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Article

Geographical Area Network – Structural Health Monitoring Utility Computing Model

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Abstract: In view of intensified disasters and fatalities caused by natural phenomena and geographical expansion, there is a pressing need for a more effective environment logging for a better management and urban planning. This paper proposes a novel utility computing model (UCM) for structural health monitoring (SHM) that would enable dynamic planning of monitoring systems in an efficient and cost-effective manner. The proposed UCM consists of network-attached data drive that stores data from SHM logger, population count system and Geographic Information System (GIS) enhanced with a Cloud IoT data backup, display, and analysis server. The UCM using this data and data from building information systems applies a simple machine learning algorithm to generate real-time structure health and suggests re-planning of SHM units. The health of structure varies dynamically with disturbances created by higher occupancy and structure density per zone. The proposed SHM-UCM is unique in terms of its capability to manage heterogeneous SHM resources. This was tested in a case study on Qatar University (QU) in Doha Qatar, where it looked at where SHM nodes are distributed along with occupancy density in each building. This information was taken from QU simulated occupation and zone calculation models and then compared to ideal SHM system data. Results show the effectiveness of the proposed model in logging and dynamically planning SHM.

Keywords: Geographical Area Network (GAN), Structural Health Monitoring (SHM), Utility Computing (UC), Things as a Service (TaaS), Internet of Things (IoT)

1. Introduction

By 2025, more than 80% of the government, community and headquarter buildings or structures will be equipped with Structural Health Monitoring (SHM) devices [1]. Sensors diversity and parameter estimation for structural health to forecast zonal safety have always been a dream for geologists, environmental scientists, and international authorities. Utility Computing (UC) is commonly used as not having an eye on the background framework of the supply chain to deal with problems. UC is the application of cloud computing that encompasses algorithms and theorems in a way that consumer is getting direct applications and benefits like in cases of Uber, Careem, AliExpress, Food Panda and Google Maps [2-4]. UC services react with distributed Geographical Information Systems (GIS) platforms like Google Maps to enable applications like Navisworks and Building Information Modeling (BIM) resulting in heterogeneous Geographical Area Networks (GAN) [5-9]. On the other hand, Structural Health Monitoring (SHM) is a systematic framework that shows the fitness of a structure as a front-end tool-less focused on Mechanical Electrical and Plumbing (MEP) that are defined in BIM. In SHM, only derived parameters that justify the condition of structures which are visible to consumers. Building Information System (BIS) has brought

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revolution in the construction industry. It defines every single aspect of building structure feasibility, design, erection and finishing. It is necessary to apply clear and correct BIS analysis for the achievement of desired results. BIS planned SHM is the core 'lifecycle management utility' for stakeholders [10, 11]. However, in the SHM parameters driven sensors selection process for parametric SHM, sensors are not compatible with UC Infrastructure (UCI).

The SHM designs discussed in [12] is an acute process while taking into account cloud integration and real-time operations of machine learning algorithms. SHM implementations using wireless sensors networks for Internet of Things (IoT) models [13,14] need improvement in their UC aspect, that is, there must be some algorithms and data processing that can assist Open System Interconnection (OSI) model which should be application layer (layer 6), and presentation layer (layer 7) devices and applications. Deep Learning (DL) is now implemented on raspberry pi but still needs improvement for cloud compatibility and to be paired with mathematical techniques mentioned in [15]. We believe that the role of SHM is very vital in reporting disasters and handling any abnormal and hazardous condition using seismic waves analysis through several signal processing algorithms i.e. Frequency Domain Decomposition (FDD) and Eigen System Realization Algorithm (ERA) as defined in [16].

This work focuses on

- SHM UC Model (SHM – UCM) development
- Multi-Objective SHM Prediction Machine Learning Algorithm (MOSPA)

In section II, SHM UCM is explained using the GAN concept. Section III shows deployed SHM for model evaluation along with SHM nodes created in this work. Section IV discusses MOSPA, where the results are demonstrated in Section V. MOSPA is a meta-heuristic sequential set of techniques that decides and evaluates the necessity of SHM in a geographical cluster under observation. The last section gives concluding thoughts and future recommendation about the proposed work.

2. The SHM Utility Computing Model (SHM-UCM)

This work recommends a structured SHM that operates in compliance with a given Safety Integrity Level (SIL) and independently at Emergency Shutdown (ESD) level. SIL is governed by Structural Integrity Management (SIM) platform that over-rules decisions of Building Management Systems (BMSs). ESD is a binary decision based enveloped estimation that makes the structural health qualification criteria either passes or fail. SIM control parameters are set by GAN based on the geological, geographical and geo-mechanic transients' prediction assisted by weather stations. To this end, we present a SHM-GAN with heterogeneous Machine Learning (ML) algorithms engine in a distributed SIM framework at a lithosphere level, i.e., a separate SIM for a separate crust composition. Sandy, soiled, rocked and limestone based areas have different foundation requirements for different type structures. GIS has critical databases of dynamic and real-time update in datasets for real patches on the crust.

