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A Digital Twin Assisted and Embedded Strain Gauge Monitoring System

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Abstract

In this work, a strain monitoring system (strip) for assessing the road pavement distress under vehicle loads was developed. The system consists of the sensing element, the data processing and storage unit, and a graphical user interface with post- processing features. The sensing elements were designed to be adhesively bonded on the pavement and are protected by an encapsulating plastic strip. Strain data are sent to a digital reconstruction (the Digital Twin) of a real-life asset (the pavement model) that is frequently and automatically updated using data sample. This tool provides functionalities to monitor and optimize assets and make informed and data-based decisions, in the context of day-to-day operative conditions and after extreme events. These data not only include sensor data, but also regularly revalidated structural reliability indices formulated on the grounds of the frequently updated Digital Twin model.

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Keywords: Strain monitoring;Digital Twin, Machine Learning; Finite Element

1. Introduction

According to European Union Road Federation (ERF, 2014), annual maintenance spending in European road accounts to 30 billion euro, while 90% of works deal with maintenance and upgrades and 10% of investments are given for construction of new roads.

Accurate and continuous monitoring of pavement condition will allow to optimize maintenance intervals, reduce maintenance costs and extent service life. The most important requirement for such monitoring systems is to monitor the condition of the pavement in a non-intrusive and non-destructive manner. All monitoring systems proposed can be divided in two categories (Di Graziano et al, 2020): external evaluation methods and in situ pavement sensors.

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External methods detect pavement distress through deflection, acoustic emission, ground-penetrating radar, ultrasound, infrared thermal imaging and laser technology. However, their main drawback is the extensive use of personnel (Fakhri et al., 2019), high investment cost due to usage of specialized equipment (Cafiso and Di Graziano, 2009) and their inability to detect micro-damage and its development (Ji et al., 2019; Rhimi et al., 2012). Finally, external methods usually reflect the distress conditions of pavement surface rather than the internal stress/strain state and structural degradation of pavement (Dong et al., 2018).

On the other hand, in-situ pavement sensing technology is based on a wide selection of sensors (moisture, pressure, strain, temperature, etc.) able to collect pavement performance and environmental information continuously and in real-time. Studies have been done on wired embedded sensing network and their full-scale application based on structural health monitoring methodology (Alavi et al., 2016a; Hasni et al., 2017). Timm and Priest (2004) installed strain gauges, pressure cells, moisture and temperature sensors in different layers of pavement structures at the NCAT test track to investigate the dynamic responses under live truck loading.

The present work is moving forward the in-situ pavement sensing technology within the context of Industry 4.0, as depicted in Fig. 1. Measurements are taken from the physical twin (strip with sensors) to calibrate/update the digital twin. The digital twin is composed of a computational model (CM), which integrates physics-based and machine learning (ML) models. Then, a stochastic layer is added to the deterministic model, to take into account uncertainties. By utilizing strain gauge sensors placed on the pavement, strain data to calibrate/update the digital twin of the road cross section. The digital twin is composed of a high-fidelity computational model and a reduced order model based on machine learning and a stochastic layer to take into account uncertainties. The specific application support engineering and operational decisions, and it can be used for: (i) feeding information to repair/maintenance and operational parameters, (ii) setting up alarms, (iii) performing diagnosis for the pavement structural capacity in real time.

