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BUILDING RESILIENCE THROUGH STRUCTURAL HEALTH MONITORING AND RECONNAISSANCE

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Abstract

The significant worldwide population growth and urbanization of the past century resulted in an era of global development and infrastructure construction on a massive scale, including buildings and other critical infrastructure systems. Near the end of the last century of rapid development of the built environment, the societal stresses and costs associated with aging and failing infrastructure have come into focus. For the United States alone, a national infrastructure report card issued by the American Society of Civil Engineers in 2017 gave the US infrastructure a "D+" grade and noted the estimated costs associated with repair and upgrade of over $4.59 Trillion. Recognizing the associated challenges, the National Academy of Engineering has identified "restore and improve urban infrastructure" as one of the Engineering Grand Challenges of the 21st century.

On a positive note, the major advancements made in computational simulation, advanced materials, sensor and communication technologies, artificial intelligence algorithms, and science-based understanding of natural hazards, taken in combination, provide a foundation for developing methods of advanced monitoring, maintenance, and reconnaissance of infrastructure. Moreover, the mass adoption of mobile internet-enabled devices, paired with wide-spread use of social media platforms for communication and coordination, has created new opportunities to better understand human responses to extreme events. These methods have the potential to tackle the above-mentioned grand challenge and achieve resilient communities following natural hazards.

Being aware of the existing challenges and opportunities, this paper presents several efforts directed towards developing tools and methods aiming to achieve resilient communities through structural health monitoring and reconnaissance efforts. The first is a data-driven damage assessment, which utilizes Machine Learning tools, sensor data from structures and the structural engineering expertise through the so-called Human-Machine Collaboration (H-MC) framework. This framework is applied for damage assessment of instrumented buildings located in various parts of the world including the USA and Taiwan. Furthermore, use of the methodology for decision-making of performance enhancement actions is demonstrated. The second is a tool that uses Natural Language Processing (NLP) to collect news and social media posts after an extreme event to: a) create automatically generated new summaries for immediate report writing after an event, b) to extract key information, such as the recovery time, the most affected regions and infrastructure, and to relate these to the magnitude of the event, socio-economic consequences facing the community, etc. Application of this tool to several recent earthquakes are demonstrated and potential use of the tool along with extreme event reconnaissance networks, such as GEER (Geotechnical Extreme Events Reconnaissance), StEER (Structural Extreme Events Reconnaissance) and SSEER (Social Science Extreme Events Research), are explained.

Keywords: Human-Machine Collaboration; Natural Language Processing; Reconnaissance; Resilience; Structural Health Monitoring.

1. Introduction

This paper presents two major efforts directed towards developing tools and methods for achieving resilient communities through structural health monitoring and reconnaissance activities. The first of these methods is a data-driven damage assessment, which utilizes Machine Learning (ML) tools, sensor data from structures and the structural engineering expertise through the so-called Human-Machine Collaboration (H-MC) framework. This framework is applied for damage assessment of instrumented buildings located in various parts of the world including the USA and Taiwan. Furthermore, use of the methodology for decision-making of performance enhancement actions is demonstrated. The second method is based on the use of Natural Language Processing (NLP) to collect news from websites and other information from social media platforms after an extreme event. Collected news is used to generate summaries that can facilitate generation of automated reports related to natural hazards such as earthquakes and their consequences. Collected social media information is used to quantify key features related to these consequences, such as the recovery time, that can potentially be difficult to characterize by other means. Application of these tools to several recent earthquakes are demonstrated in relation to the Structural Extreme Events Reconnaissance (StEER) network.

2. Human-Machine Collaboration Framework for Damage Detection

According to the National Research Council [1], the Human-Machine Collaboration (H-MC) is a framework in which humans co-work with artificial intelligence to complete specific tasks. The purpose of this framework is to use the particular strengths of both types of intelligence, and possibly including physical capabilities, to fill in the weakness of one (e.g., the machine) by the intelligence of the other (e.g., the human). Fig. 1 presents the H-MC framework for damage detection, which uses the responses from an undamaged structure and applies novelty detection as the ML tool for new data. Novelty detection is the identification of new or unknown data that a ML system is not aware of during training. It is similar to outlier detection, however, in the case of outlier detection, the training dataset may consist of the outlier observations. The novelty model in this study develops non-parametric distribution using the training data and a distance measure of 1.5 times the interquartile range (IQR) to identify novelty, i.e., the new data is a novelty if it exists more than 1.5 interquartile range above the upper quartile or below the lower quartile. In the novelty detection approach to classification, “normal” patterns are available for training, while “abnormal” ones are missing. A model of normality with several free parameters is inferred and used to assign novelty scores $z(x)$ to previously unseen test data x. Larger novelty scores correspond to increased “abnormality” with respect to the model of normality. A threshold $z(x) = k$ is defined to identify novelty, i.e.,

$$if\ z(x) > k, x\ is\ novelty \tag{1}$$

Thus, $z(x) = k$ defines a decision boundary.

