Combination of GIS and SHM in Prognosis and Diagnosis of Bridges in Earthquake Prone Locations, A Short Survey

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Abstract – Bridge infrastructures are essential nodes in the transportation network. In earthquake-prone areas, seismic performance assessment of infrastructure is vital to identify, retrofit, reconstruct, or, if necessary, demolish the structural systems based on optimal decision-making processes. This research proposes the combined use of advanced tools used in the management and monitoring of bridges such as Geographical Information Systems (GIS) and Structural Health Monitoring (SHM) in a synergistic manner that can enable observation of bridges to construct an earthquake damage model. Post-earthquake disaster data can enhance and update this model to mitigate further damages both to the structure and transportation network in the future. Implications of new technologies such as drones and mobile devices in this scheme constitute the next step toward the future of the Cyber-Physical SHM systems. The proposed intelligent and sustainable cloud-based framework of SHM-GIS in this paper lays the core behind more robust impending systems. The synergistic behavior of the offered framework reduces the overall cost in large scale implementation and increases the accuracy of the results leading to a decision-making platform easing the management of bridges.

1. INTRODUCTION

Earthquake as a natural disaster can effectively bring parts or all the transportation network systems, especially in metropolitan areas, to an immediate halt. Underestimating the seismic risks in bridges, one of the essential components of transportation infrastructures, would bring chaos and disorder to the disaster areas. Bridges assist in transporting goods and disaster victims to and from cities and disaster sites. They are one of the elements in search and rescue in post-earthquake operations. Therefore, without proper analysis and assessment of the risk in bridges could undoubtedly cause disruptions to the transportation network and, ultimately, failure of the urban areas. This paper investigates the use of Structural Health Monitoring (SHM) and Geographical Information Systems (GIS) tools for mitigating the impacts of earthquake disasters on bridges at the response and recovery stages. What is more, it introduces a cloud-based framework which proposes the combined use of SHM-GIS as a tool to assess bridges and network systems in an improved and efficient manner compared to separate use of these items.

The efforts on the analysis of past events have considerably improved the resiliency of bridges to earthquakes, but there are still cases where they fail (Little, 2002). Moreover, bridges are considered spatially dispersed and interconnected structures. They are interdependent from each other; therefore, analyzing one bridge under seismic assessment would not necessarily provide enough information to propose suggestions and alternatives for the mitigation of future earthquakes. Moreover, although the current tools in the literature cover the basic requirements for bridge management mostly in a local manner, network-level assessment and decision-making platforms are still limited except few benchmark examples [].

SHM is a monitoring technology that can detect damage and inspect the overall performance of structures, ideally in real-time and in a continuous manner (Chang, 1998). Coupling SHM with forecast system performance, also known as Damage Prognosis (DP), can enable behavioral predictions to estimate the useful renaming time of the structures under future loads (Farrar and Lieven, 2007). Typically, SHM systems consist of arrays of sensors deployed on strategic locations on bridges that can collect critical spatial information such as vibrations, displacement, etc. As discussed earlier, the need for assessing multiple bridges on the network is essential to produce effective countermeasures, however, collocated inclusion of multiple bridge monitoring systems and their effect on transportation network will result in a considerable amount of data that is hard to capture, analyze and manage. This is where GIS comes into the picture.

GIS and its core functionality, i.e., organizing information in a standard graphical view (Tomaszewski, 2014) can aid SHM to represent better and manage the captured data. Therefore, a synergistic combination of the two systems can provide a decision-making platform to better decide on the suggestions and alternatives in disaster management and mitigation. GIS is the perfect platform when trying to analyze and show the impact of the failure of bridges on the transportation network in terms of functionality loss such as traffic delays and lack of connectivity, and economic loss in terms of local and regional level.

The new paradigm shift in the Internet of Things (IoT) has led to many new innovative use-cases of SHM. One of the examples is the utilization of drones for monitoring critical infrastructure. Drones or Unmanned Aerial Vehicle (UAV) with its existing hardware, such as digital cameras, motion sensors, and communication units can already contribute to SHM applications with minimal effort. Installing custom sensors such as vibration-based non-destructive testing (NDE) method can be useful for damage detection situations such as identifying damage in small and unreachable areas. Similar principles apply to mobile devices due to their multisensory environment and advanced computer skills (Alavi and Buttlar, 2019; Ozer, 2016). Such new innovative technology is considered as part of the shift toward cyber-physical SHM system (Ozer and Feng, 2019). Structures as the physical objects, cloud-based real-time engineering computation as the cyber objects, and the sensors as the connecting medium presents a modern infrastructure assessment and management scheme.

The paper presents background and necessary information about SHM and GIS in Section 1. Section 2 and Section 3 address standalone applications of each of the tools throughout the literature, respectively. Section 4 introduces the intelligent and sustainable cloud-based SHM-GIS framework for risk assessment of bridges in earthquake-prone locations. Machine learning as a complementary addition to SHM and GIS is explained in Section 5. Mobile device applications are still limited; therefore, drone-based SHM implications in the context associate Section 6. Finally, Section 7 concludes and highlights the future initiatives.

