the **most effective and efficient** one for REPAIR approach?

REPAIR: Methodology



City Map: Undirected Graph model of the damaged area

- Labelled undirected graph G(V,E) where
  - ✓ V= Set of vertices 'v' that represent reconstruction units
  - ✓ E= Set of edges 'e' that represent adjacency between two reconstruction units
  - ✓ d (v1, v2) = label on the edges representing a function that specifies the distance between two reconstruction units



- We have additional information on reconstruction units such as
  - ✓ number of people,
  - ✓ status of buildings,
  - ✓ cost and time for reconstruction

Physical Dependencies: Directed Graph

- Labelled directed graph G(V,E) where
  - ✓ V= Set of vertices ‘v’ that represent reconstruction units
  - ✓ E= Set of edges ‘e’ that represent adjacency between two reconstruction units
  - ✓ d (v1, v2) = label on the edges representing a function that specifies the distance between two reconstruction units

REPAIR Model: Constraints

Time : it concerns the time required to construct any damage unit/building.

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

Cost: it concerns the cost required to construct any damage unit/building.

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

Political Priority : it imposes a threshold on the plan in order to guarantee that the building plan respects the set political strategies

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

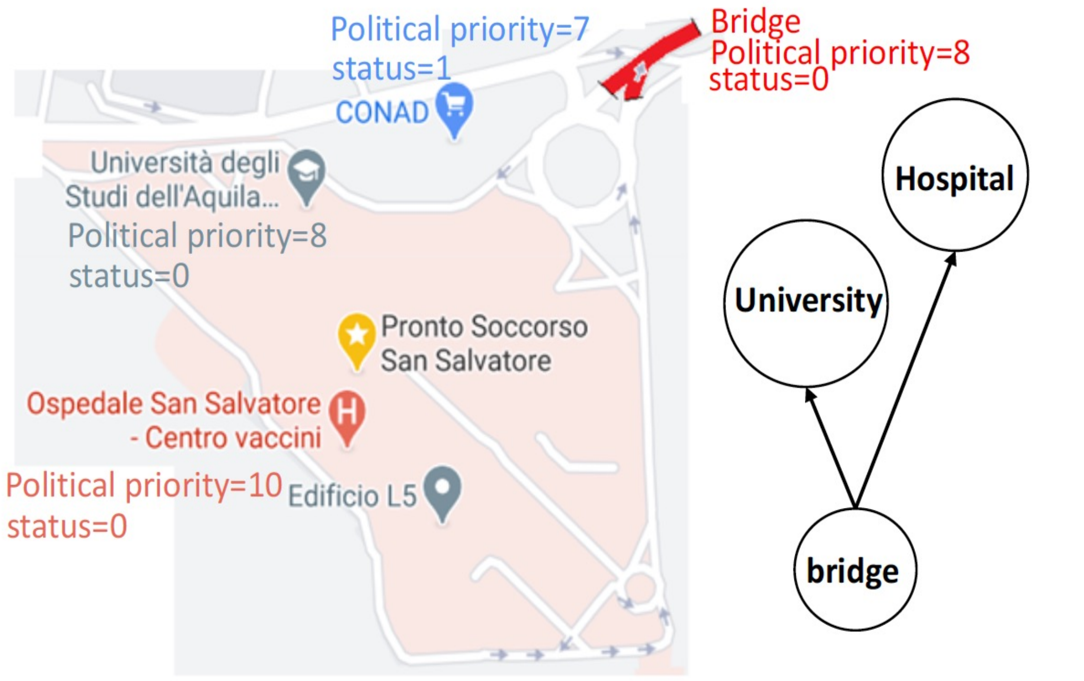
REPAIR Model: Constraints

Physical dependencies: **(directed graph)** among reconstruction units (like bridge/flyover) that impose ordering in the building reconstruction

$$\exists\ v \in P\ that\ is$$

$$e = (v, \overline{v})$$

$$\overline{v} \notin p \text{ and } s_v = 1$$



a. Enriched City Map

b. Physical Dependencies Graph

REPAIR Model: Optimization Function

Social benefits : it concerns the number of people who will use any unit/building, describe how much the plan is beneficial for the affected community