In the ideal case, where a large amount of data from the undamaged structure is available, considering data from low, moderate, and strong earthquakes, novelty detection alone could have indicated damage. However, for the buildings under considerations, data from strong but undamaging earthquakes are typically not available. Therefore, for these buildings, novelty detection may result in false positive detection for strong but undamaging events. To overcome this limitation, the human aspect of the H-MC framework is introduced. Accordingly, a response envelope is developed by a domain expert representing the probability of exceedance (POE) of damage. This is performed using for simplicity a structure-specific single-degree-of-freedom (SDOF) model to conduct nonlinear time history analyses (NTHA) for 1,710 selected ground motions. Subsequently, two features identified in a series of studies by Muin and Mosalam [2, 3] are utilized. The features are called CAV and R_{CAV}. The CAV is mathematically defined as follows:

$$CAV = \int_0^T |\ddot{u}\,(t)|dt \tag{2}$$

where $|\ddot{u}\,(t)|$ is the absolute value of acceleration at time t and T is the total duration of the recorded acceleration time history. For the CAV calculation, the considered acceleration is the building floor acceleration. Higher CAV values are expected in damaging events as they are correlated to high amplitude motions [4, 5]. The R_{CAV} is mathematically defined as follows:

$$R_{CAV} = CAV_s / CAV_l \quad (3)$$

where CAV_s is the *CAV* of the floor acceleration representing the structural response and CAV_l is the *CAV* of the corresponding linear system excited by the same ground acceleration. For an undamaged case and an accurate linear model, $R_{CAV} = 1.0$. With damage, acceleration amplitude typically decreases compared to the linear case due to the lengthening of the natural period of the structure. Thus, R_{CAV} is expected to decrease with increasing damage states.

In the H-MC framework, the CAV and R_{CAV} of the damaging events are used to develop a joint cumulative distribution representing the POE of damage which is analogous to fragility curves but with two variables, i.e., fragility surfaces. Damage is identified when novelty is detected by the ML tool and the POE shows high probability values, Fig. 1.

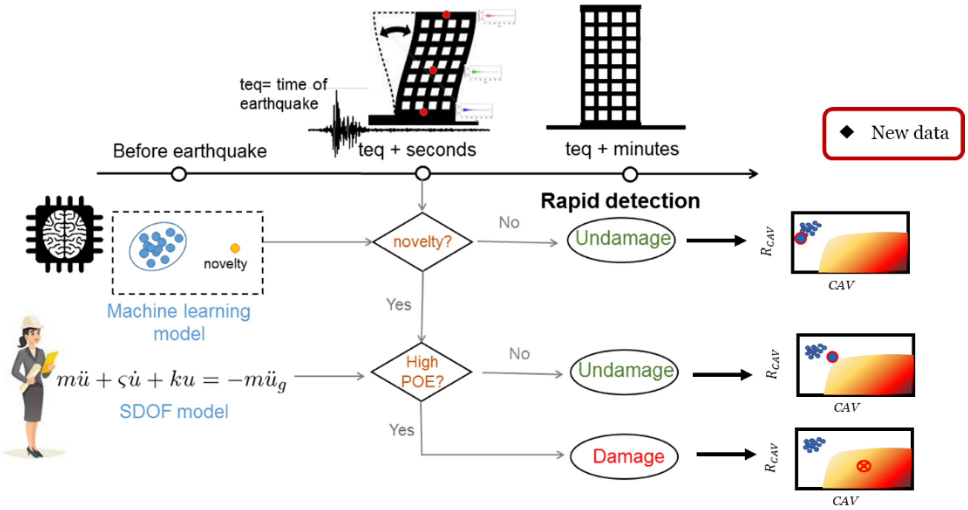


Fig. 1 – Human-machine collaboration (H-MC) framework for damage detection used in this study.

2.1 Application to CSMIP Instrumented Buildings – California

Damage assessment is conducted for buildings instrumented under California Strong Motion Instrumentation Program (CSMIP). Some of the previously studied buildings and the corresponding recorded strong motions are considered herein. Moreover, buildings that captured responses of multiple earthquakes are ideal for this study. Table 1 lists buildings selected in this study covering a wide range of primary lateral force resisting systems (PLFRS) and a variety of building heights.