2. OVERVIEW OF THE TOOLS

This section discusses an overview of the SHM and GIS and their combined use in seismic performance assessment of the bridges. Although SHM systems mainly circle civil/mechanical/aerospace infrastructures, GIS has a vast list of applications and is an integral component of decision making in many disciplines (Chrisman, 1999).

2.1. Structural Health Monitoring (SHM)

Non-destructive testing (NDE) for damage detection or identification through a series of sensors (either stationary or mobile) placed on a structure refers to as SHM. A vertical hierarchy is typically considered in order to identify damages. A pioneered damage typology scheme was offered by Rytter (Rytter, 1993). Damage state was categorized in 4 levels, namely:

1. Existence of damage – Detection
2. Position of damage – Location
3. Severity of damage – Extent
4. Prognosis of damage – Prediction

In such a hierarchy, knowledge of the previous level is required for complete damage identification. This means that the success at each level depends on how well the lower levels perform. Damage could relate to any changes in the structural behavior of a structure that can change its current or future performance. By definition, change refers to a baseline that makes damaged and intact states comparative (Farrar and Worden, 2007). Many works have reviewed SHM applications in variety of disciplines such as (Arcadius Tokognon et al., 2017; Feng and Feng, 2018; Sony et al., 2019). The 4-stage damage identification is the center of every SHM application. As shown in Figure 1, the SHM comprises of many other elements and features.

In SHM paradigm, we first need to answer the following questions and carry out the procedures defined below (Farrar et al., 2001):

1. Why there is a need to evaluate damages and damage description? (Operational evaluation)
2. Which quantities need to be selected and measured, which type of sensors are required, and how often the data should be collected? (Data acquisition)
3. Extracting low-dimensional feature vectors and excluding redundant information in addition to data condensation. (Feature selection)
4. Verifying the significance of the extracted feature using statistical analysis. (Statistical model development (Feature discrimination)

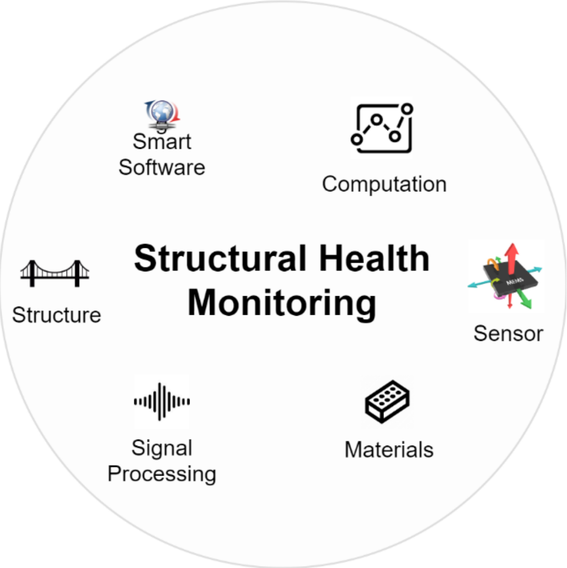

Figure 1: SHM Domain

Conventional sensors used in SHM are accelerometers, strain gauges, corrosion sensors, fiber optic sensors (Noel et al., 2017), camera image/video processing (Yang et al., 2017), and many more. Deployment of these sensors requires one to determine the best optimal locations along the span or piers of a bridge since measuring, for instance, and vibration needs multiple placements of accelerometers to start the modal analysis of the bridge. Many algorithms could be employed in optimal sensor placement (OSP) techniques to identify these critical locations. Genetic algorithm for OSP of a long-span railway steel bridge in (Deshan Shan et al., 2011) and, modified variance (MV) method in (Chang Minwoo and Pakzad Shamim N., 2014) for Northampton Street and Golden Gate Bridge are among many of the examples in OSP studies. In addition to these, environmental factors such as weather conditions and fluctuations in temperature should also be taken into account as some sensors may have limitations under harsh conditions (Sohn et al., 2003). A wireless sensor network (WSN) based SHM system architecture is shown in Figure 2.

