Soft computing algorithms for infrastructure monitoring. Preliminary results of PROION project

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ABSTRACT

Structural health monitoring of civil infrastructures is a complex engineering problem that requires the use of advanced soft computing algorithms. The rapid advances in soft computing have been a step forward in the direction of infrastructure monitoring. The field of computer science has given promising results in monitoring systems when applied along with engineering technologies. In this framework, Artificial Intelligence (AI) Deep and Machine Learning applications, Neural Networks, Fuzzy Logic, Fuzzy Cognitive Maps (FCM), Genetics Algorithms and Hybrid systems are growing exponentially in the field of structural health monitoring, including structural recognition, change detection, crack detection, damage identification, damage quantification and damage prediction. Specifically, some of the above-mentioned more sophisticated infrastructure soft computing monitoring algorithms are utilized to generate strategies and processing pipelines towards structural building damage mapping and assessment. In this paper remote sensing data, acquired by Global Navigation Satellite System (GNSS), Synthetic Aperture Radar (SAR), Light Detection and Ranging (LiDAR) and Unmanned Aerial Vehicles (UAV) sensors will be processed and a state-of-the-art unified platform imbedding Neural Networks, Fuzzy Cognitive Maps and Hybrid systems in the field of Structural Health Monitoring of civil structures is proposed.

Keywords: Infrastructure, point cloud, 3D, DSM, TLS, UAV

1. INTRODUCTION

Infrastructures are primarily conceived as technical civil structures, built by humans to facilitate the circulation, delivery, and distribution of goods, and dealing with services. Such infrastructures have existed since the ancient times, and society has made itself dependent on their proper support. The availability of proper and safe infrastructures provides high living standards in urban as well as in rural environments. Livelihoods are at the same time dependent on them, and service interruptions are mainly perceived to be destructive. Influencing factors for an increasing dependency on infrastructure services are ongoing urbanization, Internet of Things, digitization of society and mainly industry, artificial intelligence, economic globalization, and other economic and social actions. These developments bring economic and social prosperity, but also expose society to new risks. One remarkable feature of civil infrastructures is that despite most of them being technical structures, they are almost invisible to the end user, the customer at home. The society and the individual have an almost blind trust in the daily availability of essential services, which aggravates the element of surprise in a blackout. The criticality of infrastructure services becomes most evident and visible in case of a failure when services and resources are suddenly not available anymore due to natural disasters and other causes of accidents but also due to criminal actions including terrorism. As a result, the last 2-3 centuries the term "Critical Infrastructure" (CI) has emerged on the academic, scientific and government communities. [1-4]. Indeed, for the last few decades our societies are heavily dependent on several complex CIs [1]. "Critical Infrastructure" (CI) is a term defined by the government to describe an asset, system, or part located in a crucial place of a country and which is essential for the maintenance of vital societal functions, health, safety, security, economic or social well- being of people [1-2]. Any destruction or disruption of any of them that would result on the failure to maintain the operational functions of the infrastructure would have a significant impact in the country. A critical infrastructure of a country (or a region) provides the essential services that underpin a society and serve as the backbone of the country's (region's) economy, security, and health. There is a need for simple, feasible, and standardized criticality analyses despite the wealth of knowledge already created [2-3]. The development of criticality criteria, or infrastructure-related risk criteria, is an ongoing activity in many countries since the beginning of this century. Some provinces have created their own criticality criteria like the British Columbia in Canada (PEP 2007) [5]. Because of all these issues and uncertainties as well as with several physical disasters upon the planet the last 20-30 years, the scientific area of Soft Computing and structural health monitoring is in all critical studies of the world.

Structural health monitoring of civil infrastructures is a complex engineering problem that requires the use of advanced soft computing algorithms. The rapid advances in soft computing have been a step forward in the direction of infrastructure monitoring. In this framework, Artificial Intelligence (AI) Deep and Machine Learning applications, Neural Networks, Fuzzy Logic, Fuzzy Cognitive Maps (FCM), Genetics Algorithms and Hybrid systems are growing exponentially in the field of structural health monitoring, including structural recognition, change detection, crack detection, damage identification, damage quantification and damage prediction.

In this paper soft computing algorithms for critical civil infrastructures are reviewed and some of them are selected to study the behavior of specific civil sites of Western Greece. More specifically a software platform is developed for the continuous monitoring of high priority infrastructure. In section 2 the problem definition and a short literature overview is provided. Section 3 presents certain advanced soft computing algorithms with an emphasis in the scientific area of fuzzy logic and fuzzy cognitive maps (FCM). The PROION project is briefly outlined in section 4. Section 5 describes the simulation studies been conducted and the discussion of the obtained results using real data from three specific sites of the broader area of Western Greece is provided. Finally, section 6 provides some interesting conclusions and future research directions.