Among the selected fifteen buildings, nine of them are undamaged (U) and in operation at present, four are retrofitted (R) and currently in operation, and two have been demolished (Demo). One of the four retrofitted structures (station 24386) suffered severe damage during the 1994 Northridge earthquake while the other three are voluntarily retrofitted to seismically strengthen them. The buildings have different occupancy types and PLFRS.

When the H-MC framework for the damage detection is applied to the selected building data, the results are revealed through contour plots. For each building's roof response, there is one plot with axes of measured *CAV* and R_{CAV} values. The superposed dots represent the roof response data points from all the events recorded for that building. The colored envelope is that for the POE with higher probability shown with a darker color. Damage is identified when novelty is detected by the ML tool and the POE shows high values. When the dot is blue (filled) in color, it is labeled as an undamaged event. On the other hand, when the dot consists of the red cross (open) mark, it is labeled as a damaged event. Clearly, the damaged events are located in the darker region of the envelope.

Figs. 2 and 3 show the damage detection results by the H-MC framework. Fig. 2 shows that the undamaged buildings are correctly detected by the algorithm as being indeed undamaged. For brevity, 6 out of the 13 undamaged building responses are shown here. In some cases (such as stations 24322 and 58354 in Table 1), novelty detection or POE envelope alone results in false positive detection but when used together with ML using the novelty concept, these false positive results are successfully eliminated. On the other hand, Fig. 3 shows that the H-MC framework is accurately detecting damage for station 24386 after the damaging event occurred. For station 01260, records are available from only the damaging earthquake. Therefore, the ML part of the framework is not possible to be applied for this building. However, by using the POE envelope alone, the damage is also correctly detected for this case.

Table 1 – Selected ground motion records and scale factors.

Index	**Station**		**PLFRS**	**Condition**	**# of EQs**	**# of sensors**
	Number	Name				
1	12267	Hemet – 4 story hospital	RCSW	U	10	10
2	58483	Oakland – 24 story residential building	RCSW	U	12	16
3	24579	Los Angeles – 9 story office building	RCMRF	U	4	18
4	24463	Los Angeles – 5 story warehouse	RCMRF	U	6	13
5	24322	Sherman Oaks – 13 story commercial building	RCMRF	U(R)	6	15
6	23634	San Bernardino – 5 story hospital	SMRF	U	5	12
7	57357	San Jose – 13 story government office building	SMRF	U(R)	3	22
8	24629	Los Angeles – 54 story office building	SMRF	U	7	20
9	3603	San Diego – 19 story commercial building	SEBF	U	3	16
10	58019	Stanford – 4 story residential building	WF	U	3	10
11	89494	Eureka – 5 story residential building	RM	U	7	13
12	58196	Berkeley- 5 Story parking structure	SCBF	U(R)	8	16
13	24386	Van Nuys- 7story hotel	RCMRF	D(R)	8	16
14	58354	Hayward - 13-story CSUH Admin Bld	RCMRF	Demo	2	16
15	01260	El Centro - Imperial Co Srvcs Bld	RCMRF	Demo	1	13

2.2 Application to the Tai-Tung Fire Bureau Building – Taiwan

In this section, the H-MC framework is applied to the recorded strong-motion data of Tai-Tung Fire Bureau building located at Tai-Tung city in Taiwan. The reinforced concrete building suffered severe damage after a M 6.2 earthquake in 2006. The building was instrumented with 22 accelerometers. Fig. 4(a) shows the sensor locations. In this study, *CAV* values calculated from channels 7, 8, 9, and 10 and R_{CAV} values calculated from channels 16, 17, 19, and 20 are utilized for damage detection. Strong motion records from five events, including the damaging event, are utilized in this study, Table 2. Chu and Lo [6] reported possible nonlinearity during the event no. 3, hence, while developing the novelty model, events no. 1, 2, and 4 are utilized in the training set. All the events are utilized as the test set. In order to develop the POE envelope, the period reported in the literature has been used. It is noted that the period corresponding to the primary lateral force resisting system is used to develop the SDOF model.