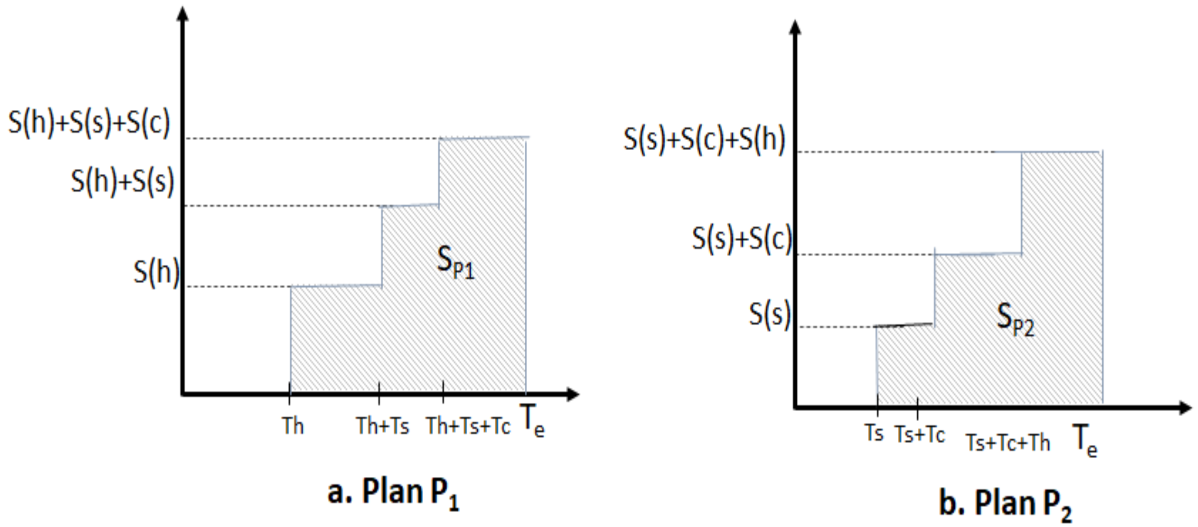
$$S_P = \sum_{v \in P} S(v).(T_e - T_v) \qquad S(v) = \left[\alpha.b_v + \beta \left(\sum_{u \in V | s_u = 1} \frac{S(u)}{d(u,v)} \right)\right]$$

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

REPAIR Model: Optimization Function

Plan: Every plan has order to reconstruct units with respect to social benefits of effected communities

Example : Let's reconstruct School (S), Hospital (H), and Cinema (C) by following different order of reconstruction.



PlanP1:

$T_e = 6$ $T_h = 2$ $T_s=1.5$ $T_c=1$
S(h)= 2000 S(s)= 1000 S(c)= 600
$S_p = 11400$

PlanP2:

$T_e = 6$ $T_h = 2$ $T_s=1.5$ $T_c=1$
S(s)= 1000 S(c)= 600 S(h)= 2000
$S_p = 9600$

REPAIR Model: Implementation

- We solve the model using reinforcement learning (RL) because we wanted the novel technologies to solve our problem and to evaluate to what extend reincorfement learning can support in post-disater reconstruction processes.