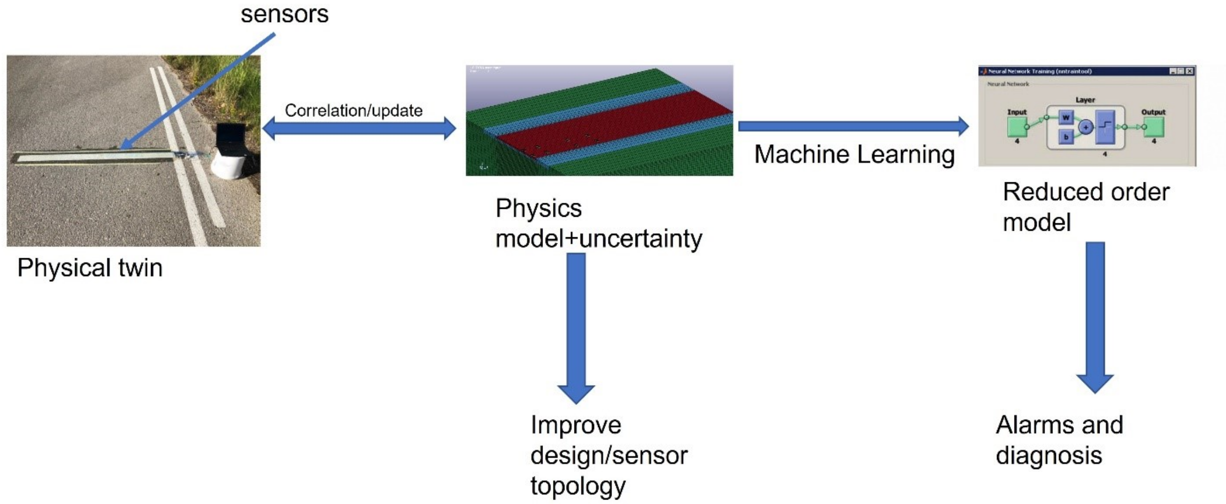


Fig 1. Digital twin framework

2. Hardware and sensor design

For the strain measurement, a single (quarter bridge) strain-gage configuration was used. Since there is no possibility of utilizing active-dummy method for temperature compensation, a KYOWA SELCOM strain gage was the next best solution. Due to the coarseness of the pavement surface, a large gage length was required. These led to the selection of KYOWA's KC-80-120-A1-11 strain gage. This has 80 mm gage length, and 120 Ohms of resistance. It has a limited temperature range in which it is self-compensated (10°C to 60°C), meaning that in cold days a drift is expected. For maintenance reasons, the gage lays far from the rest of the circuitry (wheatstone bridge, signal conditioning and logging), typically in the range of 5 meters. Due to this length of the cables, a 3-wire connection is

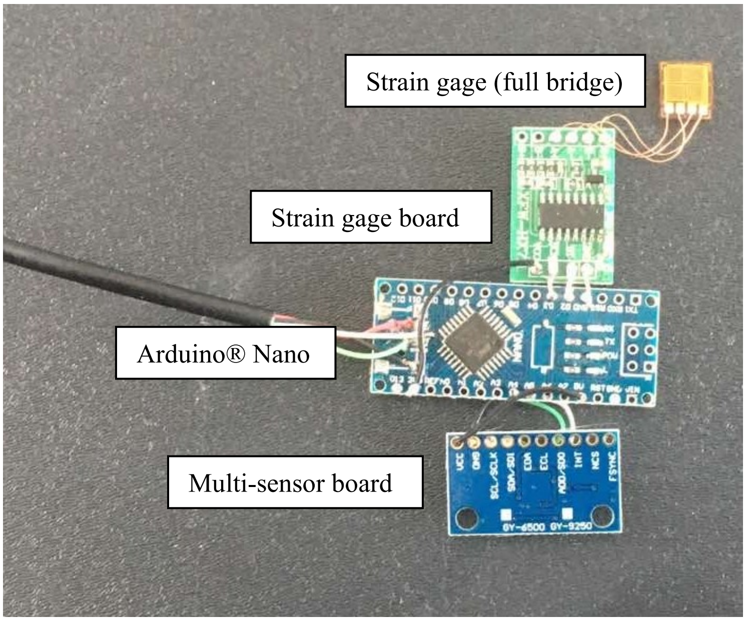
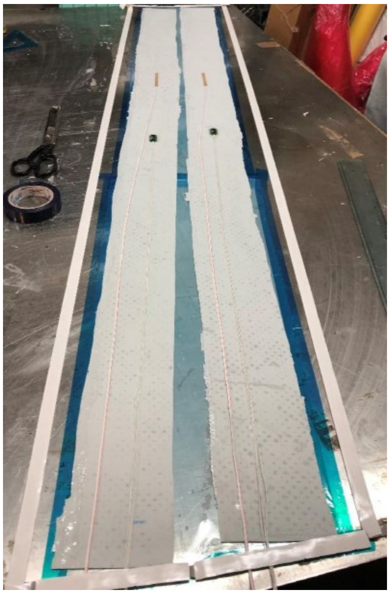


