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

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Outlines

- Motivating Scenario
- Main Challenges
- Research Problems
- Proposed Methodology
- Evaluation and Results
- Conclusion and Future work

Motivating Scenario

- ➢Natural disaster
- ➢Post disaster
  - ✓ Relief
  - ✓ Recovery
  - ✓ Development

Motivating Scenario

✓Development

- Reconstruction of buildings
- Reconstruction of roads/bridges
- Social benefits of effected community

Main Challenges

- ➢ Manual rebuilding plan is error prone
- ➢ Existing models do not consider key attributes:
  - ✓ Social benefits
  - ✓ Political Priorities
  - ✓ Physical Dependencies

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?

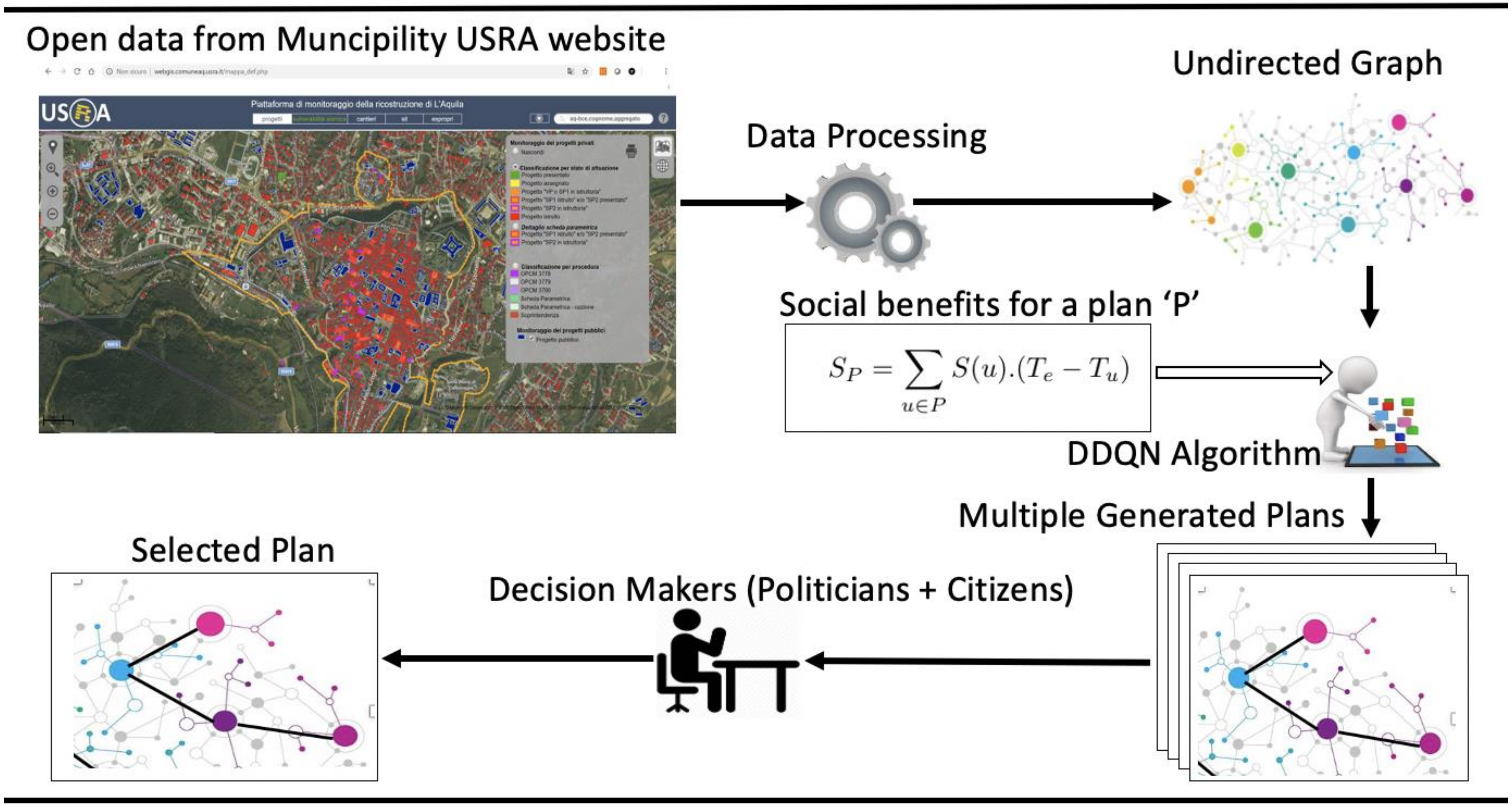
RQ4: Which is the most **efficient approach** that, leveraging on the defined rebuilding planning model, provides alternative rebuilding plans on real case studies?