2. PROBLEM DEFINITION AND LITERATURE OVERVIEW

The structural health monitoring of critical civil infrastructure issues is very crucial for the smooth moving of all activities of the society. Today the threats that the infrastructures are faced with, are due not only to natural disasters and other causes of accidents but also due to criminal actions including terrorism. The critical infrastructure issues include structural recognition, change detection, crack detection, damage identification, damage quantification and damage prediction. Reducing the vulnerabilities of critical infrastructures and increasing their resilience is one of the major objectives of any country. An adequate level of protection must be ensured and the detrimental effects of disruptions on the society and citizens must be limited as far as possible. Any country must be able to identify, prioritize, and coordinate the protection of critical infrastructure and key resources; and to facilitate sharing of information about physical and cyber threats, vulnerabilities, incidents, potential protective measures, and best practices.

The problem is to develop advanced soft computing intelligent algorithms and tools for assessing the need to improve the protection of critical infrastructures. The question here is how fuzzy logic and fuzzy cognitive maps can provide an all-hazards cross-sectoral approach to meet this objective.

This problem has been addressed using soft computing algorithms for infrastructure monitoring by several scientists the last 2-3 decades. A recent paper by Altabey and Noori (2022) [6] stresses the importance of developing and introducing Artificial Intelligence based methodologies for the structural health monitoring of infrastructure systems and the analysis and feature extraction of sensor data. Research by Ghiasi et all. (2021) proposes a data analysis approach in Handling Structural Damage Detection under uncertainty via Non-Probabilistic Meta-Models and Interval Mathematics [7]. Deep learning (DL) is used in understanding natural disaster scenes from mobile images [8]. A structural health monitoring approach using machine learning and cumulative absolute velocity features is proposed in [9]. An interesting study in 2006, [10], where a pattern recognition approach for structural health monitoring is presented that uses damage-induced changes in Ritz vectors as the features to characterize the damage patterns defined by the corresponding locations and severity of damage. Unlike most other pattern recognition methods, an artificial neural network (ANN) technique is employed as a tool for systematically identifying the damage pattern corresponding to an observed feature. This important aspect of using an ANN in the design of a SHM is its design but this is usually skipped in the literature. This study shows how critical has been the study of SHM of infrastructures since the early 2000s. In study [11], the monitoring of bridge infrastructure using soft computing techniques is presented. As early as 2006 the contribution of radar interferometry to the assessment of landslide hazards was analyzed and presented in [12]. Three years later in 2009, a review of the status of satellite remote sensing and image processing techniques for mapping natural hazards and disasters was provided in [13]. The interest of soft computing by the research community is shown with a recent study in 2021 [14].

3. ADVANCED SOFT COMPUTING FOR INFRASTRUCTURES

The rapid advances in soft computing have been a step forward in the direction of infrastructure monitoring. The field of computer science has given promising results in monitoring systems when applied along with engineering technologies. Geographic Information Systems (GIS) and Remote Sensing (RS) have become recognized and utilized as critical tools, methods, and data sources for locating, monitoring, and analyzing human crises and natural hazards in the past few decades. In addition to GIS, data fusion between optical, radar, and thermal imagery is recognized as playing a major role in emergency management of natural hazards. More recently advances in Artificial Intelligence (AI) Deep and Machine Learning applications, Neural Networks, Fuzzy Logic, Fuzzy Cognitive Maps (FCM), Genetics Algorithms and Hybrid systems are growing exponentially in the field of structural health monitoring, including structural recognition, change detection, crack detection, damage identification, damage quantification and damage prediction.

Artificial Intelligence (AI): The term Artificial Intelligence (AI) has never been clearly defined [15]. Over the last 50-60 years the concept of what defines AI has changed many times. The central idea of AI has been that of developing "intelligent machines" which are capable mimic humans. This central idea was the main theme of the summer workshop at Dartmouth College in 1956. Most people accept that human beings have unique capabilities of interpreting the physical world. In addition, using the information we perceive and comprehend to affect changes [16]. To build intelligent machines more efficiently we should use ourselves as blueprint. Over the last 50-55 years several AI amazing innovations have been developed and significant scientific results [17-22].

Machine learning (ML) is one of the first methods that was developed of AI technologies [23]. Basically, it involves the development of computer architectures that can learn based on available data of the system under study. A ML system learns by experience. AI and ML have been the two basic topics for the last 35-40 years [24-25]. Some experts are confused by these two terms since they are quite different. In the early stage of AI many sources used them interchangeably which does not help the overall field [24,26].

Neural Networks (NNs): Neural networks (NNs), also known as artificial neural networks (ANNs) are a subset of ML and are at the heart of AI. A NN in theory is a network or circuit of biological neurons. On today's scientific world, a NN is an artificial neural network, composed of artificial neurons or nodes [27] used specifically for solving (AI) problems. Neural networks (NNs) are designed to recognize patterns as a set of algorithms, modeled after the human brain. Over the last few decades, neural networks (NNs) have seen successful developments that have several applications in many scientific areas especially in health, energy and environment, image processing and monitoring [27-28].