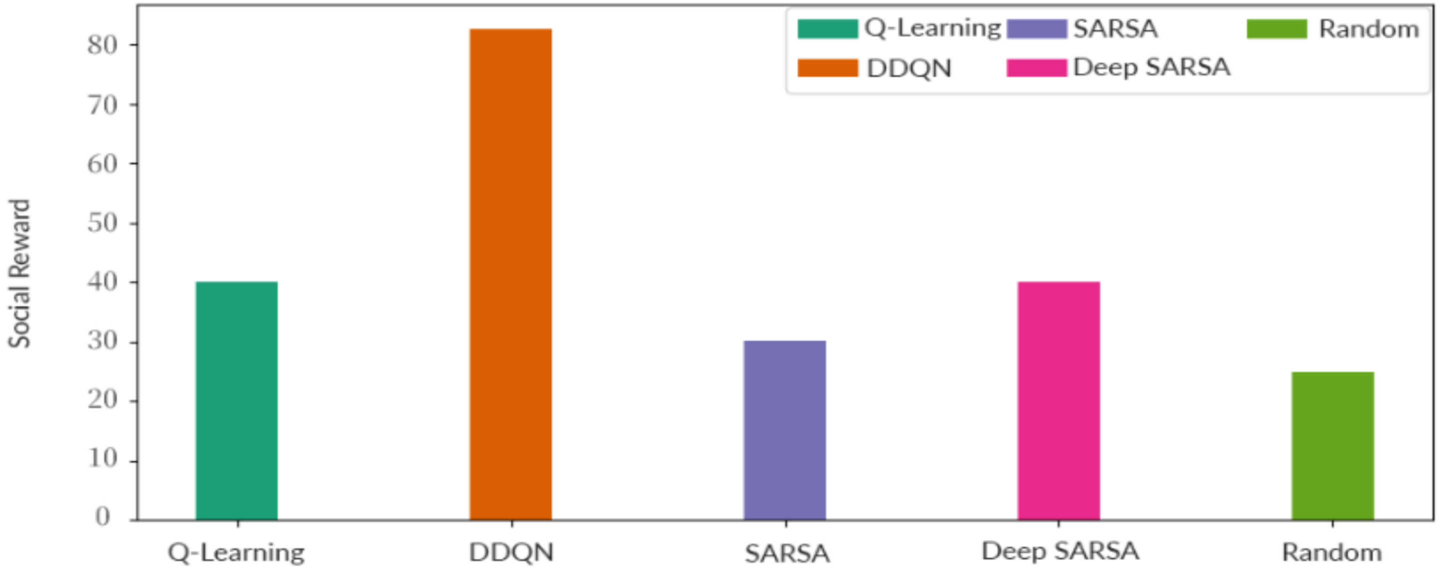
- From the systematic mapping we found no other research groups have investigated such a technology

- In order to select the best RL algorithm to use we conducted a set of experiments

Selecting the Reinforcement Learning Algorithm

- Comparison of reinforcement learning (RL) algorithms
  - ✓ Q-Learning
  - ✓ Double Deep Q-Network
  - ✓ SARSA
  - ✓ Deep SARSA
- Random Agent (as baseline)