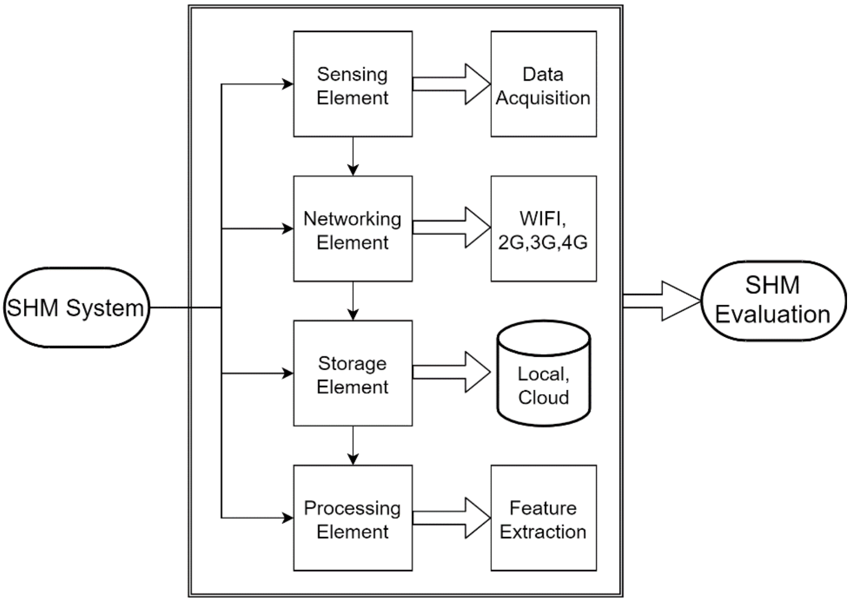

Figure 2: SHM system architecture

2.2. Geographical Information Systems (GIS)

GIS constitutes many aspects, as shown in Figure 3. A visually explanatory platform involving GIS manages multiple data from different sources on separate layers allowing simulation and modeling of all data and their influence on one another. GIS and its useful applications in many disciplines, especially in disaster management cases, comprise of shortcomings. The time, effort, and possibly money that is essential for advanced GIS may deter usage of the tool completely. Applicability constraints clearly can be seen when analyzing earthquake disasters and its implication on the network, which could produce tens of thousands of spatially – possibility not uniformly distributed data that can make the processing and analyzing, a complicated and time-consuming process (Tomaszewski, 2014).

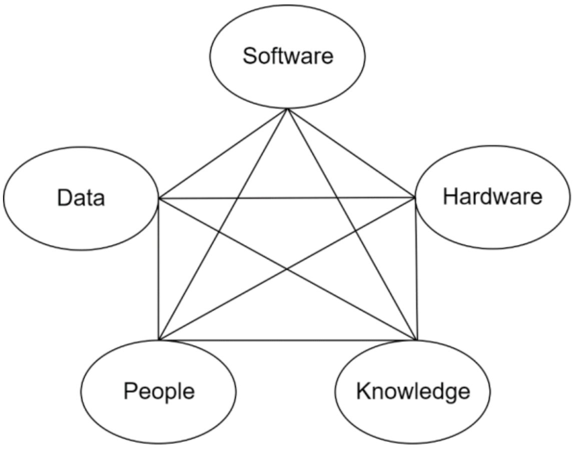

Figure 3: Component of GIS, adapted from Tomaszewski (2014, p. 75)

GIS maps with different layers are available online [1] ; however, the currency of the information provided may be of concern. Therefore, in some cases where there is a lack of information on the GIS maps (e.g., unknown bridge locations or highway network information), one needs to spend hours to acquire these data and import them into the correct location on the maps.

3. BRIDGES PERFORMANCE ASSESSMENT

The subsequent sections review SHM and GIS applications for bridge management and monitoring. Both tools are discussed considering the features they possess solely based on their system architecture. In addition to standalone applications, a brief review of SHM-GIS applications is also presented.

3.1. Bridges Performance Assessment Using SHM

Accelerometers are widely used sensors in SHM systems due to their low cost and easy installation, as well as their easy integration with other methods such as GPS for better accuracy in inverse structural dynamics. Meng, Dodson, & Roberts (2007) introduced their GPS-triaxial accelerometers approach for the structural response of the Wilford Bridge in Nottingham. Another similar study on a pedestrian bridge was conducted by Moschas & Stiros (2011). In both studies, time synchronization between GPS and accelerometers and the problem of different sampling rates of the systems which require sophisticated filtering techniques are some of the matters that need consideration in future studies. Other than using individual sensors deployed over a bridge, with the advent of smartphones, one can use the said devices to acquire vibration data from citizens' smartphones in the paradigm of crowdsourcing applications (Ozer and Feng, 2017, 2016).

As with the development in technology and an increase in the complexity of human-made civil structures, there is a need for a more efficient and long-term solution for some of the conventional sensors used in today's SHM applications (Casas and Cruz, 2003). Optical fiber sensors (OFS) provides improved quality of data acquisition, reliability, easy installation, and lower lifetime cost (Lopez-Higuera et al., 2011). The fidelity of OFSs in large and critical SHM systems often prevails over the high initial investment costs.

Another recent advancement in the SHM application is the use of digital video cameras with computer vision algorithms to identify displacement and vibration values. Specifically, in inaccessible locations on bridges, a

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[1] Natural Earth Data, Esri Open Data, USGS Earth Explorer, OpenStreetMap

contact-less vision approach is proven to be active and flexible in extracting information than other methods (Feng and Feng, 2017). In (Ye et al., 2013), charge-coupled device (CCD) digital camera with extended zoom up to 100m was performance-checked on Tsing Ma bridge and the results were compared to MTS[2] 810 material testing system. In another research (Khuc and Catbas, 2017) displacement of a bridge was tested in a non-contact vision approach and the difference in the results was less than 5% from using conventional sensors