Deep Learning (DL): Deep learning (DL) is considered as the new "master" for all AI, ML, and NN research been conducted lately. The last few decades, DL is one of the most highly sought-after skills in AI technologies. DL software attempts to mimic the human activity in layers of neurons in the neocortex, where 80 percent of the human brain thinking occurs [29]. However, this software practice and promising to solve all challenging problems of the society, has led to many breakthroughs as well as many disappointments. Computer scientists due to several improvements in mathematical methods and algorithms with the help of increasingly powerful computers, could model many more layers of virtual neurons than ever before [30]. The last two decades or so, Deep Learning (DL) has been promoted as a new scientific field which intricate and challenges slightly the whole theoretical foundation of the AI theory. Indeed, DL is visiting AI, NNs and ML with the main objective to redefine them using several new scientific breakthroughs. DL has been characterized by many academicians and experts as a buzz word for AI, NNs and ML all together [31].

Fuzzy Cognitive Maps (FCM): Fuzzy Cognitive Maps were first introduced by Kosko [32] and the main scope is to combine the methods of fuzzy logic and neural networks. It is a very new method with less than 35 years of being used for modeling Complex Systems with all the characteristics of such systems. A detailed presentation of FCM is provided in [33]. FCM can investigate complex situations and deal with fuzzy or uncertain environments, through the implementation of a reasoning process [33]. FCM methodology is a proper tool for decision-making systems and as will be shown in this paper, differs from statistical methods.

In their effort to model the operation of the system, FCMs encapsulate experts' accumulated knowledge and experience of the system's behavior in various circumstances. The extracted knowledge is first converted into linguistic variables and then into numerical values through defuzzification. In other words, they denote the parameters of the examined system with a modeling process consisting of an array of interconnected and interdependent nodes Ci (variables), as well as the relationships between them W (weights). Concepts take values in the interval [0, 1] and weights belong in the interval [-1, 1]. Figure 1 shows a representative diagram of an FCM. An FCM can deal with complex dynamic systems and is able to examine situations during which the human thinking process involves fuzzy or uncertain environments, using a reasoning process that can deal with uncertainty and ambiguity descriptions.

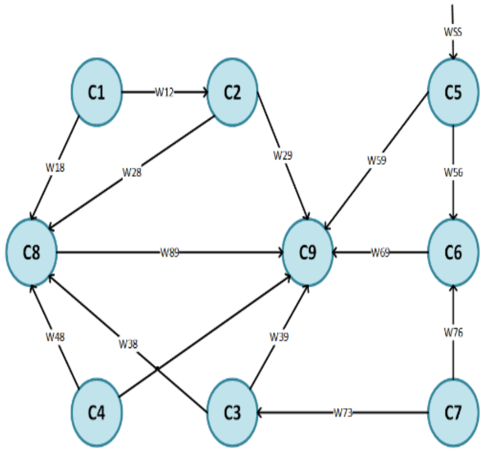

Figure 1: A simple Fuzzy Cognitive Map (FCM)

A Four steps algorithm for the development of a FCM is given in details in [33-34].

There are three types of interconnections between two concepts C_i and C_j and their weighted relationship w_{ij}:

$w_{ij} > 0$, an increase or decrease in C_i causes the same result in concept C_j.

$w_{ij} < 0$, an increase or decrease in C_i causes the opposite result in C_j.

$w_{ij} = 0$, there is no interaction between concepts C_i and C_j.

The absolute value w_{ij} is the degree of influence from C_i to C_j.. During the simulation the value of each concept is calculated using the following rule:

$$A_i(k+1) = f(k_2 A_i(k) + k_1 \sum_{j=1, j\neq i}^{N} A_j(k) W_{ji}) \qquad (1)$$

where N is the total number of system's concepts, $A_i(k+1)$ is the calculated value of the concept C_i at the iteration step $k+1$, $A_j(k)$ is the value of the concept C_j at the current iteration step k, w_{ij} is the weight of interconnection from concept C_j to concept C_i and f is the sigmoid function. "k_1" expresses the influence of the interconnected concepts on the configuration of the new value of the concept Ai and "k_2" represents the proportion of the contribution of the previous value of the concept in computing the new value. The sigmoid function f is defined as:

$$f = \frac{1}{1+e^{-\lambda x}} \qquad (2)$$

Where λ>0 determines the steepness of function f. The initialized values of the FCM's concepts are re-calculated after each iteration step, depending on their weighted relationship between them. To stop the calculations, a steady state must be achieved, with no (or below a threshold) changes in concepts values. A more comprehensive mathematical presentation of FCMs with application to real problems with very useful results is provided in [33].