Comparison of RL Algorithms



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

Double Deep Q-Learnig Network

- Markov Decision Process

- Bellman Equation

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

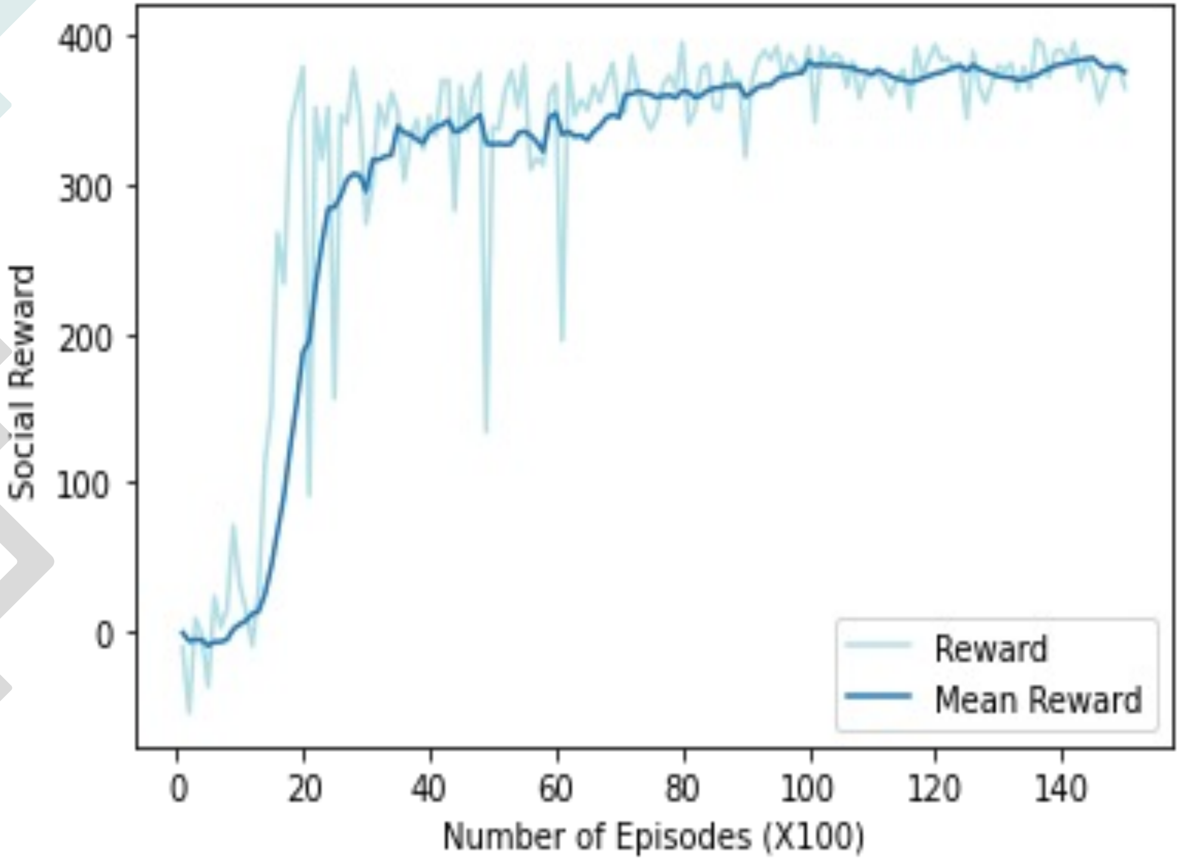
- Neural Networks

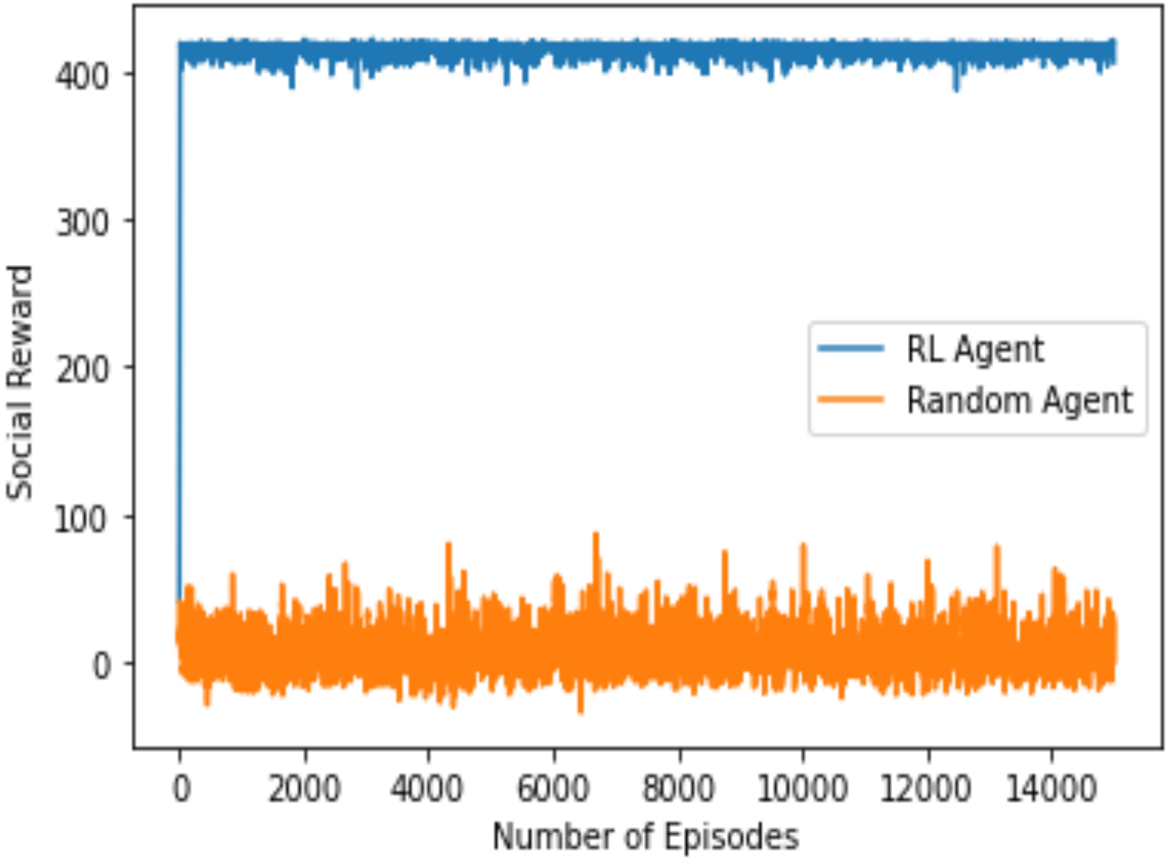
$$L_i(\theta_i) = E[(\overbrace{S_r(v) + \gamma \max_{a' \in A_v} Q'(s',a';\theta_i^-)}^{\text{Q-target}} - \overbrace{Q(s,a;\theta_i)}^{\text{Q-network}})]^2$$

Implementation: Fixed Parameters

Fixed Parameters	Value
Optimizer	Adam optimizer, learning rate = 0.001
Loss function	Mean squared error
Q-Learning function	$Q(s,a;\theta) = S_r(v) + \gamma \max_{a' \in A_v} Q'(s', a'; \theta_i^-)$
Batch size	32
Steps before training	15000
Maximum memory size	2000
Political Priority	Minimum=1 , 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)

Implementation: Agent Training and Testing





Evaluation and Results

- Case Study: Sulmona Dataset
  - ✓ 597 damage buildings out 1214
  - ✓ 470 damage roads out of 3476
  - ✓ Generate undirected Graph

- Case Study: L'Aquila Dataset
  - ✓ 37 damage buildings out 133
  - ✓ 20 damage roads out of 150
  - ✓ Generate undirected Graph

Cycle: Training of agent on behalf of input parameters

Plan: Multiple plans are created after every cycle

Evaluation on Sulmona Dataset

First Cycle Reconstruction Plans

Budget: $100000 Time:60 Months						
Sr. No	Units ID	Type	Buildings	PD	PP	Sp
1	35	Building	130	96	8.6	6257
2	690-783	Road				
3	732	Building				
4	434	Building				
5	1166	Building				
6	432	Building				
7	911	Building				
8	1213-681	Road				
9	582	Building				
10	85-82	Road				
–	–	–				
226	131	Building				

Budget: $100000 Time:60 Months						
Sr. No	Units ID	Type	Buildings	PD	PP	Sp
1	65	Building	134	92	8.5	6254
2	516-1071	Road				
3	906-912	Road				
4	912	Building				
5	1166	Building				
6	432	Building				
7	911	Building				
8	1213-681	Road				
9	582	Building				
10	85-82	Road				
–	–	–				
226	131	Building				

Evaluation on Sulmona Dataset

Parallel Units Reconstruction

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]
-	-
52	[1131,1072,131]