3.2. Bridges Performance Assessment Using GIS

GIS, as explained earlier, can be considered as a database management system capable of storing, analyzing, and displaying such data in a standard graphical interface. In the area of bridge performance assessment, standalone applications of GIS mostly concentrate on risk assessment and life-cycle risk analysis. Spatially distributed information along with multiple independent parameters of bridges and networks, call for a management system that could operate and analyze under different scenarios. Integrating bridge inventory information with earthquake parameters required to produce fragility curves to determine bridge damage state as the input parameter for initializing spatial analysis is widely used in many studies. In a seismic risk assessment (SRA) based methodology for the Shelby County, Tennessee (Werner et al., 2000), 384 bridges in the network were assessed from multiple pre-generated earthquake models. Then, the traffic delay output was utilized to estimate the economic loss of the highway system. In the study done in St. Louis metropolitan area (Enke et al., 2008), ArcView was used as a spatial tool for mapping, locating, and setting up earthquake scenarios to evaluate the indirect economic loss, which was more significant than direct loss. Cheng, Wu, Chen, & Weng (2009) introduced a bridge repair/rehabilitation decision-making model where ArcGIS was used to identify alternative routes where detours were placed to reroute traffic. Later the economic loss model including the rehabilitation cost as well as additional costs through redirecting traffic was constructed. The decision-making model at the end offered either the lowest cost or the shortest duration of repair.

Another use of GIS is in the life-cycle assessment (LCA) of bridges. Deterioration of bridges over their lifetime and external attributes such as environment and traffic can influence the service life. In their research (Babanajad et al., 2018), they introduced an LCA framework for the U.S. Bridge Inventory, rating the inventory as a whole. Their Long-Term Bridge Performance Portal (LTBP) incorporated GIS and Google Maps to query multiple information. An overview of the bridge management system using GIS refers to Figure 4.

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[2] http://www.mts.com/en/index.htm

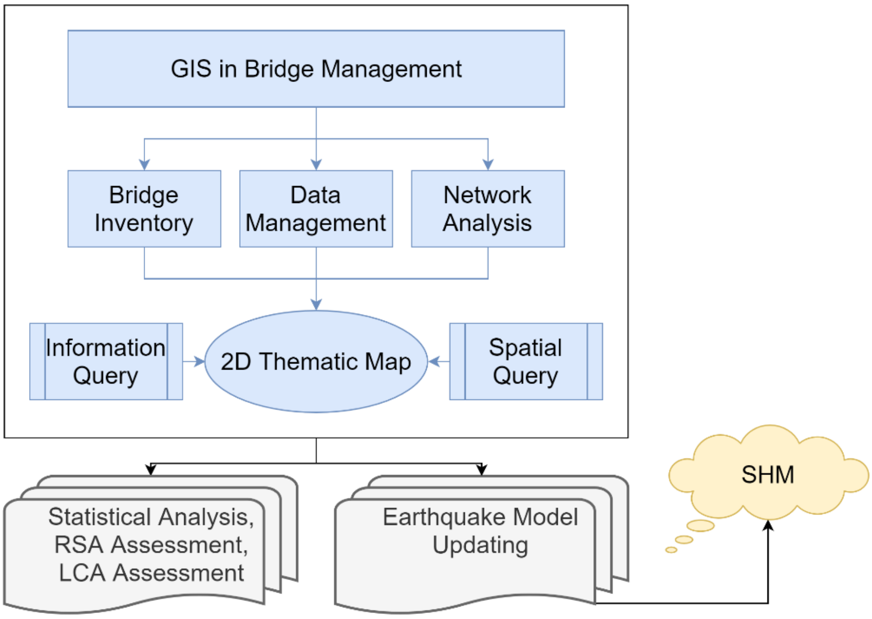

Figure 4: GIS system design for bridge management

3.3. Bridges Performance Assessment Using SHM-GIS

Combining the above-said tools into one network, it provides not only the capabilities of the instruments alone but also extra useful features that would not have been attainable otherwise. In the study by (Jeong et al., 2017), a cloud-based cyberinfrastructure framework was presented. Apache Cassandra open-source as a column-oriented database and Microsoft Azure was used for the database management system and cloud provider, respectively. The web user interfaces for data extraction and information visualization on Google Maps was also provided. The Long-Term Bridge Performance (LTBP) Program[3] , as also briefly mentioned in the previous section, is an initiative by the Highway Administration (FHWA) in 2008 envisioning a 20-year comprehensive field data collection from a sample of bridges in the U.S (Parvardeh et al., 2016). The program consists of analyzing bridge performance under deterioration. As previously discussed, the field data are gathered and maintained from different NDT techniques. The web-based platform containing the National Bridge Inventory (NVI) with GIS capability can enhance the quality of management of bridges by bridge owners as well as researchers to better understand the performance of bridges. A conceptualized GIS-based structural health monitoring was proposed in (Shi et al., 2002). SQL Server database and Maptitude GIS were used to input and store bridge and sensor data and to visualize in an interface to view and extract the bridge/sensor information. Table 1 Summarizes the above information and compares different features of bridge damage for risk assessment.

