IoT/Edge Structural Health Monitoring System as a Life-Cycle Management tool for SDG-11 using Utility Computing Platform

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Abstract: - In view of the intensified disasters and fatalities caused by natural phenomena and sporadic urban expansion, infrastructure safety and sustainability is a cynosure of Sustainable Development Goal 11 for 2030. This work proposed a novel Internet of Things Edge structural health monitoring system focused on E/CN.3/2016/2/Rev1 and A/RES/71/313-E/CN.3/2018/2 charters of the United Nations Development Program. This work is an archetype of a safety operations support system for regional SDG-11 using a novel melioration in our previous works SHM-UCM [1, 2] to enable the building owners and service companies in supporting the state agencies in achieving SDG-11 regarding safe infrastructure life-cycle as the multi-objective function of cost and sustainability. Results exhibited this work as a reference model for ISO/TC211-WG4 solution for SDG-11 as a synergy of ISO/IEC JTC SC 41 (Internet of Things) and ISO/IEC JTC SC 42 (Artificial Intelligence).

Key-Words: - SDG-11; infrastructure health monitoring (IHM); geomatic analytics; sustainability assessment; Internet of Things (IoT).

1 Introduction

Chronological and random natural disasters occurring across the globe have a vital impact [3] on state-level infrastructure safety and sustainability. The desultory chaos and disasters have a direct impact on regional [4] economics, and future investment plans irradiating need for a real-time safety operations support system (SOSS) to stipulate the regional sustainability. The sustainable development efforts were observed using the GDFI-Simulator [5] for Africa, America, Asia, Europe and Oceania in the 19th and 20th centuries. The UNO Documents E/CN.3/2016/2/Rev1 presented [6] in 2016 and A/RES/71/313-E/CN.3/2018/2 presented in 2018 by Statistical Commission of the UN Economic and Social Council held credibility of a constitution in geographic SDGs. The GDFI-Simulator [7] work for safety and lifecycle costs epitomized gaps as real-time sensing system architecture required to optimize the trade-offs in regional development and sustainability matrix. The community sustainability indicators (CSIs) for assessing the urban community safety in Malaysia [8] was a substantial effort and a nascence for brisk global sustainability systems(GSS). The risk interpretation and action framework for responses to natural hazards review and the role of urban actors to coordinate and contribute to sustainability cost [9] depicted a need for an integrated and enmeshed SHM IoT/Edge SOSS.

In SDG-11 literature, a momentous rapture for GRSS in [10] was based on the meta-analysis of an etymological journey in resilience and disaster risk reduction from 1973, illuminated 38 cases with an obligation of dexterous SOSS. The urban sustainability through infrastructure safety [11] was demonstrated with systems of systems gap. The theoretical and empirical perspectives explained in [12] need to be formulated in the form of a reference model for resilience systems design. The mapping of nine narratives M1, M2, M3, N1, N2, N3, CT1, CT2 and CT3 in figure 1 [13] were very practical safety design markup but still craved artificial intelligence and standardized geo-spatial sensing capabilities as addressed in [1, 2]. The life-cycle sustainability and assurance elevated in SDG-11 and [14] for infrastructure disaster management (IDM) created an obligation for usage for infrastructure safety systems (ISS) as reality towards sustainability against natural calamities. This created an opportunity for infrastructure health monitoring systems, i.e. SHM sensing capabilities as a sustainability assessment tool for rapid resilience response in GRSS as a reliable MGCM system.

By 2025, more than 80% of the government, community and headquarter buildings or structures [15] will be equipped with SHM IoT and Edge devices. Sensors diversity and parameter estimation for structural health to forecast zonal safety [16, 17] has always been a dream for geologists, environmental scientists, and international authorities. Utility Computing (UC) is a necessity [1, 18] nowadays, like water, food, and shelter. It is commonly used as a surface-level comprehensive tool instead of having an eye on the background framework to deal with problems. UC is an application of cloud computing [19] that encompasses algorithms [1, 20] 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 [21-25]. UC services react with distributed [26] Geographical Information Systems (GIS) platforms like Google Maps to enable applications like Navisworks [27] and Building Information Modeling (BIM) resulting in heterogeneous [2, 28] Geographical Area Networks (GAN). On the other hand, SHM is a systematic framework that shows the fitness of a structure [29] 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 a revolution [30] in the construction industry. BIS planned SHM [31] is the core 'lifecycle management utility' for stakeholders. However, in the SHM parameters driven sensors selection process for parametric SHM, sensors are not compatible with UC Infrastructure (UCI).

SHM implementations using wireless sensors networks for Internet of Things (IoT) models [32, 33] needed improvement in their UC aspect; i.e. some algorithms and data processing that could assist Open System Interconnection (OSI) model which should be application layer (layer 6), and presentation layer (layer 7) devices and applications. Deep Learning (DL) was implemented [34] on the raspberry pi 3 but still needed improvement for cloud compatibility and to be paired with mathematical techniques. The role of SHM is very vital in reporting disasters [35] and handling any abnormal and hazardous conditions using seismic waves analysis through several signal processing algorithms i.e. Frequency Domain Decomposition (FDD) and Eigen System [36] Realization Algorithm (ERA).