Fig 2. Electronic Boards assembly

deemed necessary. The Wheatstone bridge is connected directly on an HX711-based load weighing module board. This has a 128-gain factor (default) and a 24-bit AD converter. It has a maximum sampling rate of 80 samples per second, which is adequate for the application. Finally, the digital output is connected onto an Arduino® Nano board, where the data are analyzed. In Fig.2, the assembly is shown. A four-gage (full bridge) sensor is connected for calibration purposes.

3. Encapsulation and installation

Since the strain gage must be placed onto the pavement, it must be protected, along with all the relative cabling and boards. The protection must cope with all the environmental and mechanical loads, ensuring functionality of the equipment for the entire service life. A typical encapsulation procedure involves the casting of the equipment into a polymer, whereas the means of integration and fixing are provided by a case that surrounds the casting. In the case of placement onto the pavement, an extra requirement is that of the height, that should be kept at a minimum (under 5 mm, and ideally under 3mm). Towards meeting these requirements and providing a solution for an integrated construction safe to be handled, transported and installed, a Fiber Reinforced Polymer (composite) strip was designed. 4 layers of E-Glass fabric, at 280 g/m^2 were used, along with a toughened epoxy resin system. The strain gage and its cabling were placed inside this structure, during the lamination procedure (between the 2nd and 3rd layer, Fig.3).
Using the same technique, it is possible to also encapsulate all the electronics (boards) as well. This has a total height penalty equal to the height of the thicker board, but it adds great versatility, enabling the system to upgrade to full autonomy (no cabling and electronic box on the roadside). Upon polymerization, a flexible strip with a thickness of no more than two millimeters was produced. These strips can be installed onto the pavement surface using a two-component epoxy adhesive. A secure bond is created, and if an overlay of appropriate road marking material is applied, an almost seamless integration to the pavement is created. Several strips were installed in various roads for durability assessment. A life span of over two years is expected. In Fig.4, a single installed strip is shown, during some trials.

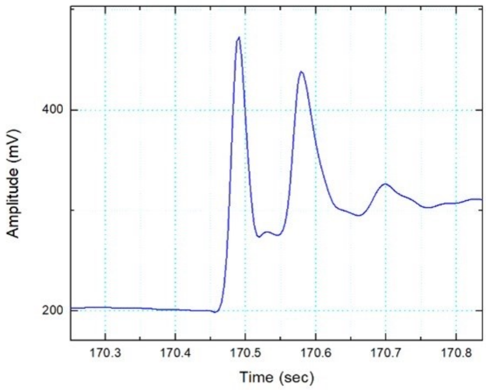


a

b

Fig 3. 2 m length GRP strips during lamination (a) and strips with encapsulated sensors and electronics (b).

a



b

Fig 4. Field test of installed equipment (a) and field strain measurement of a single event (b).

4. Digital Twin development

As a starting point for the Digital Twin development, a three-layer viscoelastic 3D finite element model was created in LS-DYNA software. One of the most important aspects in modeling such systems, is the discretization and the model dimension that allows modeling accurately the structural response of a of a semi-infinite space using a finite domain. This model has dimensions 9 m along the vertical z direction, 23 m along the lateral (transverse) y direction and 20 m along the longitudinal (traffic) x direction. It consists of three layers fully bonded to each other and to the supporting soil with the top one being the asphaltic layer of thickness 0.175 m, the intermediate one, the granular base layer, of thickness 0.225 m and the bottom one, the subgrade layer, of thickness 9.00 m.