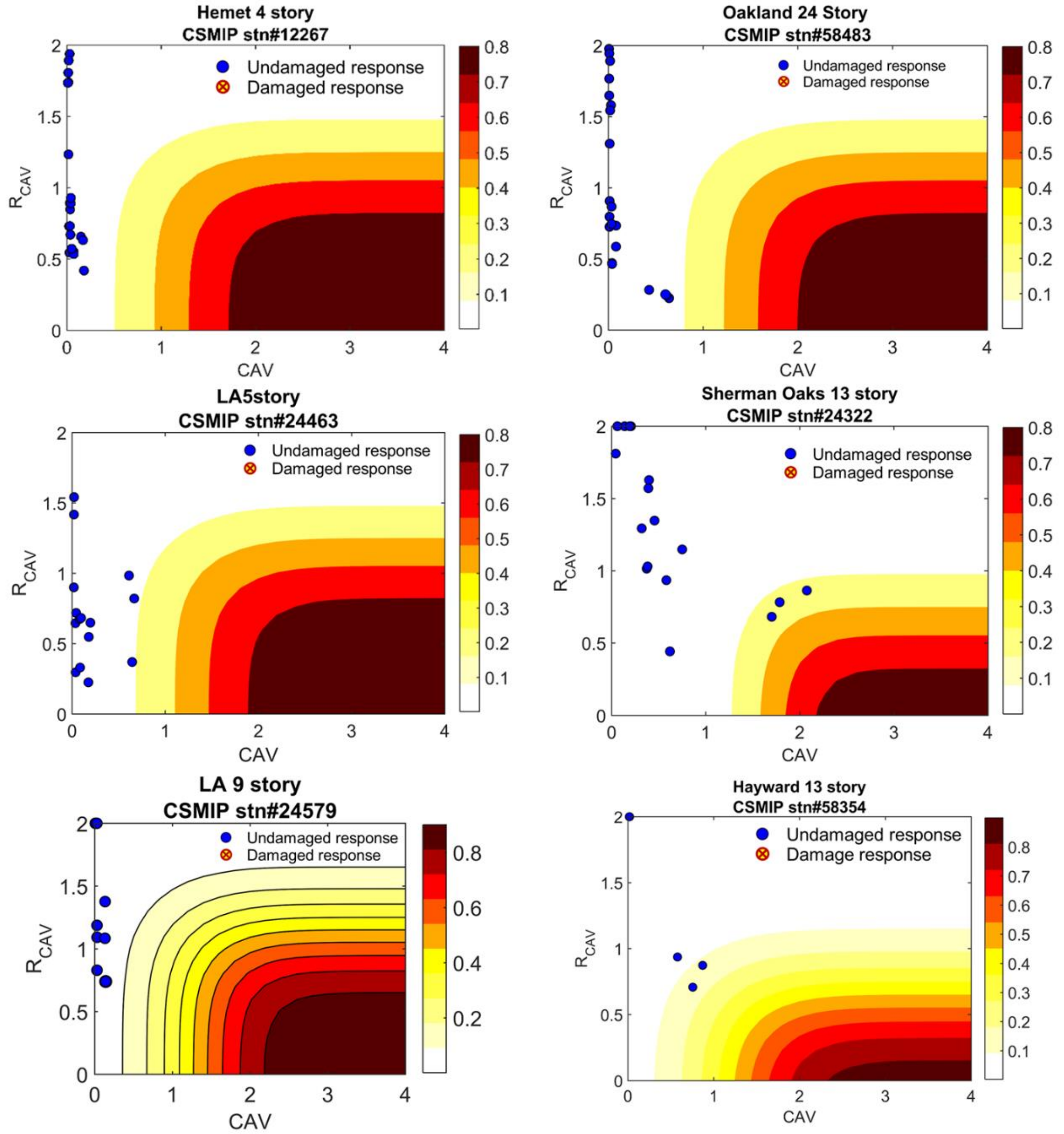


Fig. 2 – H-MC framework results showing accurate undamaged condition detection of RC buildings.