Since 2000, a number of studies have examined the NLH learning method providing results and solutions to this issue [35,36]. This learning algorithm triggers the nodes of the system simultaneously interacting with their values in the same iteration step, so they are updated. The initial weights defined by experts are modified using the following relationship:

$$w_{ij}^{(k)} = g \cdot w_{ij}^{(k-1)} + h \cdot A_j^{(k-1)} \cdot \left(A_i^{(k-1)} - \mathrm{sgn}(w_{ij}) \cdot w_{ij}^{(k-1)} \cdot A_j^{(k-1)} \right) \tag{3}$$

where, coefficients g and h are important to control parameters with values $g \ni [0.9, 1]$ and $h \ni [0, 0.1]$, called weight reduction parameter and learning parameter respectively.

The weights w_{ij} are updated for each iteration step and then the updated values are imported in Equation (1) to compute the new values of concepts at the current iteration step. The weights' update procedure (learning) ends when the following criteria are met. The first one concerns the minimization of a loss or cost function F_1 which is the sum of the square differences between each Desired Output Concept i (DOC_i) and a target value T_i. $T_i$is defined as the mean value of the range of $DOC_i = [T_{imin}, T_{imax}]$.

$$F_1 = \sqrt{\sum_{i=1}^{m} (DOC_i - T_i)^2} \tag{4}$$

$$T_i = \frac{T_i^{\min} + T_i^{\max}}{2} \tag{5}$$

The second criterion is the minimization of the variation of two subsequent values of Desired Output Concepts:

$$F_2 = \left| DOC_i^{(k+1)} - DOC_i^{(k)} \right| \tag{6}$$

At the termination of the learning procedure the new final weight matrix w_{ij} with the DOCs are returned.

4. THE PROION PROJECT

"PROION" is a research project, focused on the development of a platform for the continuous monitoring of high priority infrastructure (public infrastructure, dams, bridges, etc.) in the broader area of the Hellenic Supersite, named Enceladus. The project started on September 2020 and it was financially supported by the European Union and the Hellenic government. Three areas with different characteristic were selected as test sites. The infrastructures consist of: a) The concrete building of the department of Geology in the Patras University campus, b) a large earthfill dam near to the city of Patras, c) many small houses located in a small village named Krini which is established on an active landslide. In the three test sites, the installation of the following equipment was performed: a) three-axis accelerometers (Figure 2 left part), b) aluminum corner reflector (Figure 3 right part), c) low cost Global Navigation Satellite System sensor (Figure 4). A 3D base map (3D point cloud) derived from Terrestrial Laser Scanner and Unmanned Aerial Vehicle was also developed for each test area. The GNSS measurements, the accelerometer measurements and the ground deformation measurements derived by the interferometric processing of Sentinel-1 data were analyzed using soft computing algorithms in order to identify any possible displacement. Then another algorithm checked the fused result with the base map (3D point cloud). If the displacement overpasses a certain threshold an alert is generating through an innovative decision-making and support tool. The whole system is integrated in a modern Webgis platform.

Following the general description of the project, an overview of the algorithms developed with the framework of the proion project and how they are combined to provide a decision on the structural health of an infrastructure, is provided.

As mentioned above 4 different types of data were provided, data from UAVs/TLS, InSaR, GNSS and Accelerometers. The system designed is briefly described in Figure 5. The proposed system will consist of two different modes one Real Time in case an event occurs and one Near Real Time, approximately every 12 days, when the data from the satellite are updated. Based on the data analysis a decision will be taken on whether the detected differences on the data pose a potential threat on the structural health of the building or not.

Real Time vs Near Real Time: The system is set to operate on a Near Real Time basis, every 12 days, to evaluate new data however in case an event happens the Real Time mode will be activated and the system will proceed to an ad hoc operation in order to assess the situation. For this to happen the accelerometers installed on the different sites will serve as a triggering point. Once the measurements received pass a predefined, from the experts, setting point the whole procedure will be triggered.

Figure 2: At the left: the 3D axis accelerometer and the low cost GNSS receiver that were installed at Asteri Dam. The red arrow shows the accelerometer while the blue one shows the GNSS antenna. The box contains all the other necessary equipment. At the right: Aluminum corner reflector installed in Patras University Campus.

Figure 3: Low cost GNSS sensor installed on the roof of a building in the center of Krini village. The arrow shows the antenna.

Data Analysis – GNSS and InSar: To evaluate the data received from these two sources a Long Short Term Memory (LSTM) network was used. This type of Recurrent Neural Networks is capable of learning long-term dependencies, especially in sequence prediction problems. In the case of the PROION project we use each set of data to create a prediction on the next expected position. The prediction is then compared to the real measurement received and the difference of these two measurements in then used as an input to the assessment algorithm.