This discretization consists of 280,000 8-noded 3-D solid finite elements and having in total 24 degrees of freedom, as shown in Fig. 5a.

a b

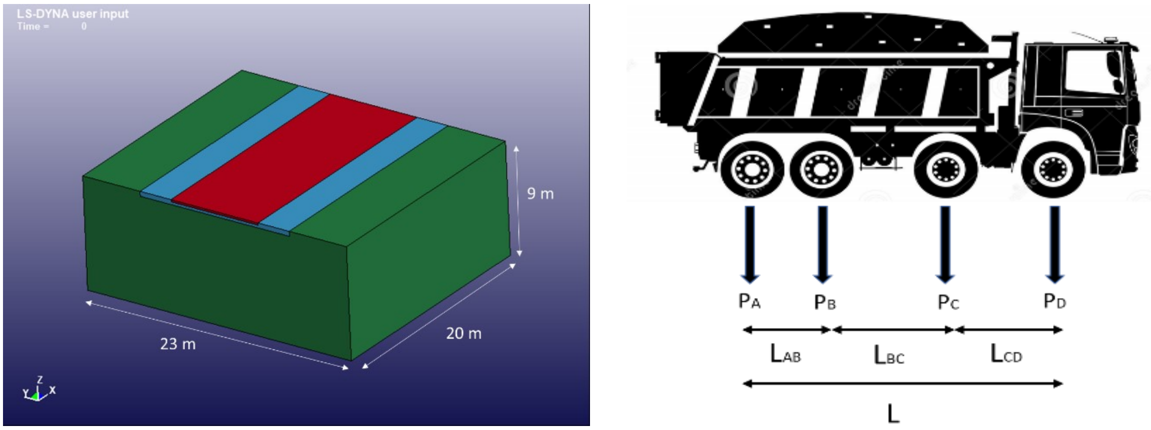


Fig 5. Road finite element model (a) and heavy vehicle loads and axle dimensions (b)

Because the vertical faces of the model and the bottom horizontal face of the pavement model are artificial boundaries, waves generated by the motion of the vehicle along the surface of the pavement propagating inside the pavement domain, are reflected at those artificial boundaries and pollute the wave propagation inside that domain. For this reason, non-reflecting boundaries were activated in LS-DYNA code (LS-DYNA Manual, 2021).

For the modeling of the moving load, the loading conditions assumed by Beskou (2016a) were used. More specifically, a typical heavy vehicle is considered as the one shown in Fig. 5b, with four axles of concentrated loads $P_A = P_B = P_C$=16 kN and P_D=32 kN and axle distances L_{AB}=1.40 m, L_{BC}=2.95 m and L_{CD}=2.05 m. Thus, the total axle length L=6.40 m and the total weight of the vehicle is 80 kN. Regarding the application of these loads on the pavement, the method proposed by Huang (2004) was followed, where the applied moving loads on pavements distributed on the pavement can be simulated by applied pressure on a rectangular surface. In this model, each wheel was simulated by using a rigidwall block. The load of each wheel was applied on the respective rigid block and the pressure on the pavement surface from each rigid block is handled via a contact algorithm. The vehicle movement is modeled by applying velocity boundary condition of LS-DYNA on the rigid blocks. This way of introducing the loads allows a straightforward parametrization of vehicle velocity and load of each axle.

Considering the material models for the pavement, the base and sub-base were considered to be elastic and the top asphaltic layer viscoelastic, with nominal properties obtained from Beskou et al (2016b).