Furthermore, regional sustainability intents observed in [1-36] had the gaps in physical and real application centered SOSS design and implementation. The regional sustainability based on cost metrics and sustainability functions utilizing MOSPA in SHM-UCM [1, 2] with geo-analytics capabilities would have been a huge service to geo-SOSS. The improvement in limitations of [1, 2] was accommodated in this work by improving the system architecture from regional sustainability [37] prospect by RSS, i.e. SURFmap. The National System of the Statistical and Geographic Information (NSSGI); the National Geo-Statistical Framework (NGF), and the Global Statistical Geospatial Framework (GSGF) in [38] had a noticeable gap of real-time geo-informatics and infrastructure analytics. The contribution OGC Web Processing Service (WPS) and Table Joining Service(TJS) for standard geo-spatial data statistics required MGCM and geomatics agility. The integration of geospatial information and UNECE statistical standards at Statistics Finland [39] was an excellent conceptual framework with a desideratum of cyber-physical geo-information system evaluation and statistical tasks agility enhancements engine. The advancement in sustainability development indicators(SDIs) using SOA [40] for implementation of ISO/TC211 for standard layered architectures utilizing the information and communication technologies(ICT) backbone to architect OGC applications by Olaf Østensen [42] was a motivation behind this work. This work focuses on:

1. Infrastructure Sustainability Model (ISM)
2. Implementation System Design for SDG-11
3. SDG-11 Map Generator (SMG)

In section II, ISM is explained using the cost equations from [1, 2] and geo-spatial life-cycle operations safety variables. Section III cadastral and geo-analytics perception of ISM for SDG-11 for a geographical cluster under observation.

2 Problem Formulation

In urban infrastructure there are more than hundreds of structures with more than thousands of real-time variables monitored at extreme data rates modeled as ISM in this work. The stakeholders, authorities and service companies confront following needs to solve their problems:

1. A single coordination model to stream-line infrastructure systems heterogeneity.

2. A real-time formulation of anomalies and costs expected from sensor time vectors as a function of life-cycle sustainability cost.
3. Real-time geo-spatial mapping of disasters and SDG-11 zones.

3 Problem Solution

The problems addressed were proposed as a stepwise solution in the sections below. The following steps were taken to address the common challenges:

1. First, the modeling of problems as a function of the cost was carried out in the urban canvas.
2. SDG-11 live mapping our geo-plots.
3. Proposal for a comprehensive cyber-physical system to achieve proposed goals.
4. Customization of existing SHM systems to address SDG-11.
5. Integration example of an algorithm from application prospect.

3.1 Infrastructure Sustainability Model (ISM)

First, the coordination model to relate cost and anomalies. Let t be the time vector for time-series variables as a set of Vectors V with n variables in a multi-sensing monitoring system with heterogeneous data rates D, vector V is given as a function of time.

$$V(n, t) = \{V_1(n_1, t_1), V_2(n_2, t_2), V_3(n_2, t_2), \ldots\ V_n(n_n, t_n)\} \quad (1)$$

There exist area-abnormalities or geospatial-anomalies as a set $A= \{A_1, A_2, A_3, \ldots\ A_n\}$ in real-time magnitudes M that have an unacceptable difference of ΔA from normal or safe values N ensuring sustainability termed as geo-temporal vectors filter(GTVF).

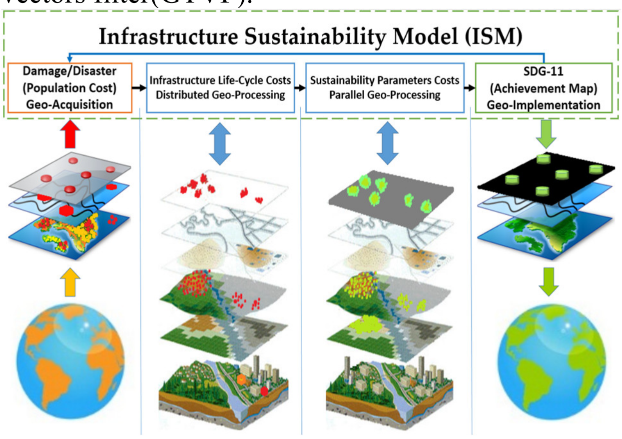


Fig 1. Overall ISM-SG11 Block Diagram

Let us say M>N or M<N in range a = ±10% from recent value is written as:

$$\Delta A(V(n_1, t_1), V(n_2, t_2)) = (M-N)/N \quad \forall$$
$$\Delta A \in [-0.1,+0.1] = \{a \mid -0.1 \leq a \leq +0.1\} \quad (2)$$

Each combination of ΔAs is called chaos amplitude, The product of amplitude ΔA and duration of chaos T_{CHOAS} is directly proportional to infrastructure lifecycle (ILC) cost vector C_{ILC} given as:

$$C_{ILC}(\Delta A, T_{CHOAS}) \propto \int_{A1}^{AN} \Delta A \times \int_{T1}^{TN} T_{CHOAS} \quad (3)$$

This model works on all the data streams of isometric condition monitoring systems or all SHMs with same architecture, i.e. identical sensor types, number of nodes, polling rate or sampling rate, and communication infrastructure that can rarely happen at regional level due to variety of vendors and solution providers and terms of service level agreements(SLAs). SLAs in this work are based on SDG-11 domains centered statistical analysis on the % of the occurrence of ΔA for unique costs C_{ILC}.