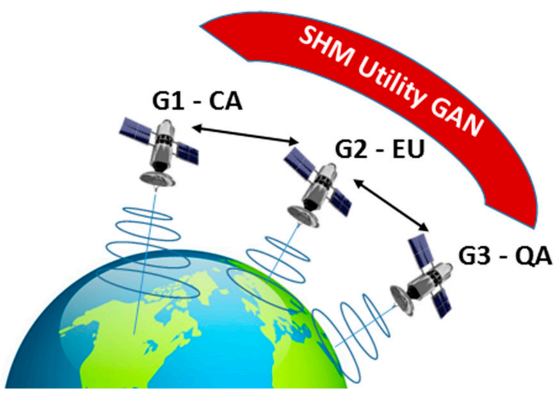

Figure 1. SHM Utility GAN

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Figure 1 illustrates the proposed conceptual model of SHM-UCM networked through a mesh of SHM-GAN of the geospatial orientation of satellites dedicated for SHM. Three heterogeneous intracontinental patches are selected G1 for Canada, G2 for European Union and G3 for Qatar. Three different sizes have been selected to realize that freedom of observational geophysical patch selection. One each satellite i.e. G1, G2 and G3 decisions are made by MOSPA (proposed algorithm). This SHM-GAN enables globally engineered and administered implementation schemes for SHM for governments to reduce routine exhaustive calculations by Project Management Consultants (PMC). Quick tendering, systematic City and Regional Planning (CRP) initiatives are examples of noticeable outcomes of this SHM-UCM, to mention few.

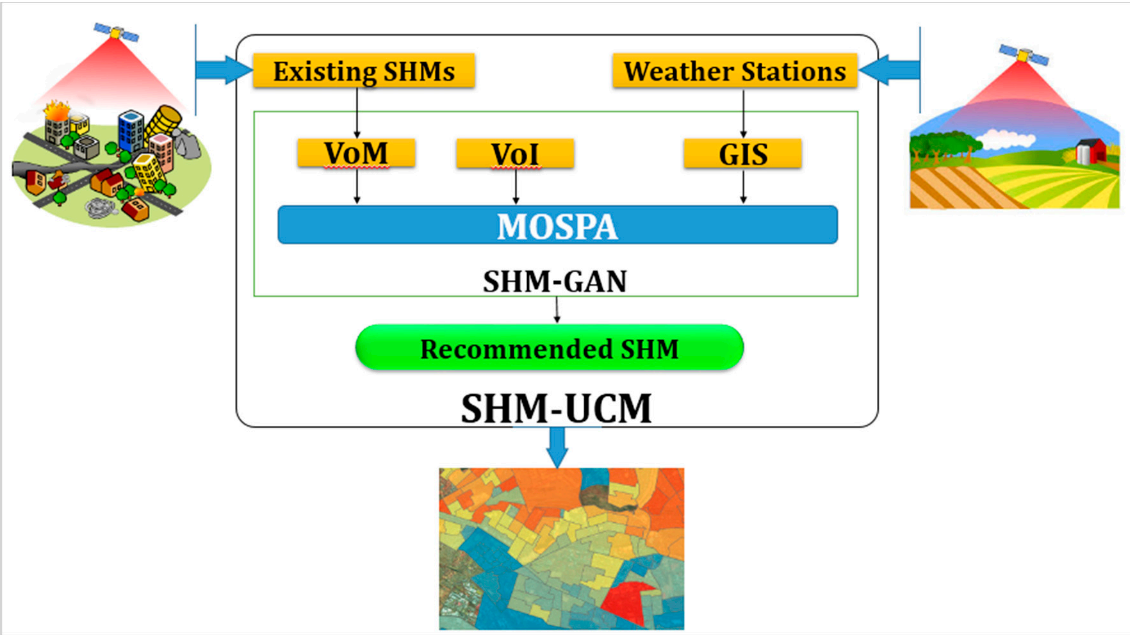

Figure 2. SHM-UCM

Figure 2 shows a complete overview of proposed SHM-UCM. It is evident that the data is taken from Existing SHM systems, Weather Stations GIS and VoI, analyzed by proposed MOSPA algorithm - resulting in SHM-GAN i.e. satellite-based system running MOSPA. This complete analysis of input data and resulting in a geo plot for dynamically planning of SHM systems is 'Structural Health Monitoring Utility Computing Model'.