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[3] https://fhwaapps.fhwa.dot.gov/ltbpp/

Table 1: Comparison of Different Bridge Assessment Techniques

Application	Sensor(s) requirement	Structural Damage Assessment	Database Management	Spatial Analysis	Decision Making Feature	Risk Assessment Feature	Scalability	Cost
GIS	×	×	✓	✓	✓*	✓*	Low	Low
SHM	✓	✓	×	×	✓*	✓*	Medium	Medium
SHM-GIS	✓	✓	✓	✓	✓	✓	High	Medium
✓* indicates in limited scenarios given the use-case of the application								

4. INTELLIGENT SHM-GIS CLOUD-BASED BRIDGE MONITORING SYSTEM

In this section, an intelligent SHM-GIS cloud-based framework is introduced and discussed. Individually deployed GIS and SHM tools discussed above may have their benefits in bridge monitoring, specifically for small scale applications. However, in large scale deployments considering the size and the complexity of the application, it may result in higher overall cost and less accurate results. It is, therefore, recommended that combined use of the tools on a cloud-based platform could enhance their performance. Furthermore, cloud-based platforms allow collaboration of different stakeholders enabling each party to add, edit on top of the existing data, and performing simultaneous analysis.

The nature of SHM systems in terms of sustainability already considers the three components of a sustainable approach, i.e., economic, social, and environmental. These include a reduction in traffic delays and downtimes, which subsequently lead to lower carbon dioxide emission and, lastly, the expected economic loss. These are mainly related to the network aspect, but the same can be said to the structure itself, i.e., bridge. Bridge monitoring can provide useful information in terms of the remaining helpful time and any maintenance that may be necessary for the future, which can help minimize the costs and maximums the life expectancy by early retrofitting or reconstructing.

Similarly, GIS can help bridge managers to have a better understanding of the structures and their behavior under different conditions. GIS can deliver a decision-making platform (Băneş et al., 2010) for the risk assessment of bridges and their cascading failures on the network, thus offering a complete management tool that could provide sets of strategies depending on the application use.

The new paradigm shift to cloud computing and web-based applications marks the SHM-GIS cloud-based platform a necessity in today’s technological world. Not only it provides the core functionality of the tools, but instead, it goes further to expand its roots for even more cost-effective, efficient, and sustainable solution in bridge prognosis and diagnosis. Synergistic use of SHM and GIS can develop or update earthquake models on the fly and provide a more accurate damage estimate of the bridge and its effect on the network.