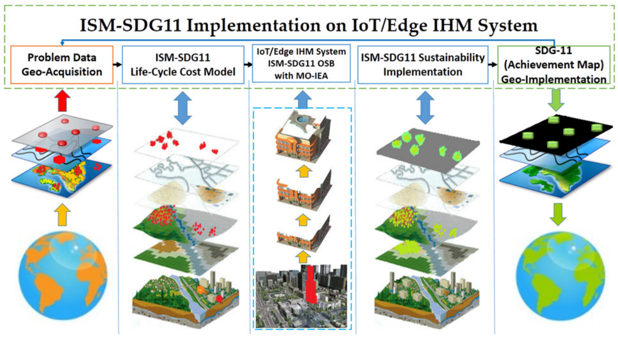


Fig 2. ISM-SG11 Implementation Overview

In figure 2, in the center, there is a chronological structural healing or recovery diagram showing the different states. A ISM_{STATE} parameter is introduced here that assists in real-time expenditure tracking. Let US be a unique set of regional structures deployed with V-SHM as a unique cluster or set of sensors variables in V sent through B. Let SHM-SENSOR be a unique set of sensors. Let the number of real-time state variables for a unit ISM model be geo-event be $ISM_{STATE}(Loc)$ for a single IHM cloud and given as:

$$ISM_{STATE}(Loc) = {}^{D}C_{B} \times {}^{US}C_{V\text{-}SHM} \times {}^{V}C_{SHM\text{-}SENSOR} \quad (4)$$

The overall SHM cloud dashboard is displayed after this step. The percentage health H of structures is computed as the number of variables N_V divided by the number of classified anomalies N_A multiplied by 100 and is given as:

$$H(\%) = (N_V / N_A) \times 100 \quad (5)$$

The live geo-analytics is the most popular tool used by local authorities is another visualization that expert systems use to assist the decision making. A binary matrix operation has been used in this work i.e. load Google Maps frame in matrix G and subtracts it from $ISM_{STATE}(Loc)$ Matrix RSS with geo-spatial coordinates of areas or structures with nodes having sequence numbers > 2^{16} as shown in figure 2.

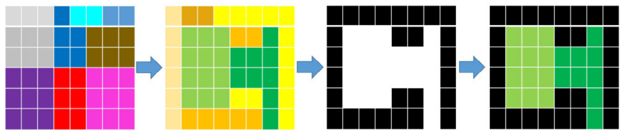


Fig 3. ILC Adaptive Filter Subtraction Process Block Diagram for SDG-11

In figure 3, the left-most is the actual geo-plot as matrix from Google Earth, middle-left is the implementation of MOSPA [1], middle-right is the area with cost or expenditure applied and at the right-most is the area under ISM-SDG11 recovery operations. The safe area on the map with active recovery was modeled green and waiting was bordered green with computation $ISM_{STATE}(Loc)$ in progress and unrecoverable as black. Geo-spatial images are treated as matrixes with selected latitude and longitude bounds with each patch as a pixel for the respective color model used e.g. RGB, CMY, etc. The matrix operation subtraction needed same dimensions as R for row and C for column given as:

$$ISM_{STATE}(Loc)[RxC] = G(Layer)[RxC] - C_{ILC}(Layer)[RxC] \quad (6)$$

3.2 IHM Utility Computing Model (IHM-UCM)

This work recommended a structured SHM that operated 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 pass 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 an IHM-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 updates in datasets for real patches on the crust.

Fig 1. Overall RDPP Hardware Block Diagram

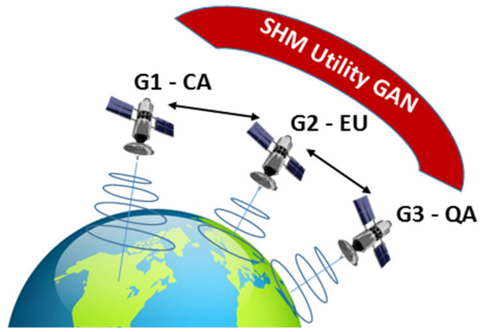


Fig 4. SHM Utility GAN [1] Architecture

Figure 4 illustrates the proposed conceptual model of IHM-UCM networked through a mesh of IHM-GAN of the geospatial orientation of satellites dedicated to 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 the freedom of observational geophysical patch selection. One each satellite i.e. G1, G2 and G3 decisions are made by MOSPA. This IHM-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.

3.3.1 Deployed Structural Health Monitoring Systems

An 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 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. An SHM system is a unique system that has to serve the purpose of the lifecycle evaluation of structure for a structure for the next 10 years. 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 (VoI) is evaluated and finalized by multi-disciplinary Subject Matter Experts (SMEs) inputs to ML algorithm.