3. Structural Health Monitoring Systems

The Body Area Heterogeneous Network (BAHN) for the SHM system is designed for a structure in which after hundreds of iterations in BIS frameworks, Value of Information is evaluated and finalized by multi-disciplinary Subject Matter Experts inputs to ML algorithm. A SHM is a sequential and systematic process in which the end product is a trustable abstract decision parameters dataset based on the data collected from SHM system variables. Firstly, the SHM is developed and deployed on structures-specific mandates that need to be monitored (e.g. residential, commercial, bridges, tunnels). SHM system architecture is based on extracting upper and lower bounds of Finite Element Analysis (FEA) data. By upper and lower bound we mean the maximum and minimum values at which the structure is expected or meant to stay fully fit. A SHM system is a unique system that has to serve the purpose for lifecycle evaluation of structure for a structure for the next 10 years.

In Figure 3, a common SHM system has been shown based on Level of Detail 6 from BIS documentation for a particular structure [refs]. This SHM system includes several sensors to measure the structure health which includes weight (load cells), water level, moisture (hygrometer), balance (gyro sensors), temperature (thermocouples or resistance temperature detectors), accelerometers (vibration), pressure indoor and outdoor (piezo-electric sensors), collision or obstacle detection in

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vicinity (ultrasonic sensors or sonar), tilt and inclination (tiltmeter) and wind speed (anemometer). Secondly, the location and data communication is being achieved using GPS and GSM/GPRS, respectively. The variables shown vary from structure to structure and is a complex set of the formulation by a multi-disciplinary team. These variables can vary the SHM parameter estimation and feature extraction; in other words, directly affect the technical assessment of VoI of the respective structure. These SHM sensors have specific orientation and locations, which are calculated as per geospatial constraints. These sensors vary based on VoI calculated for the building and expected enormity of the disaster. This work is an effort toward the development of a smarter service oriented UCM that will bring the multi-disciplinary procedures and practices under one umbrella called SHM-UCM.

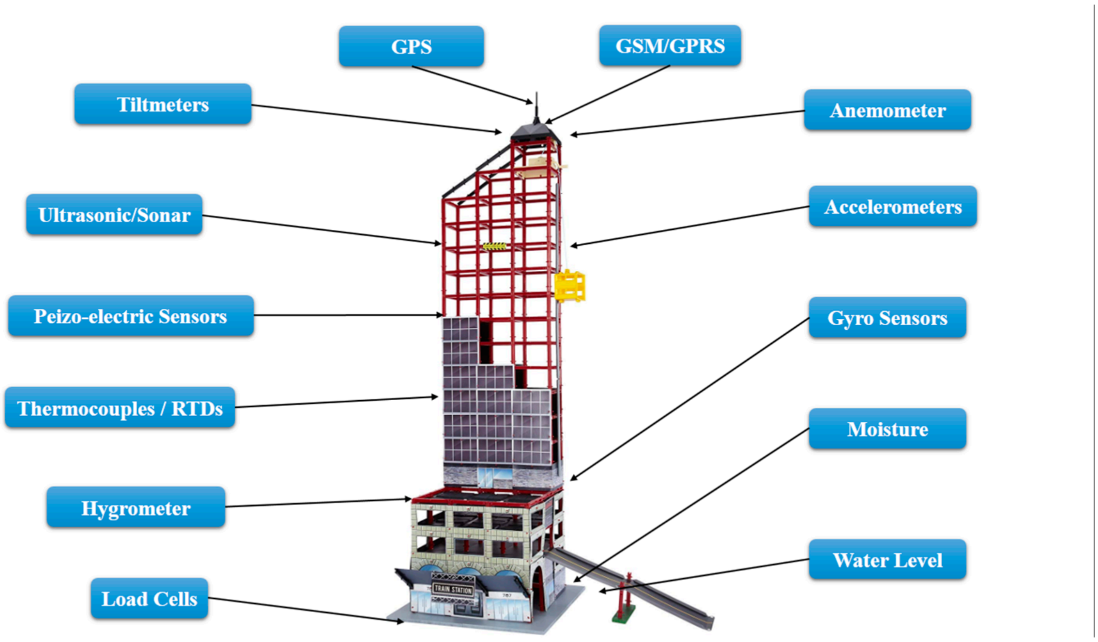

Figure 3. SHM by Lifecycle Management/Long Term Evolution

By 2018, the exponential rise in SHM nodes deployment has been registered across the world at institutional and organizational level with different topologies, architectures, and frameworks on various IoT platforms [17 – 18]. For in-situ long-haul seamless monitoring, a most successful and frequent node architecture is used, which comprises a range of sensors, application specific scale Signal Conditioners (SCs), and high-resolution Analog to Digital Converter (ADC) chips and microcontrollers (e.g. Intel 8051, Microchip P18F458 and ATMega32).

Figure 4 illustrates a typical SHM node used for heterogeneous Body Area Network (BAN) implementations for existing SHM systems [19]. It has to go through a sequence of primitive data processing methods to be compatible with SHM systems. This SHM Node has to be orchestrated like a cloud framework ZeRo Client (ZRC), ThiN Client (TNC) and ThicK Client (TKC) nodes so that it fits in the ecosystem of Industry 4.0 standard for SHM systems.