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

Our solution

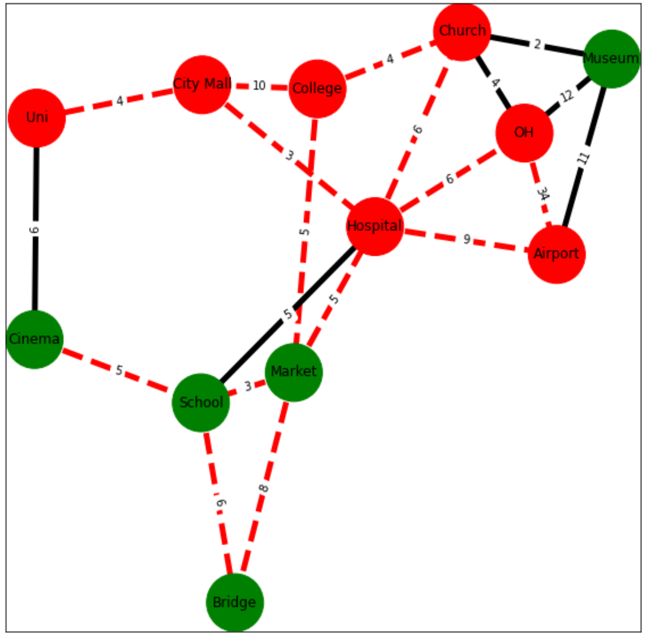
- Data Processing: from GIS data to a graph model
- Mathematical modeling
- Model solution by using Double Deep Q-Learning Network (DDQN)
- Validation on Sulmona dataset