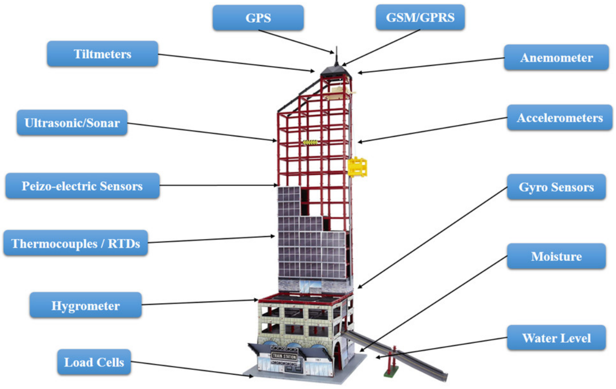


Fig 5. SHM by LM/LTE

In figure 5, an SHM system has been shown for a specific structure with multiple variables obligatory for fitness for a given structure. The instruments shown in figure measure physical quantities of structure i.e. 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 vicinity (ultrasonic sensors or sonar), tilt and inclination (tiltmeter) and wind speed (anemometer). Secondly, the location of and data communication is being achieved using GPS and GSM/GPRS respectively. The shown variables varied structure to structure and is a complex set of the formulation by a multi-disciplinary team. The variables shown in figure 4, can vary the SHM parameter estimation and feature extraction in other words directly affect the technical assessment of VoI of the respective structure. 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.

3.3.2 SDG-11 Application Specific Standard Part (SDG11-ASSP) Nodes for IHM-UCM

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

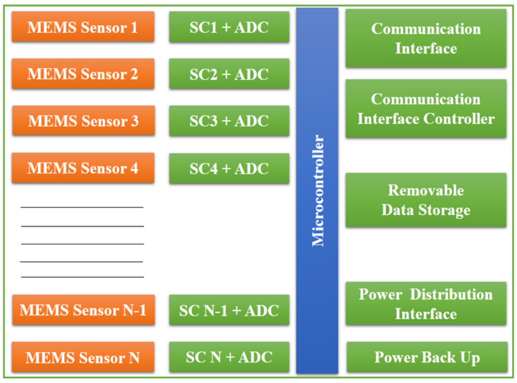


Fig 6. Conventional SHM Node Block Diagram

Figure 6 reflects a typical or conventional 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 Column SHM Node has to be orchestrated like a cloud framework ZeRo Client (ZRC), ThiN Client (TNC) and ThicK Client (TKC) nodes to fit in the ecosystem of Industry 4.0 standard for SHM systems.

The SHM nodes proposed in this work are IHM-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. The SDG11-ASSP fills the gap of providing the utility of high-resolution data for NDT and NDE assessment procedures.

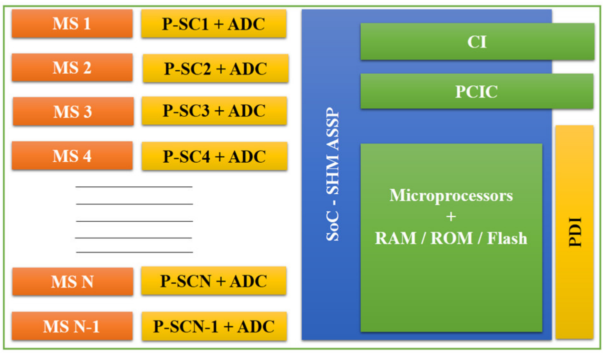


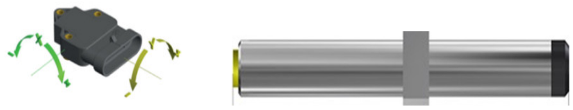
Fig 7. SDG11-ASSP ZRC Node Block Diagram

In Fig 7, an SDG11 Application Specific Standard Part (SDG11-ASSP) ZRC Node is illustrated. It includes MEMS Sensors along with Programmable SC (PSC) to make it compatible with monitoring specialized sensors and Programmable ADC (PADC) that can adopt scaling and range recommendations for particular observational criteria. The SHM-SDG11-ASSP ZRC nodes proposed in this work need no external instrumentation assistance for SHM operations. 'STM32F10RBT6' CPU interfaced with inclinometers sensors is the basic element of nodes.

These nodes include:

- SSN – 2 Sensors
- CSN – 7 Sensors

These nodes are using CANopen for HBAN segregated at Out Surface Board (OSB) TNC using a CAN-to-USB adapter as shown in Fig 6.



a. SSN b. CSN

Fig 8. SDG11-ASSP ZRC Node Block Diagram

In Fig 8, two SDG11-ASSP ZRC nodes are shown i.e. Seismic Sensors Node (SSN) and Cylindrical Sensors Node (CSN), both with remotely programmable and configurable parameters, which we developed in-house.