The SHM nodes proposed in this work are UCM coherent framework. The obligation of extreme sensitivity, scalability and sampling frequencies is imposed to achieve the variable data processing constraints for feature extraction techniques, Non-Destructive Testing (NDT) methods, and Non-Destructive Evaluation (NDE) procedures. It is repugnant to hire a new (different) team for detailed SHM parameter assessment every time. A SHM-Application Specific Standard Part (SHM-ASSP) fills the gap of providing the utility of high-resolution data for NDT and NDE assessment procedures.

In Figure 5, a SHM-ASSP ZRC Node is illustrated that includes MEMS Sensors along with Programmable SC (PSC) to make it compatible with monitoring using specialized sensors and Programmable ADC (PADC) that can adopt scaling and range recommendation for particular observational criteria. The SHM-ASSP ZRC nodes proposed in this work need no external

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instrumentation assistance for SHM operations. 'STM32F10RBT6' CPU interfaced with inclinometers sensors are basic elements of nodes.

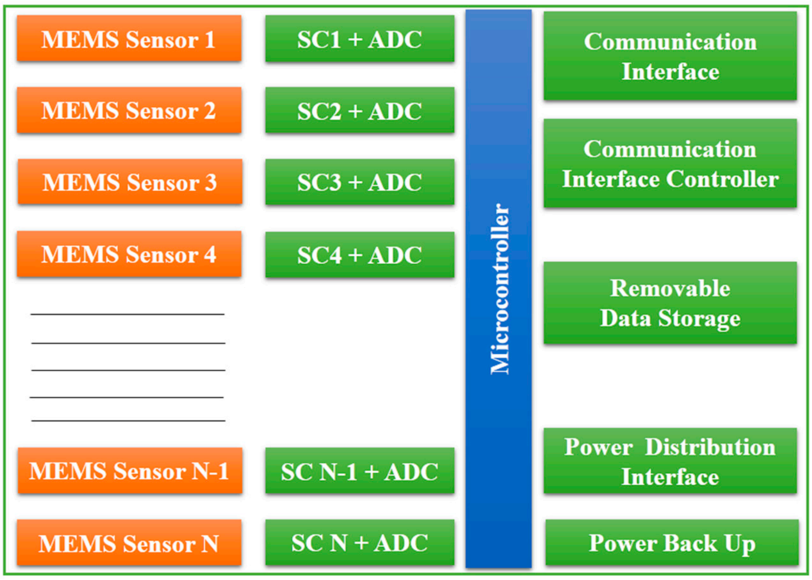

Figure 4. Conventional SHM Node Block Diagram

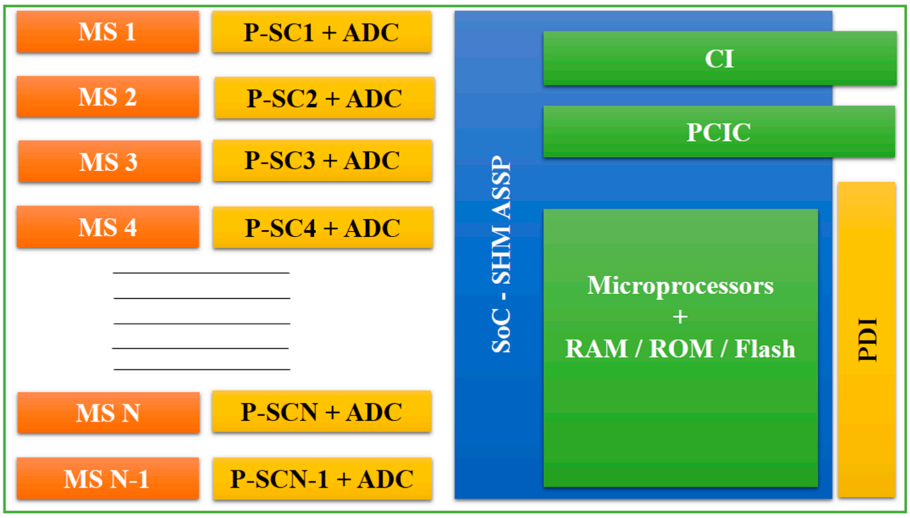

Figure 5. SHM-ASSP ZRC Node Block Diagram

These nodes, which are developed in-house, are shown in Figure 6 and include:

- Seismic Sensors Node with 2 SHM Sensors
- Cylindrical Sensors Node full-fledged with 7 SHM Sensors

These nodes utilize CANopen industrial protocol paired with CAN-USB adapter to interface with an Out-Surface Board (OSB), in case of underground deployment, that transfers sensors readings wirelessly or wired to a gateway.