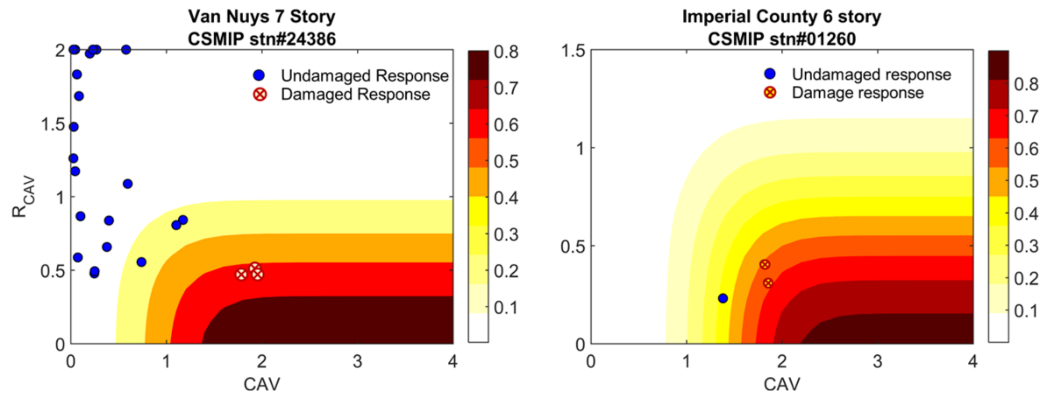
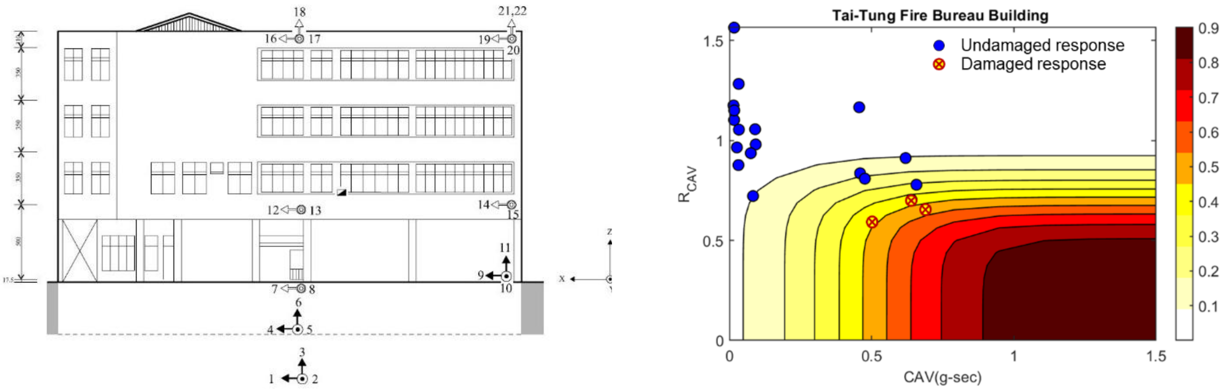


Fig. 3 – H-MC framework results showing accurate damaged condition detection of two buildings.

Table 2 – Records used from Tai-Tung Fire Bureau building.

Event No.	Date (dd/mm/yyyy)	Magnitude
1	04/08/1999	4.8
2	24/09/2002	5.2
3	10/12/2003	6.4
4	28/12/2005	4.7
5	01/04/2006	6.2



(a) Sensor locations

(b) Plot generated by the H-MC framework showing the damaged condition detection

Fig. 4 – Tai-Tung Fire Bureau building, Taiwan.

The H-MC framework detects damage in two of the four responses produced by the damaging event no. 5, Fig. 4b. The third damage is detected for the event no. 3 (M 6.4 earthquake). Chu and Lo [6] stated the possibility of nonlinearity during this event in their study although no visual damage was detected. The present study provides further evidence that the structure was most likely inherently weakened by the event no. 3 and became vulnerable to damage for subsequent earthquakes.

3. Natural Language Processing (NLP) for Earthquake Reconnaissance

Natural language processing (NLP) is a subfield of linguistics, computer science, and artificial intelligence concerned with the interactions between computers and human (natural) languages, with the objective of processing and analyzing large amounts of natural language data. In the context of reconnaissance for earthquakes and other natural hazards, it is used here for three purposes: 1) Automated data (news & social media) collection hosted at the Pacific Earthquake Engineering Research (PEER) Center server, 2) Automatic summarization for reconnaissance report generation, and 3) Use of social media to extract information related to earthquake consequences, such as recovery time.

3.1. Automated Data Collection from News and Social Media Websites

This section outlines the process of automatic data collection immediately after an earthquake. The automatic data collection script is written in Python and utilizes U.S. Geological Survey (USGS) Earthquake Hazard Program API (Application Programming Interface) [7]. The program is scheduled to run every day in the PEER server and query new earthquakes from the USGS API. Only earthquakes that have magnitude greater than or equal to 5 and USGS PAGER alert level in either yellow, orange or red are recorded. When such a new earthquake is detected, the program starts collecting related social media data from Twitter and related news articles from News API [8]. Tweets are collected over a period of two weeks or more using the keyword "earthquake" and the earthquake location name. Tweets are also collected in local language to capture local changes more precisely. News articles related to the earthquake are collected for duration of a week or less. The news articles data is then used in the automatic text summarization and the social media data is used in the recovery time analysis detailed in the next two sections. The diagram in Fig. 5 summarizes the described automatic data collection workflow.

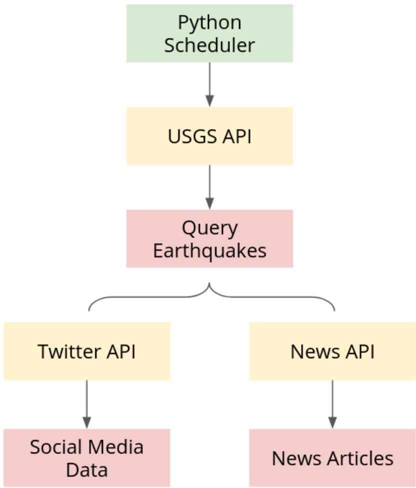


Fig. 5 – Automatic data collection workflow.