Data Analysis – UAV/TLS: To evaluate this set of data a Deep Neural Network (DNN) was used. By using this type of method, we were able to map the difference between the initial image of data with an updated one where there is a suspected difference to the landscape. The algorithm uses the difference between the two images to yield a decision whether the difference between the before and after are considered as possible structural damages.

Decision Making: In cases when a decision has to be made, whether the results of an algorithm are indicative of possible infrastructure damage and further investigation is needed by means of data analysis or the final decision of the system on the overall structural health of an infrastructure is due, Fuzzy Cognitive Maps are the method that is applied. The outputs of the data analysis procedure along with extra parameters, defined by experts, serve as inputs to the fuzzy cognitive map. Weights based on the knowledge and experience of experts are the starting point of defining the relationships between the different concepts which are then trained to yield the final results.

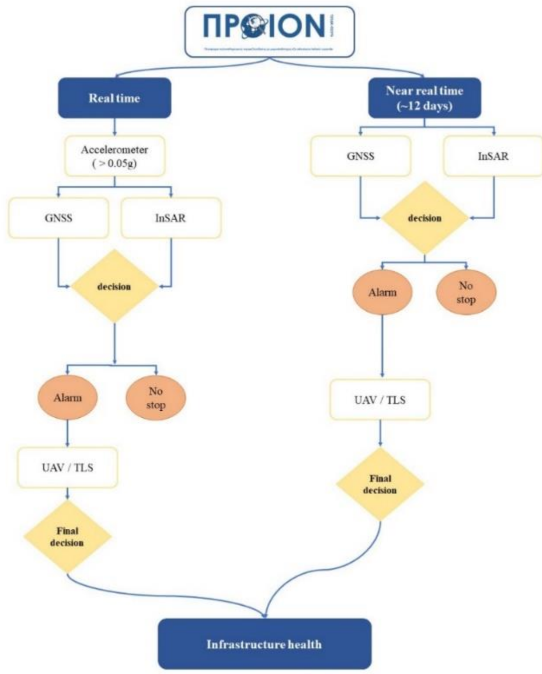

Figure 4: Description of the proposed system.

5. SIMULATIONS AND DISCUSSION OF RESULTS

In this section on the paper we will provide some simulation results based on the algorithms developed with the framework of the PROION project.

LSTMs for GNSS and InSar data

The data are received through satellite every 12 days. They show the position of a point, there is one measurement per day. The form of the data received are shown in the following table.

Table 1: GNSS data from Krini Station

Date	East (UTM)	North (UTM)	Up
04/10/2014	584054.7874	4227265.743	788.4089
05/10/2014	584054.7832	4227265.739	788.4158
06/10/2014	584054.7835	4227265.741	788.4157
07/10/2014	584054.7828	4227265.738	788.4025
08/10/2014	584054.7841	4227265.74	788.4167
09/10/2014	584054.785	4227265.737	788.4218
10/10/2014	584054.7852	4227265.739	788.426
11/10/2014	584054.7841	4227265.737	788.4142
12/10/2014	584054.7849	4227265.736	788.4048
13/10/2014	584054.7851	4227265.737	788.4084

Based on the data an LSTM network is created and trained in order to predict the net expected position of the East, North and Up positions. In order to train the network 12 days of measurements are used. The network is trained for each axis separately and also cumulatively by calculating the vector of the measurements and feeding it into the network. In the following figures the results of the training and testing procedure of the LSTM network are presented.

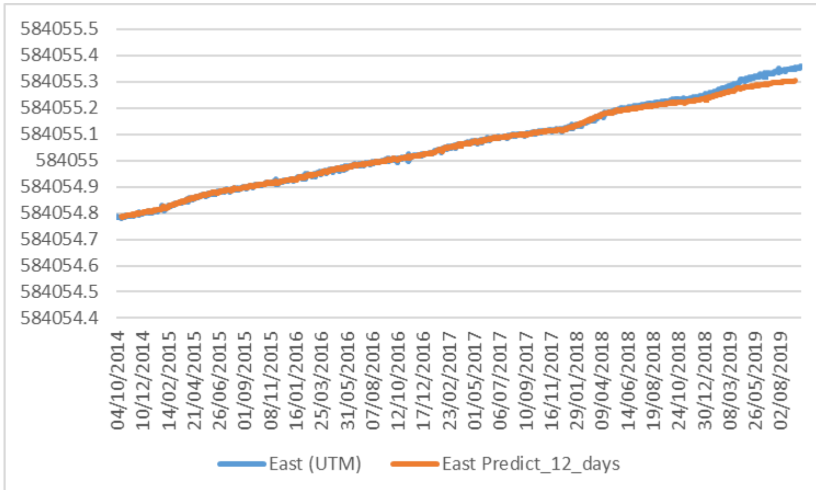

Figure 5: East Actual vs Prediction (train and test datasets)

As we can see from Figures 5-8 the predictions follow the trend of the actual data and in some cases e.g. Figure 7 they show less fluctuations. The error is rather small, the order of magnitude is in mms. It can also be observed that the results are even more accurate when we combine the three coordinates and train the LSTM using the vector.