Proposed Methodology



Graph model of the damaged area

Labelled undirected graph G(V,E) where

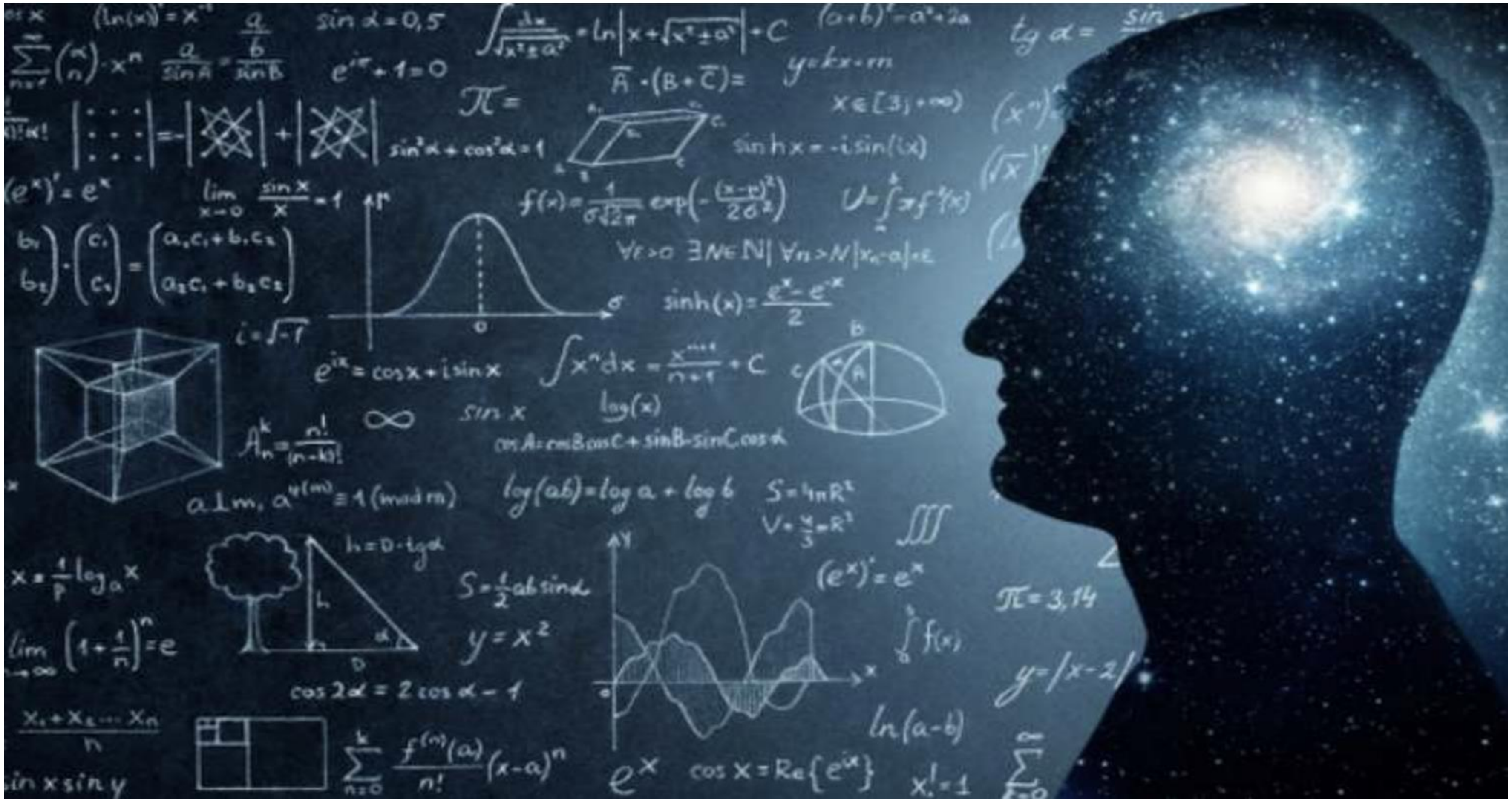


- ✓ V= Set of vertices ‘v’ that represents single reconstruction unit
- ✓ E= Set of edges ‘e’ that represents adjacency between two reconstruction units
- ✓ d (v1, v2) = label on the edges representing a function that specify the distance between two reconstruction units

We have additional informations on reconstruction units such as

(e.g number of people, status of buildings, cost and time for reconstructions)

pdRPP-Mathematical Model



pdRPP- Model Constraints

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

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

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

$$\text{Political Constraints :} \frac{\sum_{v \in P} P_v}{|P|} \geq 80$$

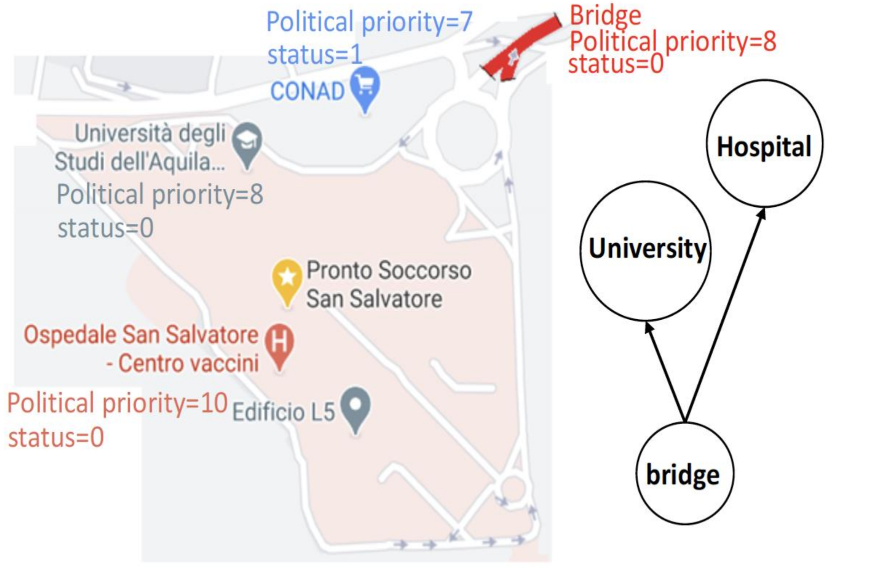
pdRPP- Model Constraints

<u>**Physical dependencies:**</u> among reconstruction units (like bridge/flyover) that impose ordering in the building reconstruction