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(a) SSN (b) CSN

Figure 6. SHM-ASSP ZRC Nodes

It is noteworthy to highlight that these nodes are enhanced with remotely programmable and configurable parameters.

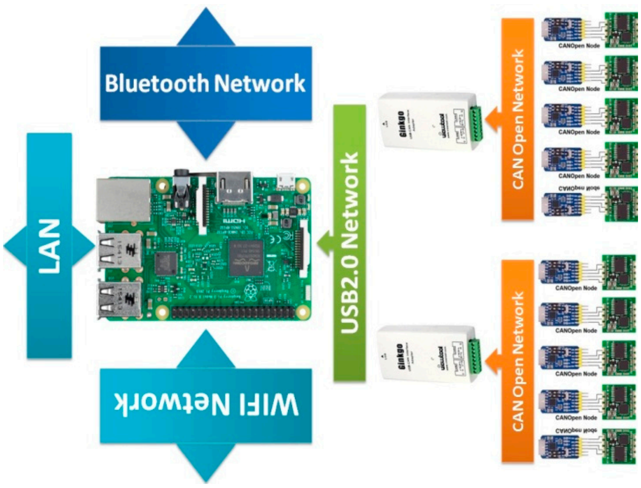

Figure 7. SHM-OSB TNC

Figure 7 shows an OSB that has a micro expert system with multiple resource-constrained Machine Learning SHM Algorithm.

4. Multi-Objective SHM Prediction Machine Learning Algorithm

SHM is highly feasible for bigger structures, especially community buildings, where structure value and human lives are critical. Multi-Objective SHM Prediction Machine Learning Algorithm (MOSPA) takes into account the results for occupation count and SHM system parameters, then train a ML algorithm to give a geo plot for the dynamic planning of SHM. It uses a multi-objective Supervised ML Technique (SMLT) that streamlines the SHM Heterogeneous BAN architecture and steps of installation recommended by SHM-UCM. For occupation count, Medium Access Control (MAC) and International Mobile Equipment Identifier (IMEI) addresses along with biometric access counter values are used. The final population count is obtained by removing the overlap between the MAC, IMEI addresses and access counter using a condition-based methodology. Finally, SHM parameters are used along with occupation data to obtain a geo plot for fitness view of SHM systems.

4.1 User Identification from MAC and IMEI Addresses

A two-tier mechanism for occupant counters has been employed as occupant space called O_v. O_v is a sum of the number of MAC addresses registered in wireless routers (every PC or smart phone has a Wi-Fi card or a LAN card that has MAC address) plus IMEI that every smart phone has as a de

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facto de jure for Electronic Industry Association/Telecommunication Industry Association approved the standard. These two variables overlap but gives a complete overview of all the electronic devices in a particular location; mobile phones with SIM card and Devices connected to Wi-Fi.

$$O_v = \Sigma(MAC) + \Sigma(IMEI) \tag{1}$$

4.2 Attendance Count

For permanent inhabitants or occupants' biometric access counter, I is defined in terms of O_p as:

$$O_p = \Sigma I \tag{2}$$

Thus O is summed up as

$$O = O_v + O_p \tag{3}$$

The total occupancy probability distribution function is taken to obtain a random occupancy vector at a specific location.

4.3 Final Population Count

In a given model [20, 21], hourly Probability Distribution Functions (PDFs) that allow the calculation of the probability for a particular occupancy state occurring within a given hour is presented. Let $H = (O_1 \cdots O_m)$ denotes all occupancies that occur per second during a period of time and V_x is a vector of occupancies for room x where $x = 1,2,3, \ldots .\ y$. Let α_i denote the average occupancy for the room r_i. We calculate a vector of means $\alpha = (\alpha_1, \ldots, \alpha_m)$ and covariance matrix M from O. Using α and M, we define a Probability Density Function f:

$$f\ (O;\ \alpha, M) = 1\frac{1}{(2\pi)^{\frac{n}{2}}\ |\mathrm{M}|^{1/2}} \exp\left\{-\frac{(O-\alpha)^T \mathrm{M}^{-1}(O-\alpha)}{2}\right\} \tag{4}$$

Hourly Gaussian models with mean α_h and covariance matrix M_h, where f can give a probability of an occupancy occurring for a specific dataset O_h for hour h, is defined. Using this function, random occupancy vectors can be drawn from the distribution.

The final population count is obtained by removing the overlaps between the MAC, IMEI addresses and attendance count. A condition is applied that if the MAC, IMEI addresses are at a close distance to a person counted for attendance, all should be counted as one person. Similarly, if registered MAC s and IMEI addresses are at less than half a meter, it should be considered as single person i.e. that person has a cell phone with IMEI address and a laptop with MAC address connected to Wi-Fi but he or she has not put the attendance through biometric access count. Then after calculating the final population count at a specific time step, a PDF can be obtained.