3.2. Automatic Summarization for Report Generation

Structural Extreme Events Reconnaissance (StEER) Network is a US National Science Foundation (NSF) funded network, aiming at building societal resilience by generating new knowledge on the performance of the built environment through impactful post-disaster reconnaissance disseminated to affected communities. StEER deepens the structural Natural Hazards Engineering (NHE) community's capacity for reliable post-event reconnaissance through a) promoting community-driven standards, best practices, and training for field reconnaissance, b) coordinating early, efficient and impactful event responses, and c) broadly engaging communities of research, practice and policy to accelerate learning from disasters. One of the activities related to the coordination of early, efficient and impactful event responses is to assemble a Virtual Assessment Structural Team (VAST) and to generate a reconnaissance report or briefing within few days after an extreme event such as an earthquake. NLP is used to generate automated summaries from news articles for these reports or briefings. These automatically generated summaries are used to develop the StEER reports and briefings for the 2019 Mw 6.4 Albania and Mw 6.8 Philippines earthquakes and for the 2020 Puerto Rico Mw 5.8 & 6.4 earthquakes [9-11]. During the generation of these reports and briefings, it is observed that the use of NLP not only decreases the time to generate a report, but also increases the accuracy and abundance of information by facilitating systematic access to many identified resources that can be missed in conventional manual report preparation. Details of the adopted automatic summarization methods are described in the following paragraphs.

The task of automatic summarization is the process of shortening a text document by extracting text or generating a text in order to create a summary that best describes the original document [12, 13]. The two mainstream approaches in the field of automatic summarization are extractive and abstractive.

Extractive approaches generate summary by selecting a subset of important existing words, phrases, or sentences directly from the source text. In contrast, abstractive approaches use linguistic methods to decompose and build a semantic representation of the text and use natural language generation techniques to generate a summary [14-17]. They generate new sentences from scratch, as opposed to extracting them from the source documents. In the recent years, neural network architectures have made abstractive summarization popular. However, abstractive approaches are generally harder to develop as they require good performing natural language generation techniques, which itself is also an active research field.

In this paper, extractive summarization techniques are employed, which aim at finding a minimal set of representative sentences of the original articles that effectively summarize the entire article. In particular, unsupervised extractive summarization techniques are used herein rather than supervised techniques. Supervised approaches require a large number of high-quality annotated data to make the algorithms learn well, making them challenging to apply and deploy in practice. On the contrary, unsupervised methods do not require any training dataset and can work solely with the document to be summarized.

More specifically, the unsupervised TextRank algorithm [18] is used, which is a graph-based ranking model for text processing and demonstrated successful use cases that benefit from automatic text summarization. TextRank algorithm decides the importance of a vertex within a graph, based on text information drawn from the entire document. It is first needed to build a graph that represents the document and the relationships between words in order to apply the TextRank model. In the case of the extreme events news summaries, the objective is to extract sentences from the entire document that are more representative for the given document, and therefore each vertex in the graph represents a sentence in the text. Next, a relationship needs to be defined between two vertices or two sentences, which can be determined by "similarity" relationship, where "similarity" is measured as a function of their content overlap. Sentences that address similar concepts usually have high content overlap, and therefore a link can be drawn between any two such sentences that share common content. The overlap of two sentences can be calculated simply as the number of common words in the two sentences. A normalization factor is also added to avoid favoring long sentences. Formally, given two sentences S_i and S_j, with a sentence being represented by the set of N_i words that appear in the sentences: $S_i = w^i_1, w^i_2, \dots, w^i_{N_i}$, the similarity of S_i and S_j is defined as follows:

$$Similarity(S_i, S_j) = \left|\{w_k | w_k \in S_i \,\&\, w_k \in S_j\}\right| / \left(\log(|S_i|) + \log(|S_j|)\right) \quad (4)$$

The resulting graph is highly connected, with vertices representing sentences in the document and edges representing weights associated with adjacent sentences, indicating the strength of the relationship established between various sentences pairs in the document. The document that is to be summarized therefore can be represented as a weighted graph.