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]
-	-
52	[1131,1072,131]

Sr.No	Cycles	Units	Buildings	PD/Roads	PP	Sp
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

Evaluation on L'Aquila Dataset

Budget: $1,000,000 Time: 24 Months

Sr.No	Cycles	Units	Buildings	PD/Roads	PP	Sp
1	Cycle 1	16	11	5	9.3	3132
2	Cycle 2	19	12	7	7.9	2871
3	Cycle 3	21	14	8	6.8	2252

Results Summary

- The proposed model will be an efficient mechanism to define reconstruct plans on behalf of social benefits.
- Proposed framework provides a set of alternative plans which contain different order of reconstruction units.
- Every plan satisfies time, budget and political priority constraints.
- The proposed approach has the ability to identify and consider physical dependencies among reconstruction units.

Difference

‘PS52’ is the only approach which is considering Physical Dependencies (PD) and Social Benefits (SB) comprehensively.

Ref	Input Parameters																
PS[Ref]	Time	Cost	PP	DL	RN	CD	PD	PO	GDP	Sustainbi.	SDRC	3D	SS	Stiffness	H&C	Env.	SB
PS1	X	X	X			X			X	X	X						
PS2		X		X		X			X		X						
PS5		X						X									
PS6		X		X	X							X					
PS7		X		X													
PS9			X		X	X							X				
PS10	X	X															
PS11			X	X		X			X								
PS12		X	X		X												
PS13	X		X		X			X									
PS14				X	X	X											
PS15	X	X	X	X		X											
PS16		X	X	X							X						
PS17	X		X			X											
PS18		X		X											X		
PS19				X	X	X											
PS20	X	X	X			X		X									
PS21		X															
PS22				X	X										X		
PS24		X						X									
PS25				X		X					X						
PS26	X	X						X					X				
PS27	X			X		X								X			
PS28		X		X	X										X		
PS29		X	X	X	X					X							
PS30			X		X	X											
PS31	X	X	X	X		X			X			X	X				
PS32	X		X			X					X						
PS33		X		X		X									X		
P34				X	X	X					X						
PS35	X	X	X			X					X						
PS36		X						X						X			
PS37				X	X			X					X				
PS38		X		X					X						X		
PS39		X							X					X			
PS41	X	X								X							
PS43		X	X	X	X						X						
PS44		X	X		X											X	
PS45			X		X	X									X		
PS46		X	X		X						X						
PS47		X	X	X	X		X									X	
PS48			X	X	X	X							X				
PS49		X	X	X	X										X		
PS50		X		X	X				X							X	
PS51		X	X		X								X				
PS52	X	X	X	X	X	X	X										X

Conclusion and Future Work

- REPAIR is comprehensive and multi-attributes decision support system for post-disaster reconstruction planning.