4.4 SHM Parameters

The BIM model is the second parameter value of information VoI_{BIM} that has all the definitions i.e. floors F_{BIM}, beams B_{BIM}, columns C_{BIM}, stairs S_{BIM}, rooms R_{BIM}, halls H_{BIM}, galleries G_{BIM}, joints J_{BIM}, trusses T_{BIM}, payloads P_{BIM}, areas A_{BIM} and volumes V_{BIM}. VoI_{BIM} is a sum of functions of joints, trusses, payloads and volumes [22].

$$VoI_{BIM} = F(J_{BIM}) + F(T_{BIM}) + F(P_{BIM}) + F(V_{BIM}) \tag{5}$$

The applied physical fitness function [23] parameter, called F_{SHM}, depends on the tilt T_{SHM}, structural strain $\Delta L/L_{SHM}$, vibration V_{SHM}, temperature T_{SHM}, stress S_{SHM}, wind effect W_{SHM}, the

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ground water level L_{SHM}, humidity H_{SHM}, moisture M_{SHM} and composite material stability constant M_{CM}.

$$F_{SHM} = F(T_{SHM}) + F\left(\frac{\Delta L}{L_{SHM}}\right) + F(V_{SHM}) + F(T_{SHM}) + F(S_{SHM}) + F(W_{SHM}) + F(L_{SHM}) + F(H_{SHM}) + F(M_{SHM}) + F(M_{CM}) \quad (6)$$

Finally, the total population count along with the SHM fitness parameter can be used to train the ML-based algorithm to propose real-time optimum location of SHM devices to mitigate risks through better planning and early warnings. Nevertheless, this fosters covering wide area structures and pinpoint any landmark changes that can affect the integrity of buildings. In the following section, it can be clearly seen that the dynamic planning scheme of SHM systems, based on occupation count and SHM real-time data.

5. Results and Discussion

The chosen case study is SHM system prediction for Qatar University (QU) from GAN based SHM-UCM. The results of MOPSA are sequential in nature. First computation is runtime Variable Occupancy Model (VoM) map based on the probability density function of occupancy O given in (4). The PDF in (4) forecasts the occupancy by adopting the historical random data of O, α and M.

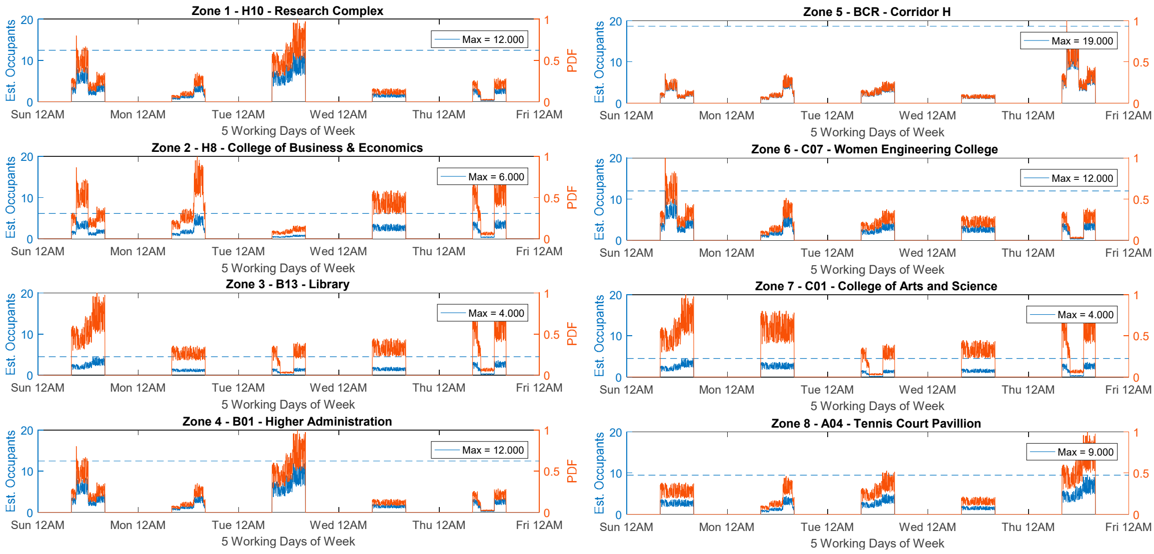

Figure 8. SHM Building Evaluation Graph

Figure 8 shows the simulation results obtained from the PDF in (4) by GAN selected zones based on the estimated number of occupants per week (5 working days). The number of occupants must not exceed the rated payload i.e. 50% of rated payload for a building in any zone. The results show that maximum occupancy was observed in Zone 5: BCR Corridor H (19 persons), Zone 1: H10 Research Complex (12 persons) Zone 4: B01 (12 persons) and Zone 6: C07 (12 persons). Here, it is worth mentioning that the results presented Figure 8 are simulated OSB based Figures, whereas Figure 11 shows GAN output i.e. geo plot of QU, in which the cumulative result is taken from 8 different nodes running over the proposed algorithm in real-time. The predicted SHM has a private cloud and a public cloud based on GAN.