Next, the TextRank model employs a graph-based ranking algorithm that takes into account edge weights when computing the score associated with a sentence in the graph. Let $G(V,E)$ be a directed graph with the set of vertices V and set of edges E. For a given vertex V_i, let $In(V_i)$ be the set of vertices that point to it (predecessors), and let $Out(V_i)$ be the set of vertices that vertex V_i points to (successors). In the current application, the document graph is an undirected graph, in which the out-degree of a vertex is equal to the in-degree of the vertex. The weighted score of a given vertex V_i is defined as follows:

$$WS(V_i) = (1-d) + d * \sum_{V_j \in In(V_i)} \frac{w_{ji}}{\sum_{V_k \in Out(V_j)} w_{jk}} WS(V_j) \quad (5)$$

where d is a damping factor that can take value between 0 and 1, indicating the probability of jumping from a given vertex to another random vertex in the graph. After the ranking algorithm is run on the graph, the sentences are sorted in reversed order of their score, ranking from the highest to the lowest, and the top ranked sentences are selected as the summary, Fig. 6.

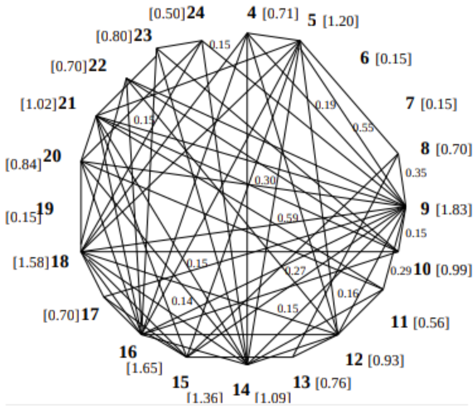


Fig. 6 – Sample graph build for sentence extraction [18].

3.3. Use of Social Media to Quantify Recovery Time

In the context of extreme events, recovery time, conceptually illustrated in Fig. 7, is the time needed after the extreme event to restore the functionality of a structure, an infrastructure system (e.g. water supply, power grid, or transportation network), or a community, to a desired level that can operate or function the same, close to, or better than the condition before the extreme event [19].

The determination of recovery time using information from social media is based on the assumption that certain keywords related to recovery, (e.g. school, office, transportation, or power outage) appear more frequently on the shared posts, tweets, etc., right after an earthquake occurs and the frequency of these words reduce as time passes. Using this assumption, the time between the occurrence of the earthquake and when these frequencies reduce to pre-earthquake levels is used as a measure of recovery time. A case study is conducted to compute the recovery time by using Weibo posts collected for the Mw 6.6 2013 Ya'an, China earthquake [20]. Conducted recovery time computations are based on the four steps below:

1. Determine factors and keywords related to recovery and assign weights to them (schools: 20%, roads: 20%, houses: 20%, offices: 20%, collapse: 20%).
2. Determine the variation of the number of posts containing these keywords with time.
3. Determine the recovery time (tr) for each factor from the frequency (f) plots, where tr = $t_1 - t_0$, t_0 is the earthquake occurrence time, and t_1 is the time when the number of posts with the considered keyword fall below a certain threshold (e.g. 15% of f_{max}) and become steady.
4. Determine the resulting recovery time as weighted average of the recovery time from each factor.

The frequency plots for the considered keywords are shown in Fig. 8, where t_1, t_0 and tr are also specified on each plot. Weighted average of tr from all factors result in an estimated recovery time of 4 days. The actual recovery time is not available for this earthquake. Therefore, it is difficult to gauge the accuracy of this estimation. There were a reasonable number of casualties and collapsed buildings in this earthquake, therefore the estimated duration of 4 days of recovery time may seem to be small, however, in some earthquakes, similar to the recent Mw 6.8, Elazig, Turkey, earthquake, building performance can be different from other infrastructure performance, where different infrastructure networks, including water supply, power grid and the transportation network may maintain their functionality as opposed to a poor performance of buildings with collapses [22]. Therefore, it may be possible that the recovery time of 4 days provide a reasonable estimation on average. Future studies will incorporate events with known recovery times to further explore and test this approach.

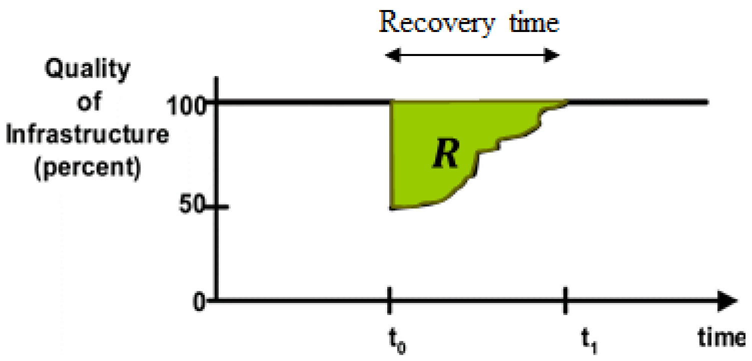


Fig. 7 – Conceptual illustration of recovery time [21].