LSTMs for UAV/TLS data

The dataset consists of point clouds mapping a slope surface. In this case the algorithm attempts to map a landslide. As it can be observed from Figures 9, 10 the landslide is quite evident. The DNN applied in this case consists of 8 layers, and the sigmoid and hyperbolic tangent activation functions were used. 100 point clusters and 20 epochs were used to train the algorithm. The algorithm predicted the existence of a landslide with 97% accuracy, the area of the landslide in presented in Figure 11.

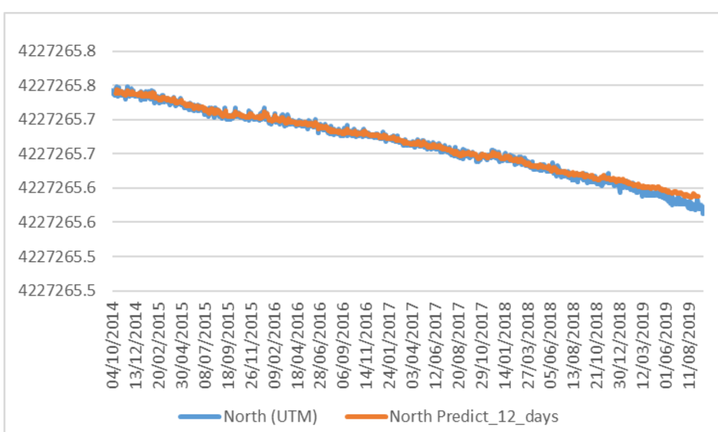

Figure 6: North Actual vs Prediction (train and test datasets)

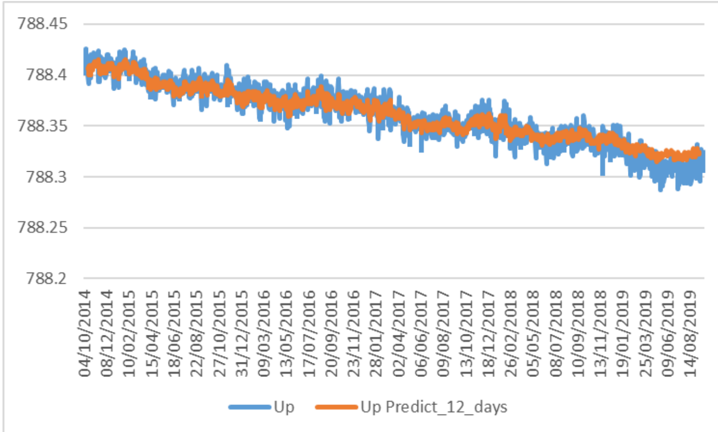

Figure 7: Up Actual vs Prediction (train and test datasets)

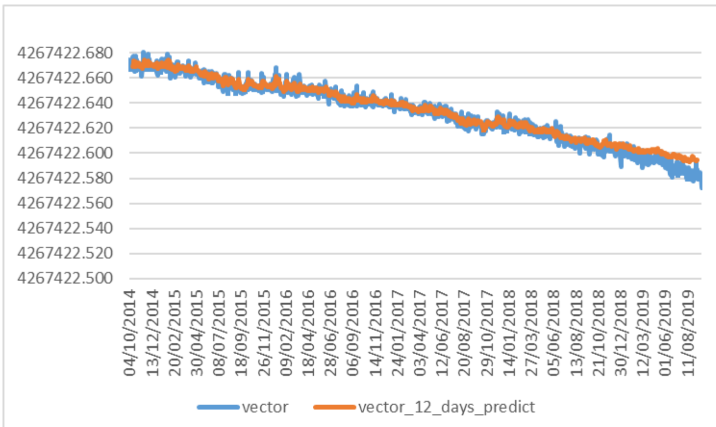

Figure 8: Vector Actual vs Prediction (train and test datasets)

Table 2: Error of the LSTM on GNSS data.