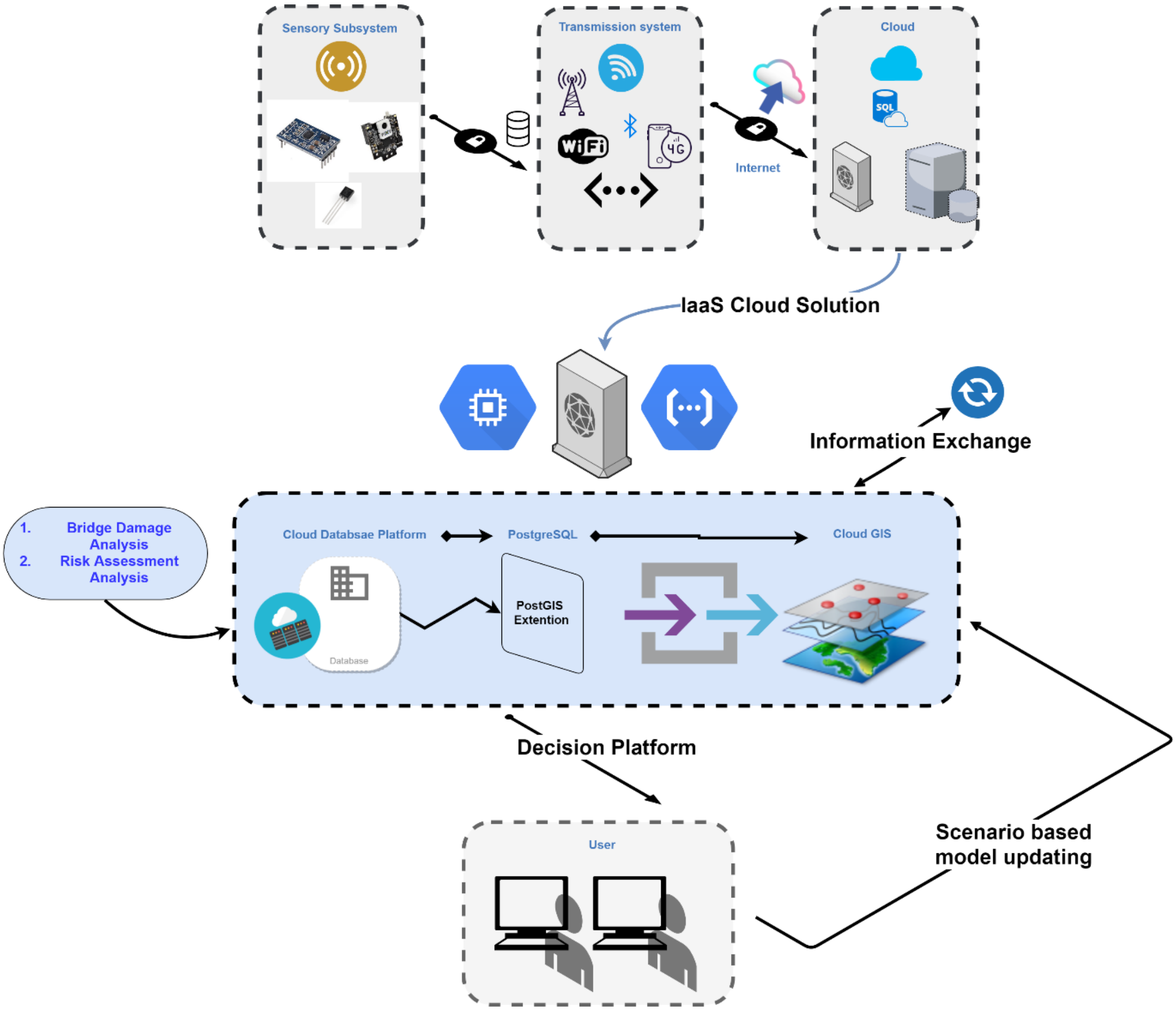

Figure 5: Framework of the system architecture

The proposed SHM-GIS cloud-based system architecture is, therefore, presented in Figure 4. The sensory subsystem layer acts as the data acquisition where it collects the data from bridges. The collected information is then transferred to a server via a different form of communication standards such as Wi-Fi, Bluetooth, cellular, etc. and later uploaded on the cloud. Due to the enormous size of the acquired data for any given time history chiefly in the extensive application of bridge monitoring, storage methods need investigation. The issue of big data and the problem of storage has led to the creation of different file structure format. Standard file formats for storing large amounts of data are 1) HDF[4] (Hierarchical Data Format), 2) netCDF[5] (Network Common Data Format). However, due to the file structure of these formats, they are not ideal in cloud computing. Many alternatives with their strengths and weaknesses are present in Matthew Rocklin (2018) webpage. HDF5 (Hierarchical Data Format version 5) can be an ideal solution in this case for storing multi-dimensional data. Bridge information such as geometry, location, etc. as well as network description such as highway information, traffic information, etc. are stored in an object-relational database management system (ORDBMS). PostgreSQL, with the extension, *PostGIS* for handling spatial data, is the common Database Management System (DBMS) for

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[4] http://www.hdfgroup.org/

[5] https://www.unidata.ucar.edu/software/netcdf/

structural health monitoring applications. PostgreSQL is an open-source DBMS that is well developed and intuitive. The relationship between the sensor data and the structural/network elements is also a one-to-many relation.

The cloud service for this system relies on infrastructure as a service (IaaS) type. IaaS services are often low-cost, more accessible and faster options over different cloud services enabling storage resiliency, frequent backup, high level of automation. Deciding which cloud provider to use depends on the performance and uptime required from the provider. A typical solution for cloud computing is Google Cloud and Compute Engine. Other services, such as Microsoft Azure and Amazon Web Services (AWS), are also available. These data then proceeds into performance analysis and monitoring of the bridges. Depending on the data type (vibration, displacement, image, etc.), different algorithms can define the damage state in the given earthquake scenario.

Incorporating the network data such as traffic delay and routing info into the database can enable the employment of a cloud GIS platform capable of visualizing, analyzing, managing, and monitoring bridges and the effects of failure of them on the transportation network. Using this information and a simple risk formula that includes direct costs such as structural loss, network loss, and indirect loss, it can provide a decision-making platform for pre- and post-earthquake disaster scenarios. The advantages of this SHM-GIS cloud-based system are as follows:

- Utilizing open-source and free software and system providers
- Ability to add/remove or change any information without the problem of proof checking for errors,
- The flexibility of the system in any application use (using a small or large number of sensors),
- An intuitive and low-cost solution for bridge monitoring (especially for bridges owners),
- The scalability of the system in terms of the location and the size of the application.

Moreover, risk assessment based on dynamic changes in the model can also serve in the system. As parameters of the model change throughout time, real-time risk assessment can assess the performance of the bridge under future loads. The data from traffic and future loading can predict the future state of the bridge, aiding bridge owners to decide about retrofitting or reconstructing all or some parts of bridge elements.

The whole system, from the data acquisition, DBMS, and user interface, can be programmed with the open-source Python programming language. Web applications, as well as mobile applications for viewing and extracting information, can also be implemented for easier and faster utilization of the data. The ability of information exchange and information sharing with other software and services is another advantage that distinguishes this from other similar systems (Ellenberg et al., 2015; Eschmann et al., 2012; Sankarasrinivasan et al., 2015). A summary of the traditional SHM-GIS damage assessment and the cloud-based variant that is tabulated in Table 2. The next section brings a recent technological implementation, aerial devices, which provide an efficient synthesis of GIS and SHM domains.