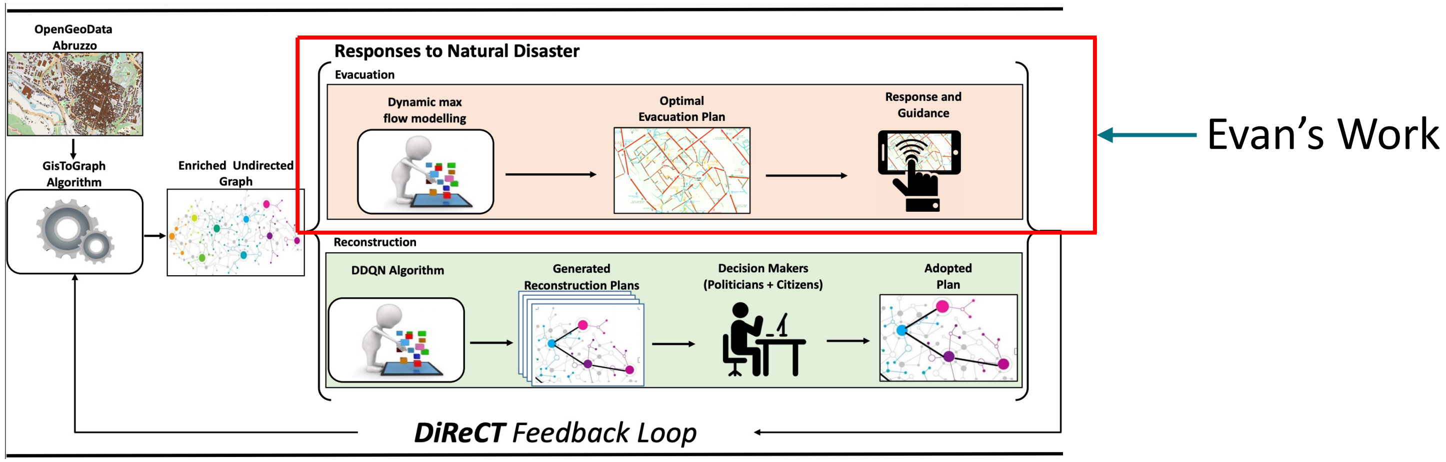
- Proposed approach is innovative which consider key attributes like social benefits, physical dependencies, political priority, time and cost.

- Used Double Deep Q-Network (DDQN) for implementation

- The proposed model minimizes human errors in reconstruction planning.

Conclusion and Future Work

- **In future** we will work on 'DiReCT' approach



- **In future** will work on assessment and rehabilitation of basic facilities of life like water and gas pipelines including street walk-ability in reconstruction plans

- **In future** will focus on quantitative research to assess damage levels accurately by using cutting edge technologies to estimate the reconstruction budget accurately

List of Publications

List of Publications

Conferences

- Social-based Physical Reconstruction Planning in case of natural disaster: a Machine Learning Approach *Conference (RCIS2020)* *<u>(Have won best reviewer award in RCIS 2020 Conference as well)</u>*
- Social-based City Reconstruction Planning in case of natural disasters: a Reinforcement Learning Approach *Conference (COMPSAC2021)*
- City Reconstruction Planner with Social Perspective *Conference (I-CiTies 2021)*

List of Publications

Journals

- Towards Effective Response to Natural Disasters: a Data Science Approach *Journal (IEEE Access 2021)*

- Reconstruction Planning approaches in case of natural disasters: A Systematic Mapping Study Journal *(ACM Computing Surveys (working progress))*

- Social-based City Reconstruction Planning in case of natural disasters: a Reinforcement Learning Approach *(extension paper of COMPSAC Conference (working progress))*

Courses and Seminars

Courses and Seminars

Undergraduate and Graduate Courses (18 CFU)

- Data Analytics (6 CFU)
- Big Data: Models and Algorithms (3 CFU)
- Open Data and Web Services (6 CFU)
- Information Retrieval (3 CFU)

Ad-Hoc Courses (22 CFU)

- Machine Learning (3 CFU)
- Electronic System-Level HW/SW Co-Design (3 CFU)
- GPU-Programming with CUDA (1 CFU)
- Reinforcement Learning (2 CFU)
- Advance Course on Data Science & Machine Learning (Summer School) (8 CFU)
- Machine Learning for Smart Cities Automation (2 CFU)
- Machine Learning over Networks (1 CFU)
- Reinforcement Learning Course (online) (2 CFU)

Courses and Seminars

- What Programs Want: Automatic Inference of Input Data Specifications
- Facing Uncertainty in Complex Cyber -Physical System Design
- Gli strumenti della comunicazione in pubblico
- Towards Compositional Transformations for Dependability Analysis of Evolving and Reconfigurable Systems
- Human behaviour modelling and simulation - an agent based approach
- From Correctness to High Quality
- Ethics and Privacy in Autonomous Systems: A software exoskeleton to empower the use
- AI Webinar Series on Deep Learning

THANK YOU FOR
YOUR ATTENTION