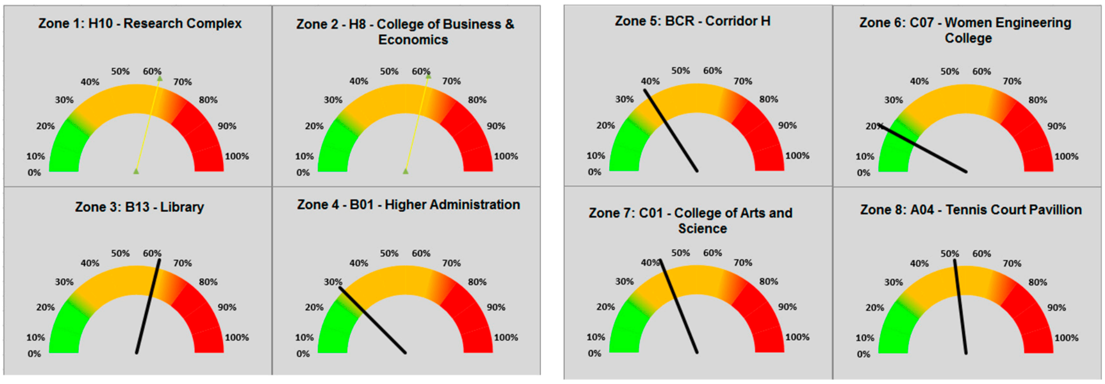

Figure 9. SHM Building Evaluation Graph

Figure 9 shows cumulative fitness percentage of structures in Zone 1 to 8 obtained by the estimated SHM system results (from (6)). Two colors of needles are visible in Figure 9, where the golden ones show maximum overshoots or SHM with maximum utilization of structure, whereas the black ones show that below 50% of sensors in SHM have almost constant values. The plots in Figure 9 are very realistic since indeed both H10 and H08 has a maximum flow of occupants that should result in maximum vibration, the maximum change in pressure, humidity and temperature.

The developed private Cloud-based SHM-UCM GUI interface in Figure 10 shows instantaneous results of SHM tiltmeter data and line plots of multiple zones (i.e. 1, 3, 5 & 7) being monitored and analyzed by MOSPA. It illustrates how the data is uploaded over website over a public and private cloud for different zones; in this case for zones 1, 3, 5 and 7 i.e. shown in Figure 9. The data of SHM sensors (i.e. tiltmeters) can also be access over this cloud SHM-UCM platform either for a specific zone or all together as in Figure 10. The tiltmeter data is in 'meter per Second Square' as it is obtained from limited bandwidth of bi-axis accelerometer. This data is clear visualization for experts to make a concise decision for optimum location of addition SHM sensors. In Figure 11, the main output geo-plot is presented that comes as outcomes from automated decision-making map for helping planning experts.