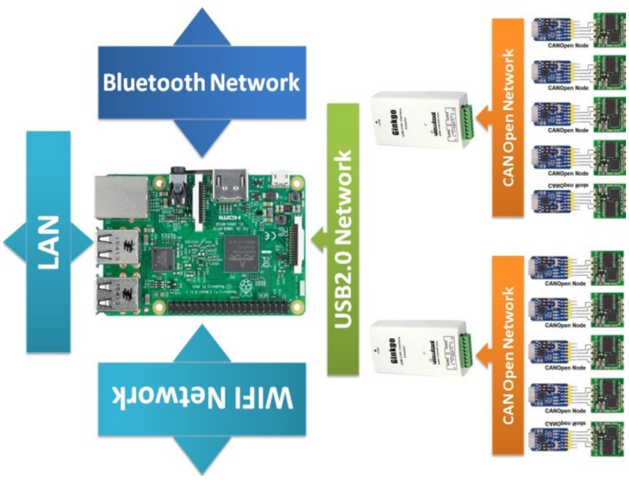


Fig 9. SDG11-OSB TNC

The SDG11-OSB in Fig 9 has a micro expert system that has multiple Resource-Constrained Machine Learning SHM Algorithms (RCMLA).

3.3.1 Multi-Objective IHM-SDG11 Estimation Algorithm

SHM is highly feasible for bigger structures, especially community buildings, where structure value and human lives are critical. The multi-objective IHM-SDG11 estimation algorithm (MO-IEA) is a real-time sustainability estimation tool. Let $H = (O_1 \cdots O_m)$ denote all occupancies that occur per second during a period of time and V_x is a vector of occupancies for room x where $x = 1,2,3,\dots.\ y$ [20, 21]. Let α_i denote the average occupancy for a room r_i. We calculate a vector of means $\alpha = (\alpha_1,\dots,\alpha_m)$ and covariance matrix M from O. Using α and M, we define a Probability Density Function f:

$$f\,(O;\,\alpha, M) = 1\frac{1}{(2\pi)^{\frac{n}{2}}\,|\mathrm{M}|^{\frac{1}{2}}}\exp\left\{-\frac{(O-\alpha)^T\mathrm{M}^{-1}(O-\alpha)}{2}\right\} \quad (7)$$

An ML algorithm is implemented for the installation of SHM-UCM based system. It uses a multi-objective Supervised Machine Learning Technique (SMLT) that streamlines the SHM HBAN architecture and steps of installation recommended by IHM-UCM.

3.3.1.1 User Identification from MAC and IMEI Addresses

A two-tier mechanism for occupant counters has been employed as an occupant space called O_v. O_v is a sum of number of Medium Access Control (MAC) addresses registered in wireless routers (as every PC or smartphone has a WiFi card or a LAN card that has MAC address) plus International Mobile Equipment Identifier (IMEI), that every smartphone has as a de facto de jure for Electronic Industry Association/Telecommunication Industry Association (EIA/TIA) approved standards given as:

$$O_v = \Sigma(MAC) + \Sigma(IMEI) \quad (8)$$

3.3.1.3 Network Attendance Count

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

$$O_p = \Sigma I \quad (9)$$

Thus O is summed up as:

$$O = O_v + O_p \quad (10)$$

The BIM model is the second parameter value of information Vol_{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}. Vol_{BIM} is a sum of functions of joints, trusses, payloads and volumes [22].

$$Vol_{BIM} = F(J_{BIM}) + F(T_{BIM}) + F(P_{BIM}) + F(V_{BIM}) \quad (11)$$

The applied physical fitness function [23] parameter called F_{SHM} depends on tilt T_{SHM}, structural strain $\Delta L/L_{SHM}$, vibration V_{SHM}, temperature T_{SHM}, stress S_{SHM}, wind effect W_{SHM}, groundwater level L_{SHM}, humidity H_{SHM}, moisture M_{SHM} and composite material stability constant M_{CM}.

$$F_{SHM} = F(T_{SHM}) + F\left(\frac{\Delta L}{L_{SHM}}\right) + F(V_{SHM}) + F(T_{SHM}) + F(S_{SHM}) + F(W_{SHM}) + F(L_{SHM}) + F(H_{SHM}) + F(M_{SHM}) + F(M_{CM}) \quad (12)$$

3.3.1.3 Final Population Count

Finally, the total population count along with the SHM location parameter can be used to train the ML-based algorithm to generate real-time SHM-based devices location so that to mitigate the risk and give early warnings. It will also help to cover a wide area of structures and pinpoint any landmark changes which can affect the integrity of the buildings. In the results section, it can be clearly seen that each location where SHM nodes are installed, the population is being monitored along with the focus towards the structure health.

3.4 SDG-11 Map Generator

Two core analysis mechanisms used for IHM-SDG11 implementation and performance analytics were Wireshark 3.0 and Python IDLE 2.7 with the following libraries:

- *NetworkX*, *Scipy*, and *Numpy* were utilized to solve the graph structures in geo-spatial computations.
- *Basemap-Matplotlib*, *network2tikz*, and *pysocks* to plot the geo-analytics of IHM-SDG11 performance analysis and operations.