Table 2: Summary of the Traditional and New Novel SHM System

Reference	System	Real-time processing	Flexibility	System Efficiency	Mobility (easy accessibility)	Maintenance and Management	Open and interoperable	Multi-purpose Decision making
(Jeong et al., 2017; Shi et al., 2002)	Conventional SHM-GIS	×	Low	Medium	Low	Low	×	×
This Study Framework	Cloud-Based SHM-GIS	✓	High	High	High	Medium	✓	✓

5. MACHINE LEARNING IN SHM APPLICATION, A COMPLEMENTARY ADDITION

Given the amount of data gathered from many different things, it is important to understand the pattern that underlines it. Day by day with increase in complexity of structures, without automatic (sometimes semiautomatic) processes to discover patterns using computer, such tasks would be infeasible and impractical. Machine Learning (ML) is considered as tool to recognize/classify information based on a learned pattern through the use of different algorithms. In general, ML algorithms are based on either 1) statistical, 2) neural or 3) synthetic approaches. The first two approaches are generally considered as the main pattern classifiers for SHM [8]. There are many works utilizing ML. For example, (Cao et al., 2018) developed a piezoelectric impedance measurement for an effective structural damage identification through an inverse analysis. Similarly (Moore et al., 2012) crack identification in a thin plate was achieved by model updating.

With the advent of ML and statistical pattern recognition algorithms, a new level can be added to the Rytter (Rytter, 1993) 4-stage damage identification. Type of damage or classification of damage is the level that is possible through the use of ML algorithms. This new step lies between step 2 and step 3 introduced by Ryteer. To illustrates this, Figure 6 depicts the 5-stage damage identification in SHM application given the domain and level of difficulty.

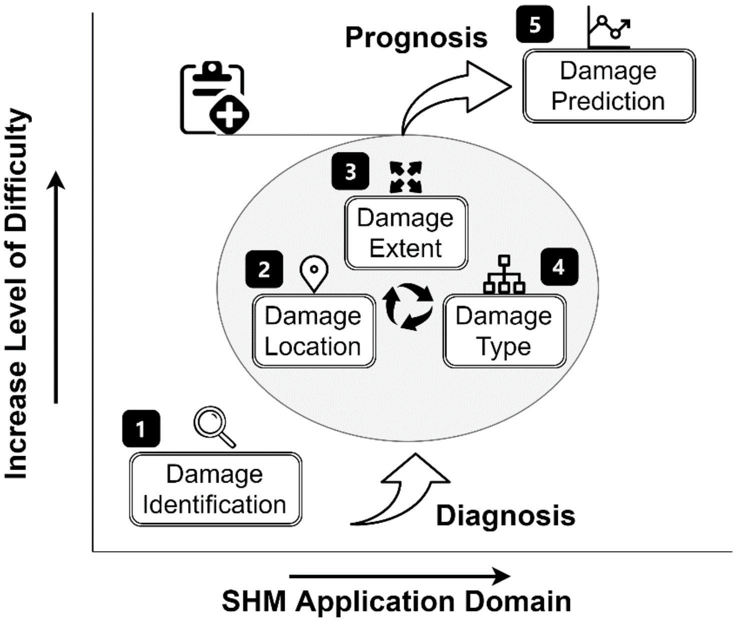

Figure 6: 5-Stage damage identification

Given that both damage and undamaged information are available, a supervised learning algorithm can effectively go through all 5 levels of damage detection. This requires many data to be readily available from the sensing systems or the physical-based models and the experiments. This is not possible in many applications and the current information for damage sate is limited, if not, unavailable. For such situations, there exists a method called unsupervised learning. In this mode, instead of learning the models and train based on the data, a rather simple approach, novelty or outlier detection is applied [10].

illustrates a statistical pattern recognition model for a typical damage assessment scenario utilizing ML. Moreover, Table shows the current reviews on ML utilization on SHM application.