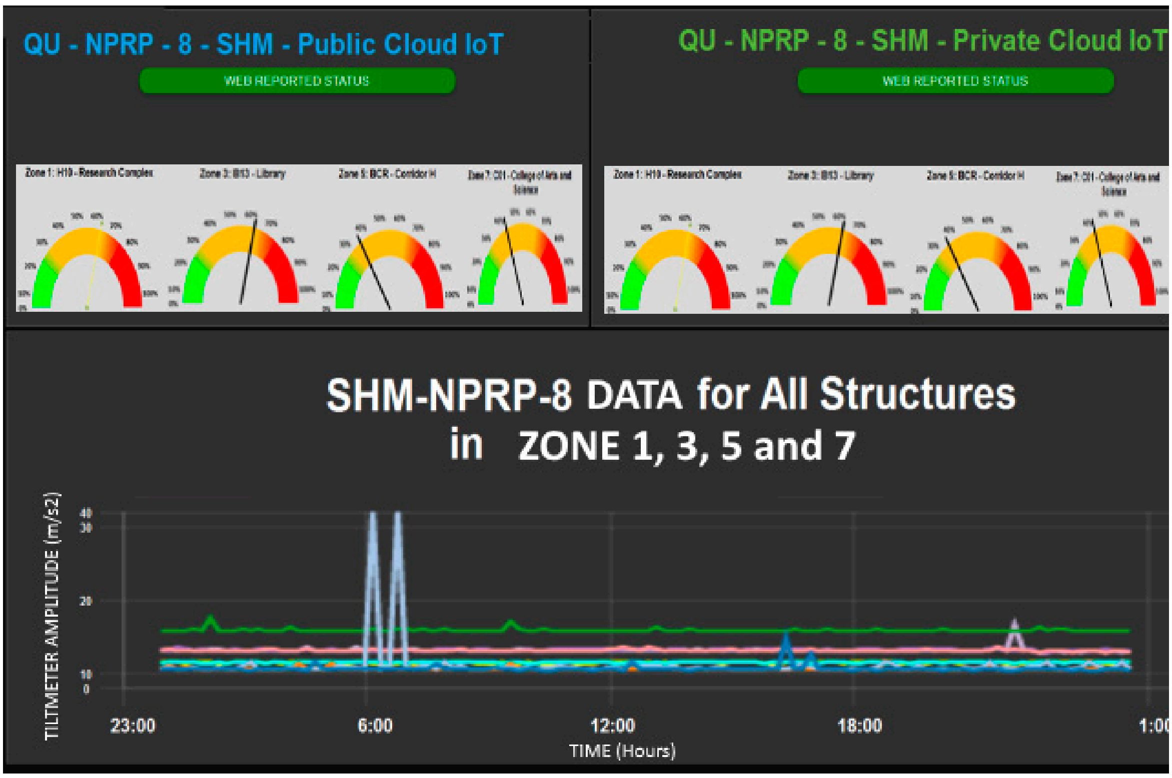

Figure 10. The dashboard of SHM-UCM predicted SHM

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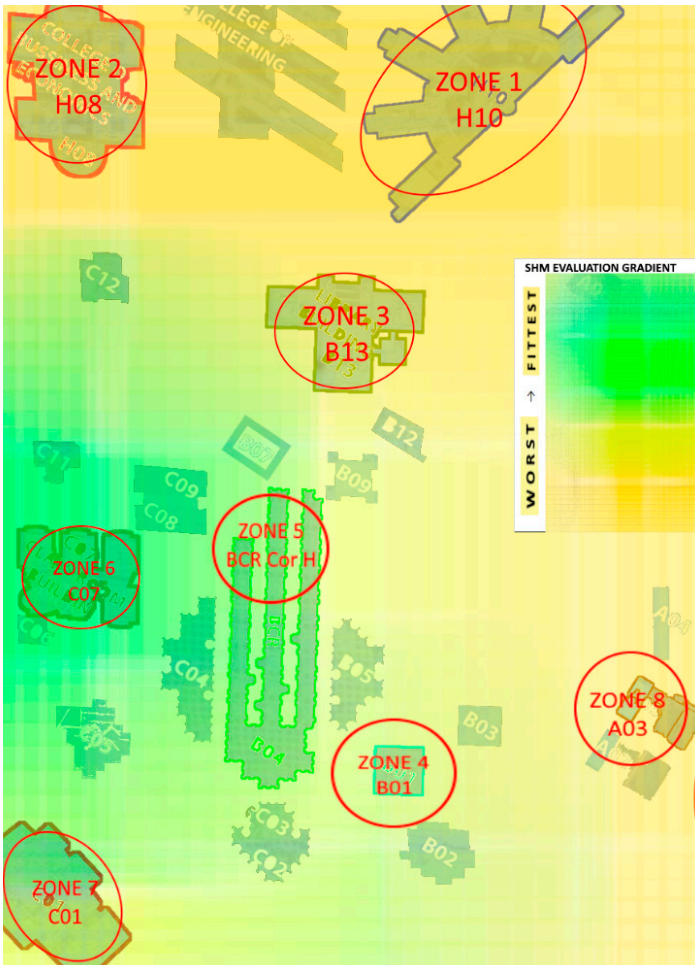

Figure 11. Geo Plot of Qatar University SHM Proposed Evaluation diagram

Figure 11 shows the resulting MOSPA geo plot that can be used for dynamic re-planning of SHM. The dark yellow reading presents unfit conditions for structure health, whereas the dark green indicates the fittest building (refer to Figure 9 for comparison). The unfit condition can be due to several reasons such as critical historical building status or higher occupancy. The proposed SHM-UCM model, working over the GAN satellite-based system, can be utilized as a tool for an in-depth survey of geographical areas as well as disaster management.

6. Conclusion

A SHM utility computing model based on geographical area networks for real-time decision making for a geospatial cluster has been proposed. Decision-making is made possible by a novel Multi-Objective SHM Prediction Machine Learning Algorithm to process variables from heterogeneous patches. The first variable was obtained from a Variable Occupancy Model and the rest from a Building Information System. A case study was conducted on Qatar University buildings to test the proposed algorithm. The results presented are an approximation of real-time analysis of structures health and identified critical cases where more SHM nodes are required to efficiently measure structural health for improved early warnings.

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review & editing, Anas Tahir, Farid Touati, Mohammed Abdulla E Al-Hitmi, Damiano Crescini and Adel Ben Manouer.

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