4 A Case Study on Qatar University Deployed IHM

The IHM deployment at Qatar University, Doha in Qatar was chosen as a case study in IHM-SDG11 as exhibited in figure 10. Three unique SHM systems were customized with SDG11-ASSP nodes and SDG11-OSB to constitute on IHM-SDG11 system architecture. The three 1 km apart unique locations, namely, B09 Lab, QU Bridge and Research Complex H10 with geometric variables monitoring capabilities for 6 months. The QU Bridge had maximum human movement (pedestrians and vehicles), the H10 had construction sites in its vicinity thus incurring various vibrations and B09. The B09 lab was our benchmarking or standard facility where we had the SHM Test bench having eight nodes.

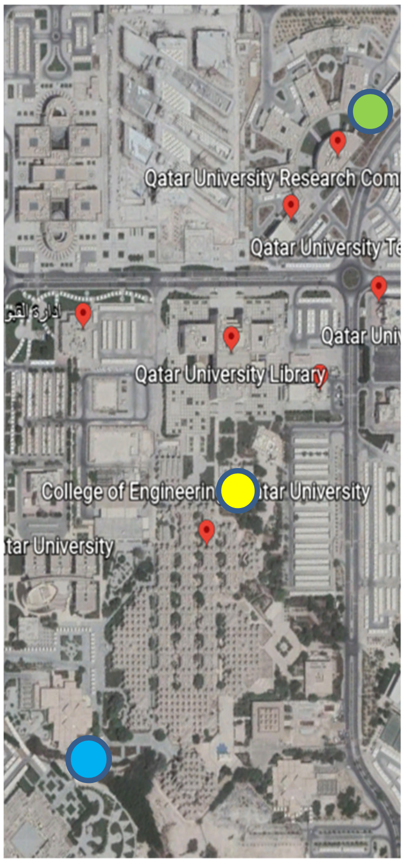
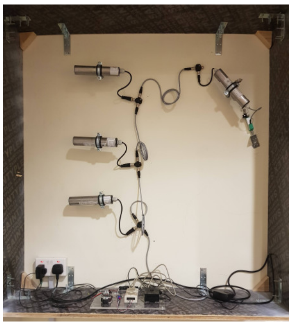


Fig 10. Case Study: QU SHM Sites Deployment Details.

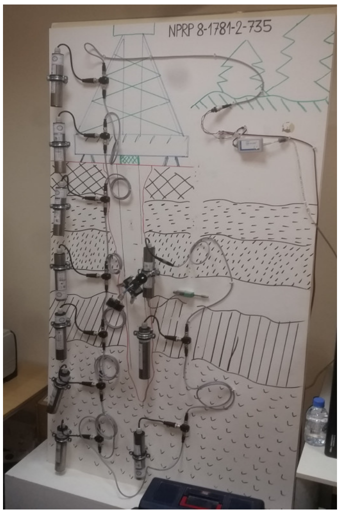
In figure The IHM-SDG11 system details for these locations are:

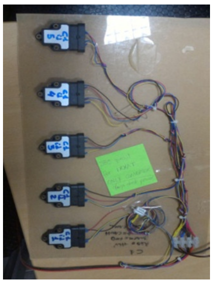
- QU bridge SHM Site (SHM-BS) System with 4 SDG11-ASSP-ZRC SSNs (in cyan).
- H10 SHM site (SHM-RC) with 4 SDG11-ASSP-ZRC SSNs (in green).
- B09 Lab site (SHM-LB) with 4 SHM-ASSP ZRC-SSNs and 10 SHM-ASSP-ZRC-CSNs (in yellow).

The entire deployment plan for case study QU is shown in Figure 11a, 11b and 11c; published in our earlier papers was uploading data to Thingspeak IoT platform by Mathworks. The details of each system as per SDG11-ASSP is given in figure 10. The cost and criticality of structures was the driving force behind these three deployments. The B09 Lab, QU Bridge, H10 were the most active area having maximum dynamics in population movements and significance in structural topologies.



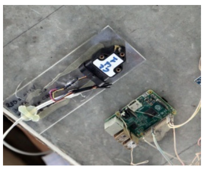
a. H10 SHM site





10 CSNs on SHM Stand   5 SSNs on Table

b. B09 Lab SHM site



OSB and an SSN

SSN

ODU

IDU

c. QU Bridge Site

Fig 11. Details of QU IHM Deployment

Figure 11 exhibited the details of SDG11-ASSP based customized deployment of the IHM system. Raspberry Pi 3 was used as an out-surface board (OSB), i.e., SHM-UCM-TNC. All CSNs and SSNs were SDG11-ASSP-ZRCs nodes. The 2km+ WiFi range extenders from CISCO were indoor data unit (IDU) and outdoor data unit (ODU). This system encompassed practical limitations that inherently was considered in our UCM.

5 Results and Discussion

The chosen case study was SHM customization and enrichment with SDG11-ASSPs as well as a full-scale ISM-SDG11 framework for Qatar University nascent from GAN [1] based SHM-UCM. The results of MO-IEA were sequential in nature for SDG11-ASSP nodes. First computation was a runtime Variable Occupancy Model (VoM) map based on the probability density function of occupancy O given in (1) and (6).