Data	Data type	Error
East	Train Score:	0.0032
	Test Score:	0.0254
North	Train Score:	0.0033
	Test Score:	0.0086
Up	Train Score:	0.0082
	Test Score:	0.0111
Vector	Train Score:	0.0032
	Test Score:	0.0067

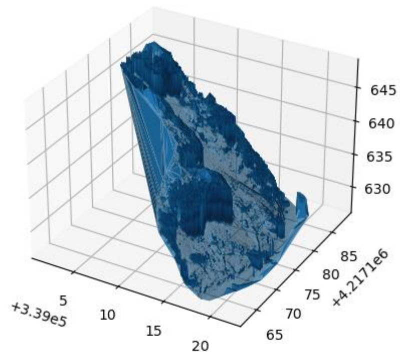

Figure 9: Area before the landslide

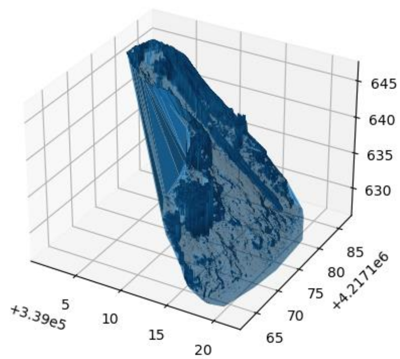

Figure 10: Area after the landslide

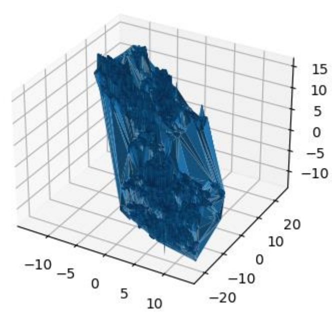

Figure 11: Difference between the two areas

6. CONCLUSIONS AND FUTURE RESEARCH

In this paper the possibility of complete automation of the health monitoring and inspection process of critical infrastructures. Our society strongly depends on several complex and interdependent critical civil infrastructures. Due to technological development, these civil infrastructures became sophisticated, complex, and essential for people, businesses, and municipalities. Indeed, any damage or deficiencies to critical civil infrastructures can cause serious consequences to the society. It is generally accepted that AI will drive the next revolution in this autonomous health monitoring of civil infrastructure. A short literature overview for the last 30 years shows the importance and seriousness of the problem been studied in this research work. Some advanced soft computing algorithms are briefly presented. In the funded project, the PROION, certain soft algorithms are used to study and examine the on-going real health monitor of three civil infrastructures in Western Greece. The selected algorithms are combined to provide a decision on the structural health of an infrastructure. Simulation studies using real data can lead us to a decision on whether the detected differences on the data pose a potential threat on the structural health of the building or not. An online platform is set up for using the proposed approach. The proposed system is still in progress. This is a very interesting and satisfying result. It is believed that this paper will afford the readers a quick familiarity with the historical background, current trends, and future prospects of this research arena. It will also help them identify the major problem areas that need immediate attention from the academic and research communities.

In the future we plan to extend the system, currently limited to the study area only. We also plan to use the advanced Fuzzy Cognitive Maps in analyzing the obtained data from the selected critical infrastructures. Future research could be the further improvement of the proposed platform for the health monitoring of critical civil infrastructures and thus to become an effective tool for operators in the sector. This would help us to assess the static and dynamic consistency of existing infrastructures and also provide a powerful means of control during the useful life of new constructions.

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REFERENCES

[1] CISA.gov, "Critical Infrastructure Sectors", An official website of the U.S. Department of Homeland Security, 2023. https://www.cisa.gov/topics/critical-infrastructure-security-and-resilience/critical-infrastructure-sectors.

[2] Fekete, A., "Common Criteria for the Assessment of Critical Infrastructures", Int. J. Disaster Risk Sci., 2 (1), 15–24, (2011), doi:10.1007/s13753-011-0002-y

[3] Fekete, A., Tzavella, K., Armas, L., Binner, J., Garschagen, M., Giupponi, C., Vahid Mojtahed, V., Marcello Pettita, M., Stefan Schneiderbauer, S. and Serre, D., "Critical Data Source; Tool or Even Infrastructure? Challenges of Geographic Information Systems and Remote Sensing for Disaster Risk Governance" ISPRS Int. J. Geo-Inf. Vol. 4, pp. 1848-1869, (2015), doi:10.3390/ijgi4041848. ISSN 2220-9964.

[4] Rinaldi, S. M., Peerenboom, J.P. and T. K. Kelly,T.K., "Identifying, Understanding, and Analyzing Critical Infrastructure Interdependencies. IEEE Control Systems Magazine Vol. 21 (6), 11–25, (2001).

[5] PEP (Provincial Emergency Program-2007), [Critical Infrastructure Rating Workbook], Provincial Emergency Program, British Columbia, Canada, (2007).

[6] Altabey, W.A. and Noori, M.,"Artificial-Intelligence-Based Methods for Structural Health Monitoring", Appl. Sci., 12, 12726, (2022), https://doi.org/10.3390/app122412726

[7] Ghiasi, R., Noori, M., Altabey, W.A., Silik, A., Wang, T., Wu, Z., "Uncertainty Handling in Structural Damage Detection via Non-Probabilistic Meta-Models and Interval Mathematics, a Data-Analytics Approach". Appl. Sci., 11, 770, (2021).