$$\exists\ v \in P\ \mathit{that\ is}$$

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

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



a. Enriched City Map *b. Physical Dependencies Graph*

pdRPP- 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

$$P = \{(v_0), (v_1)(v_2)(v_3)....\}$$

$$max \sum_{p \in P} S(v_p).(T_e)$$

Double Deep Q-Learning 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

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

pdRPP- DDQN Immediate Reward

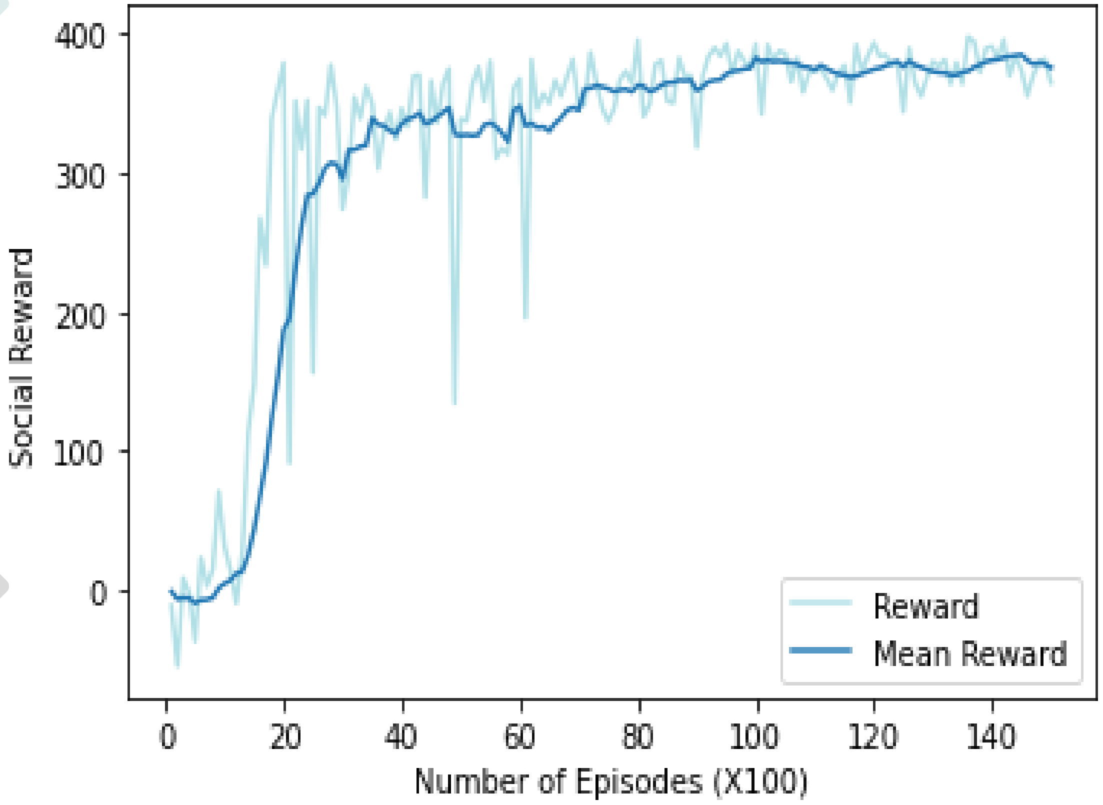
$$S_r(v) = \left[\alpha.b_v + \beta\left(\sum_{u\in V|s_u=1}\frac{S(u)}{d(u,v)}\right)\right]$$