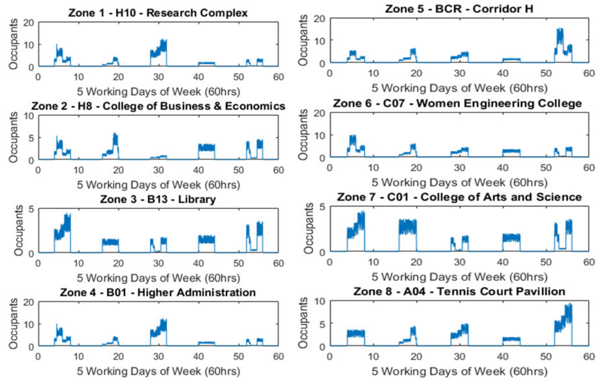


Fig 12. SHM Building Evaluation Graph

The PDF in equation forecasted the occupancy by adopting the historical data of O, α and M exhibited in figure 13.

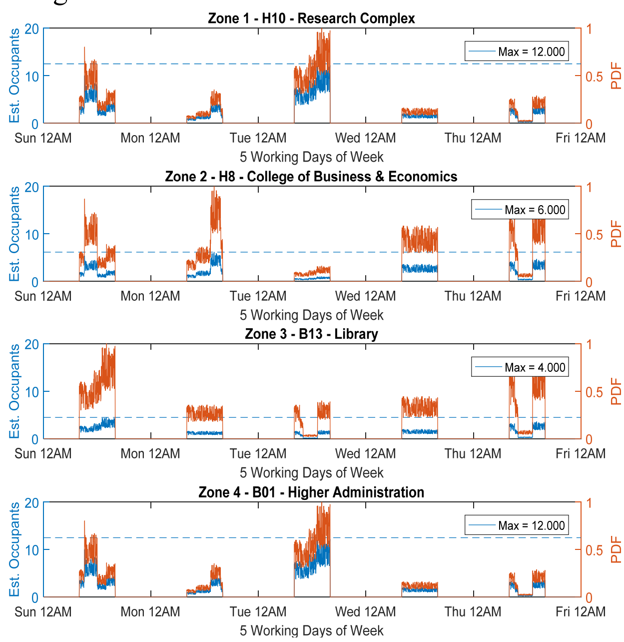


Fig 13. SHM Building Evaluation Graph

In figure 13, MO-IEA utilized the 8 zones created using the real attendance and predicted attendance to generate the expected 4 zones needed for C_{ILM} and ISMSTATE(Loc). The PDF contributed to the safety of occupants given in Figure 14.

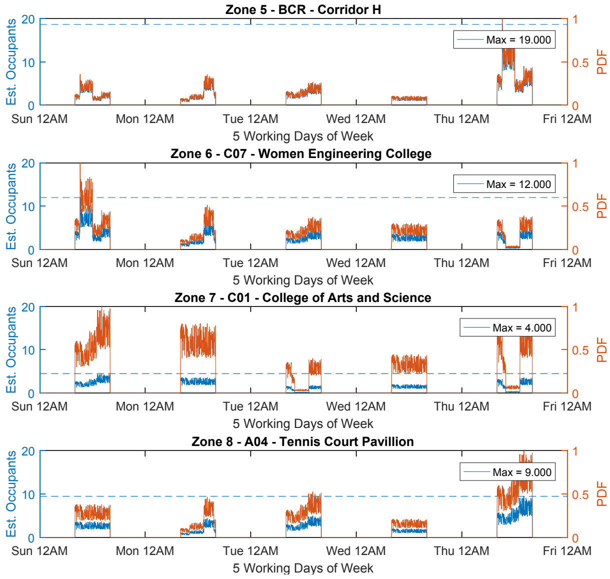


Fig 14. SHM Building Evaluation Graph

In figure 13, MO-IEA utilized the 8 zones created using the real MAC and IMEI presence to generate the expected 4 needed for CILM and ISMSTATE(Loc). The PDF contributed to the safety of occupants given in Figure 14.

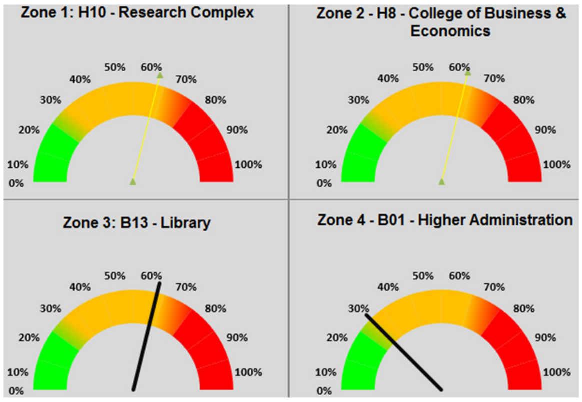


Fig 15. ISM-SDG11 Evaluation Graph by MO-IEA

Figure 15 shown the cumulative fitness percentage of structures in Zone 1 to 8. Two colors of needles are visible in Fig 8. Golden needle shows maximum overshoots or SHM with maximum utilization of structure and black needle shows that below 50% of sensors in SHM have almost constant values. Plots in Fig 8 results are very realistic being the fact both H10 and H08 have maximum flow of occupants' thus maximum vibrations, the maximum change in pressure, humidity and temperature. C07 has 20% of sensors publishing values. H10 and H08 are the fittest of structures reflected by SHM.