[8] Tang, S., Chen, Z., "Understanding Natural Disaster Scenes from Mobile Images Using Deep Learning", Appl. Sci., 11, 3952, (2021).

[9] Muin, M., Mosalam, K.M., "Structural Health Monitoring Using Machine Learning and Cumulative Absolute Velocity Features", Appl. Sci., 11(12), 5727, (2021), https://doi.org/10.3390/app11125727

[10] Lam, H.F., Yuen, K.V. and Beck, J.L., "Structural health monitoring via measured Ritz vectors utilizing artificial neural networks", Computer-Aided Civil and Infrastructure Engineering, 21(4), 232-241, (2006).

[11] Gordan M, Sabbagh-Yazdi S-R, Ghaedi K, et al., "Introduction to Monitoring of Bridge Infrastructure Using Soft Computing Techniques", Applied Methods in Design and Construction of Bridges, Highways and Roads - Theory and Practice, IntechOpen, (2022).

[12] Bernardo, E., Stefano Bonfa, S. and Calcagno, S., "Techniques of Geomatics and Soft Computing for the Monitoring of Infrastructures and the Management of Big Data", WSEAS Transactions on Environment and Development, 17, 371-385, (2021).

[13] Rott, H., Nagler, T., "The contribution of radar interferometry to the assessment of landslide hazards". Adv. Space Res, 37, 710–719, (2006).

[14] Joyce, K.E., Belliss, S., Samsonov, S., McNeill, S., Glassey, P.J., "A review of the status of satellite remote sensing and image processing techniques for mapping natural hazards and disasters", Prog. Phys. Geogr., 33, 183–207, (2009).

[15] Buchanan, B., G., "A (Very) Brief History of Artificial Intelligence", AI Magazine, 53–60, (2007).

[16] Turing, M., A., "Computing Machinery and Intelligence", Mind, 49, 433-460, (1950).

[17] Levshun, D., Kotenko, I. “A survey on artificial intelligence techniques for security event correlation: models, challenges, and opportunities”, Artif. Intell. Rev., (2023), https://doi.org/10.1007/s10462-022-10381-4
[18] Heykin, S., [Neural Networks and Learning Machines], Third Edition, Pearson Prentice Hall, (2009).
[19] Roberts, D., Yaida, S., & Hanin, B., [Frontmatter: In The Principles of Deep Learning Theory: An Effective Theory Approach to Understanding Neural Networks], Cambridge University Press, (2022).
[20] Schmidhuber, J. and Prelinger, D., “Discovering predictable classifications”. Neural Computation, 5(4), 625–635, (1993).
[21] Hawkins, J., [A Thousand Brains: A New Theory of Intelligence], Numenta, (2019).
[22] Baldi, P., [Deep Learning in Science], Cambridge University Press, (2021).
[23] Ng, Andrew, [Machine Learning Yearning], Kindle edition, (2019).
[24] Nilsson, N., [Principles of Artificial Intelligence], Tioga Press, Paolo Alto, California, (1980).
[25] Luger, F., G. [Artificial intelligence: structures and strategies for complex problem solving], Addison-Wesley, (2005).
[26] Warwick K., [Artificial Intelligence: The Basics], Routledge, (2011).
[27] [The Handbook of Brain Theory and Neural Networks], Edited by Michael A. Arbib, second edition, MIT Press, [2002].
[28] Heykin, S., [Neural Networks and Learning Machines], Third Edition, Pearson Prentice Hall, (2009).
[29] Hawkins, J., [A Thousand Brains: A New Theory of Intelligence], Numenta, (2019).
[30] Schmidhuber, J., “Deep Learning in Neural Networks: An Overview”, Neural Networks, 61, 85-117, (2015).
[31] Bengio, Y. “Learning deep architectures for AI”. Foundations and trends in Machine Learning, 2, (1), 1–127, (2009).
[32] Kosko, B., “Fuzzy cognitive maps”, International Journal of man-machine studies, 24(1), 65–75, (1986).
[33] Groumpos, P. P., “Fuzzy Cognitive Maps: Basic Theories and Their application to Complex Systems”. Invited chapter in Glykas, M. (Ed)., Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications, Springer, pp. 1-22, (2010).
[34] Groumpos, P. P. & Stylios, C. D., “Modeling supervisory control systems using fuzzy cognitive maps”, Chaos Solitons & Fractals, 113, 329-336, (2000).
[35] Papageorgiou, E. I., C.D. Stylios and P. P. Groumpos, “Fuzzy Cognitive Map Learning based on Non-Linear Hebbian Rule” in Advances in Artificial Intelligence Lecture Notes in Computer Science, Springer, 2903, 256-268, (2003).
[36] Papageorgiou, E. I, Stylios, C. D. and Groumpos, P. P., “Active Hebbian learning algorithm to train fuzzy cognitive maps”, International Journal of Approximate Reasoning, 37, 219-249, (2004).