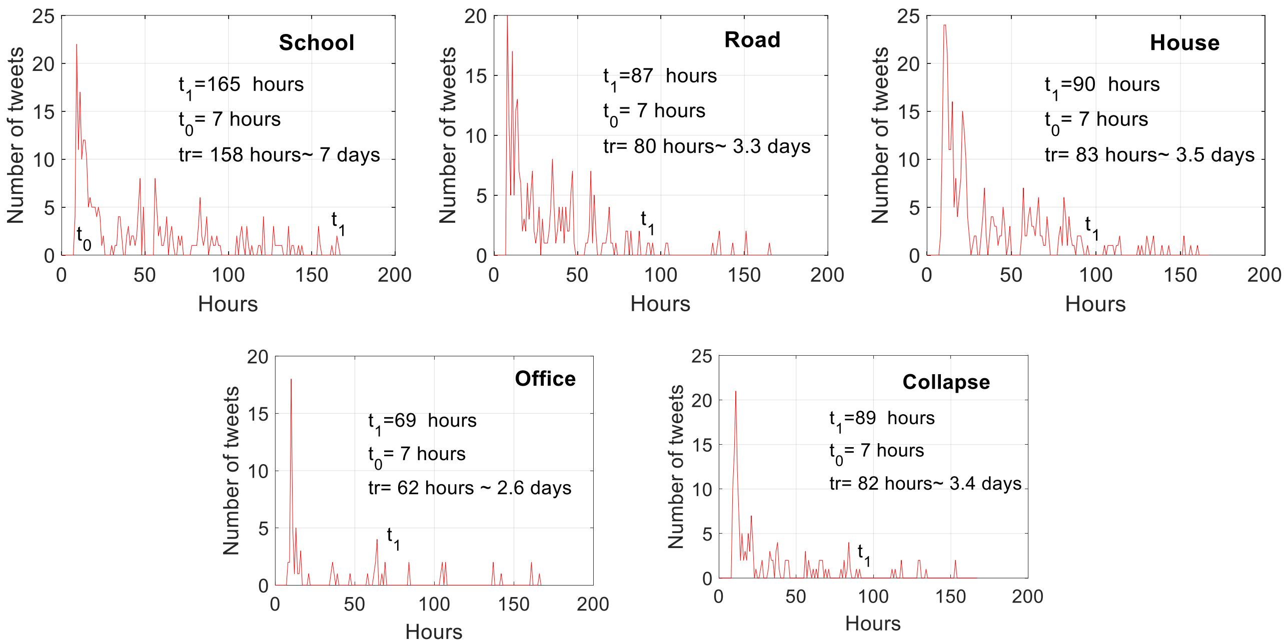


Fig. 8 – Variation of Weibo posts with different keywords over time.

4. Summary and Conclusions

This paper presented two specific efforts directed towards developing tools and methods for achieving resilient communities through structural health monitoring and reconnaissance activities. Several conclusions of the conducted study are listed below:

- An SHM framework called the human-machine collaboration (H-MC) is proposed and applied to existing structures. The H-MC framework utilizes the strengths of a machine to act rapidly following an earthquake and expertise of a human, i.e., the structural engineer to reduce uncertainty in the damage assessment process with only data from undamaged cases. The framework uses novelty detection as the ML tool and structure-specific SDOF analysis to enable rapid damage detection.
- The developed H-MC framework is applied to detect damage in selected fifteen California buildings, spanning different lateral load resisting systems, and instrumented by CSMIP. The results showed that the H-MC algorithm correctly labeled the undamaged and damaged cases.

- For the Tai-Tung Fire Bureau building located in Taiwan, the H-MC framework detected damage for the records of 2006 M 6.2 earthquake. Moreover, it indicated that the building was inherently weakened by one of the previous strong M 6.4 earthquakes.
- Overall, the proposed SHM framework facilitates a rapid and efficient decision-making process regarding re-occupancy, emergency response, and future use of the structures following an earthquake event which are essential elements of resiliency.
- A python script is made available in the PEER server for automatic collection of news and social media posts after earthquakes of magnitudes larger than 5 combined with PAGER alerts beyond green.
- During the generation of reconnaissance reports and briefings immediately after an earthquake, it is observed that the use of NLP not only decreases the time to generate a report, but also increases the accuracy and abundance of information by systematically facilitating access to many identified resources that can be missed in conventional manual report preparation.
- It is demonstrated that the recovery time after an earthquake can be estimated by considering the frequency of resilience-related keywords in social media posts.

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