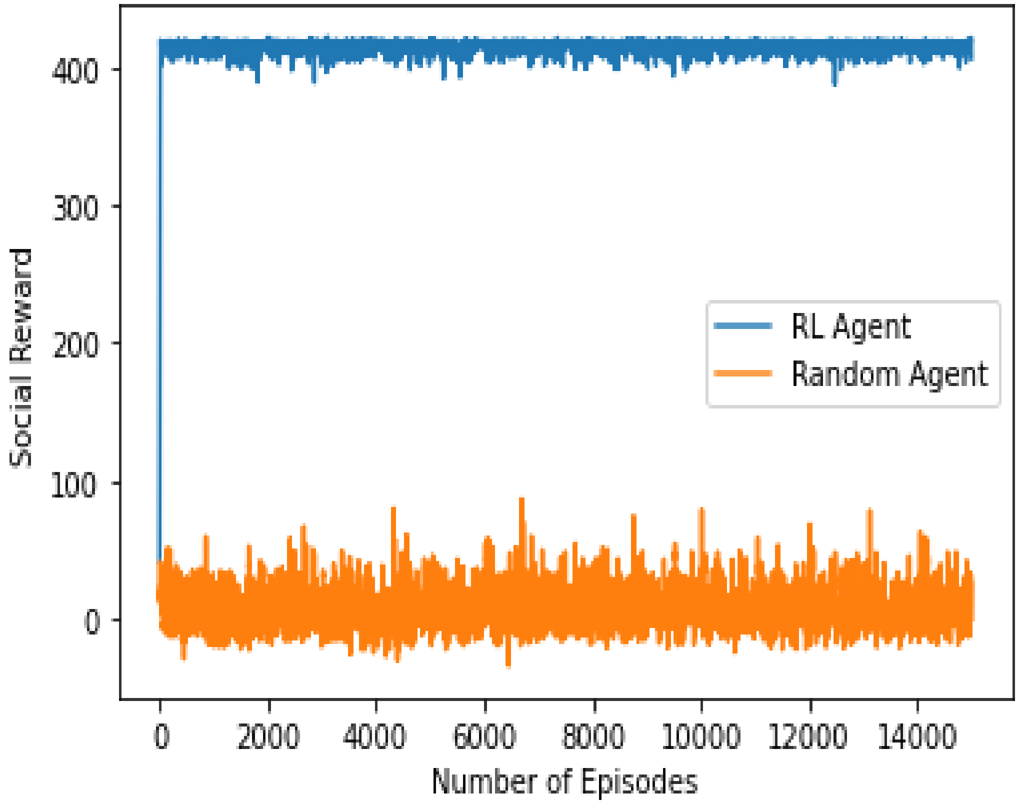
$$\alpha, \beta \in [0,1],\ \alpha+\beta=1$$

Implementation: Fixed Parameters

Fixed Parameters	**Value**
Optimizer	Adam optimizer, learning rate = 0.001
Loss function	Mean squared error, Eq. 8
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)

Implementation: Agent Training and Testing





Why we choose Double Deep Q-Learning?

- Due to dynamic action space (action space is the damage area and every unit has different attributes)
- Complexity increase in Q-Learning, SARSA, Temporal Difference, Monte Carlo once number of states (node/buildings) increased
- Increasing states and complexity problem solved in DDQN by using Neural Networks
- Fast Learning

Evaluation and Results

- Sulmona Dataset
- 597 damage buildings out 1214
- 470 damage roads out of 3476

Evaluation and Results

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 and Results

Sr.No	Cycles	Units	Buildings	PD/Roads	PP	S_P
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

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.

Conclusion and Future Work

- pd-RPP is comprehensive and multi-attributes decision support system for post- disaster reconstruction planning.
- Used Dual Deep Q-Network (DDQN) for implementation
- The proposed model minimizes human errors in reconstruction planning.
- **In future we** will investigate additional social benefits more in depth (service access quality and street walk-ability)
- **In future** work we will make comparison of pd-RPP with conventional/traditional and scientific approaches.

THANK YOU FOR YOUR ATTENTION

ANY QUESTIONS?