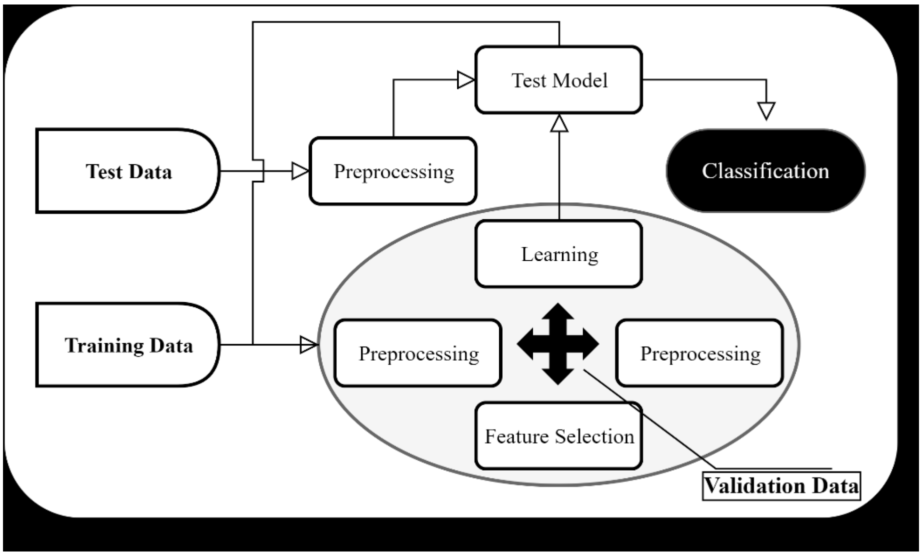

Figure 7: A Typical Machine learning model

Table 3: Works on ML utilization in SHM

Reference	Model-based	Data-Based	Application of ML/Deep Learning	Mobile Applications	Machine Vision Consideration	Novel Applications (UAV, VR, AR, etc.)
(Fan and Qiao, 2010; Gomes et al., 2019)	✓	-	✓	-	-	-
(Ye et al., 2016)	-	✓	-	-	✓	-
(An et al., 2013)	✓*	✓*	✓*	-	-	-
(Moughty and Casas, 2017)	✓*	✓	✓*	-	-	-
(Kerle et al., 2019)	-	-	✓	-	-	UAV Only

✓* indicates a little information

ML can augment SHM in many aspects which the old system is incapable of. For example, environmental and operational variabilities often times are not considered but have proven that can greatly influence in-service structures (Sohn, 2007). Including these effects by leveraging the power of ML can definitely help SHM application achieve better level of detection. Moreover, ML and deep learning can be particularly useful in bridge monitoring applications which are combined with GIS and remote sensing tools that utilize machine vision for anomaly detection or as tools in data analytics inside the GIS package.

6. DRONE ASSISTED SHM, A SYNERGISTIC MEDIUM

Drone technology, also known as Unmanned Aerial Vehicle (UAV), has seen a vast increase in usage in recent years due to the advantages they can offer and especially their deployment flexibility (Al-Turjman et al., 2019). Given their versatility, low-cost as well as ease of deployment elements of a flying piece of technology, they are becoming more and more accretive (Al-Turjman et al., 2020). There are a limited number of studies focusing on drone-based SHM systems. Most of the works aim at the post-image processing of cracks (Ellenberg et al., 2015; Eschmann et al., 2012; Sankarasrinivasan et al., 2015).

However, very few have focused on vibration-based SHM (Na and Baek, 2016), but with the advancement in machine learning and cloud computing, image processing on the fly augmented with innovative technologies is considered the next step in mobile SHM applications. Some works have already started extracting critical information from the drones (Hoskere et al., 2019) but majority of them rely on post-processing techniques. Using the framework introduced, with the total flexibility it offers, application of cloud computing can become a reality. With the GIS part of the framework, critical data points on the structure can be generated and regularly visited to detect any abnormal changes with respect to a baseline.

Moreover, with the combined use of SHM-GIS in drone-based SHM applications, both on-fly and cloud processing of information can be achieved, and immediate results can be shown as a map. The other benefit that this system also offers is the well-regulated and controlled behavior. This in turn provides total control over how the system should be implemented for the most effective use of drones.

7. CONCLUSION

Bridges are indispensable to a transportation network. Earthquakes can damage bridges and effectively disrupt the transportation network. Structural Health Monitoring (SHM) and Geographical Information Systems (GIS) are some of the tools that can mitigate, understand, and manage these issues. In this paper, a cloud-based SHM-GIS framework targets bridge monitoring in earthquake-prone locations.

SHM and GIS both have their advantages in the application of monitoring and management of bridges. However, by synergistically combining these tools, researchers and especially owners of bridges can utilize the mixed results to have a better understanding of bridge performance with a decision-making platform extension. The new paradigm shift to cloud computing has enabled us to offload both database and data computations to a cloud server. Cloud computing can increase productivity, speed, and security of data by doing so in a low-cost manner. By enabling this feature, we can utilize the power of the cloud to visualize, analyze, manage, and store multiple data from multiple bridges.

Application of cloud GIS can help to envision what would happen under different earthquake scenarios and what would be direct and indirect losses of such an event. Besides, with the help of this system, damage prediction for future events such as an increase in traffic load or deterioration of bridges and the implications of it on the transportation network can be examined.

The proposed framework uses free and open-source software and packages and can introduce a web or mobile-based application written in Python alone. With the help of the information exchange feature of the system, the beneficiaries can extract data and use them in other services or software with little to no modification. Also, this paper introduced machine learning as a complementary addition and the use of drones as a synergistic medium to SHM application that can be included in the proposed framework for the most effective implementation of prognosis and diagnosis of bridges and bridge monitoring in general.

The concept provided in this paper, with its flexible and open-source items, can be considered as the next step towards the future of the cyber-physical system (CPS) with many new features as part of the IoT paradigm shift (Al-Turjman and Malekloo, 2019). The future of the risk assessment for transportation network lies within the cloud. What will ensue from such a movement towards this paradigm are the applications of deep learning, artificial intelligence, drones, virtual/augmented reality. These are a tiny droplet in the vast ocean of the next generation sensing and monitoring applications.

As future work, the focus will be on the implementation and development of such a system in addition to including dynamic and real-time risk assessment procedures embedded into the system for further performance analysis.

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