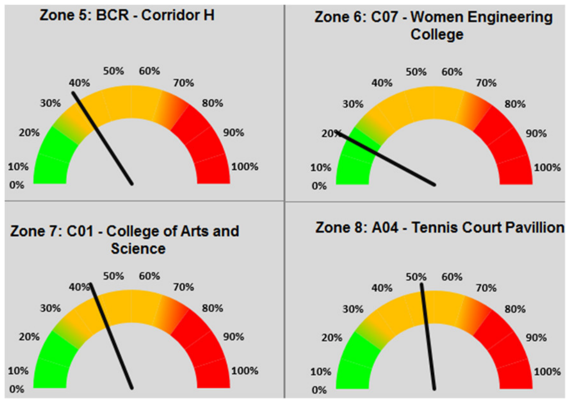
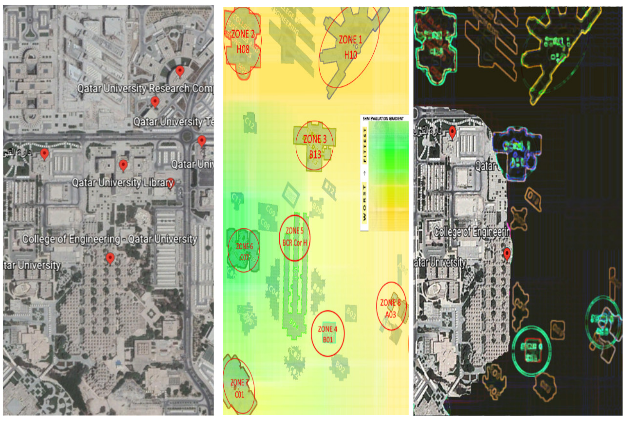


Fig 16. ISM-SDG11 Evaluation Graph by MO-IEA

In Fig 16, it can be clearly seen what is shown in Fig 14 that red color reading presents unfit conditions for structures health, whereas the green color presents the fittest building. The results in Figure 17 were totally dependent on our previous work [1, 2] as well as equations (4), (5) and (6).



a. QU Case Study b. SHM-UCM c. MO-IEA Filter for IHM-SDG11

Fig 17. SHM Building Evaluation Graph

The final step was geo-spatial plot generation for SDG-11 based on ISM-SDG11 implemented on IHM-SDG11 using SDG11-ASSPs from MO-IEA. The ISM-SDG11 estimated the SDG11 region by subtracting Figure 16(b) from Figure 16(a) as well as applying equations (5) and (6) defined in section 3.1. Figure 16(a) was the actual view without application of the QU IHM site as acquired from Google Earth. In figure 16(b), we have used a machine learning algorithm MOSPA for urban scale geo-informatics and SHM analytics presented in [2] as an applied algorithm for testing. Maximum cost leads to maximum resilience needed. In figure 16(c) the MO-IEA was applied as core contribution in IMS-SDG11 the area with active SDG-11 achievement is visible whereas area without SDG11 and in the phase of recovery is exhibited in dark. Cost refers to the real-time damage estimated and predicted lifetime damage of structures and human resource.

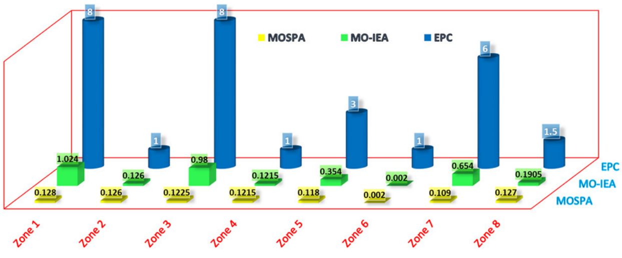


Fig 18. Cost C_{ILM} Contribution of MO-IEA in ISM-SDG11

Figure 18 is a footprint of contribution rendered by ISM-SDG11. The comparison of total cost by EPC firm at the time of construction just as a round-off reference with MOSPA and MO-IEA is also presented to understand the significance of MO-IEA as a core element of ISM-SG11. A number of more algorithms can be designed and implemented in the future for SDG11 reference architectures.

4 Conclusion

An infrastructure sustainability model for sustainability development goal 11 was designed with novel SDG11 focused multi-sensor nodes and multi-objective life-cycle sustainability algorithm. Real-time decision making was made possible by critical computations of real-time anomalies vectors from SDG11 specific nodes. The human safety was incorporated in the structural integrity to refine a collaborative model for state agencies. The first variable was the SDG11 node obtained from a variable occupancy model and the rest from ISM as a sequence of cost computations. A case study was conducted on Qatar University buildings to test the proposed framework. An SHM utility computing model based on geographical area networks for real-time decision making for a geospatial cluster has been proposed.

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