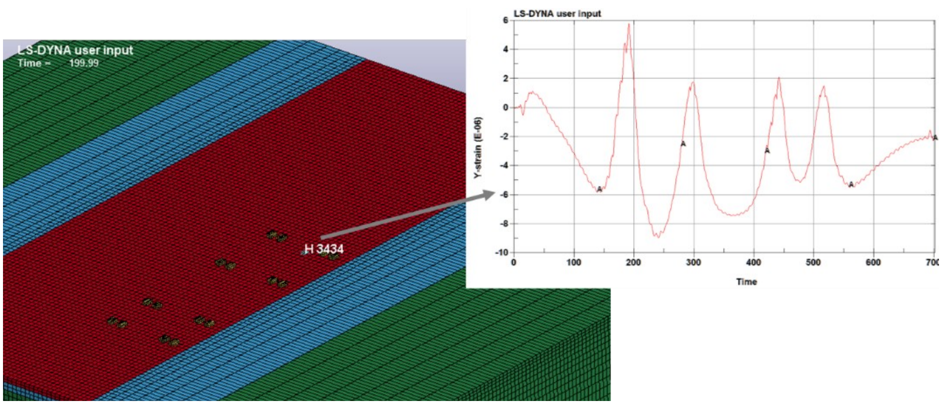


Fig 6. Indicative Strain time history obtained from the finite element model.

In order to allow the generation of the Digital Twin of the pavement section described, a stochastic simulation was performed. In a stochastic simulation, parameters that define a system can have uncertain values produced by Design of Experiments (DoE) that produce uncertain responses to the system output. For this model, the response is the strain measured in the position depicted in Fig. 6 and the response is the maximum value of top surface strain in y-direction. The DoE of the input variables was designed by using Latin Hypercube Sampling. Since its first introduction by McKay et al. (1979), Latin hypercube sampling (LHS) has been considered to be a good alternative for the Monte Carlo Sampling (MCS) because it ensures that sampled points represent a full range of each input variable and avoids unnecessarily dense sampling regions. Different from the MCS, sampling domains of input parameters are equally divided into many sub-regions, and within each sub-region, only one random point can be sampled. This guarantees that the entire space of random input parameters can be sampled independently and equiprobably.

The input variables that were randomized using LHS were the vehicle speed, the Young's modulus of base and sub-base layers, the viscoelastic parameters of the top asphaltic layer (Bulk modulus, G_0, G_{inf}, b) and the weight of each individual axle of the vehicle. It is easily understood that the number of the variables, typical for complicated systems, does not allow a statistical design without a significant number of simulations runs. Therefore, the step taken was to efficiently model this high-dimensional problem based on embedded low-dimensional structures or reduced order model (ROM). These ROMs often trade a level of accuracy for much greater computational speed. This ROM concept (also called surrogate modeling or metamodeling) allows one to emulate the complex full-order model of the pavement.

To construct the ROM for this specific problem, a dataset of 100 runs was generated using LHS, with the objective to use limited data from the finite element model and generate a computationally efficient ROM for real-time monitoring with the ability to generalize fairly well to new data.

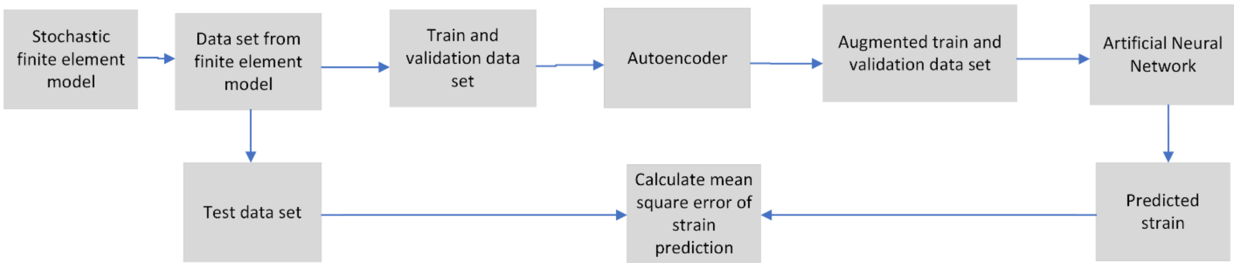


Fig 7. Process of ROM construction and validation.

Two approaches were followed, one using an Artificial Neural Network (ANN) without data augmentation and another with data augmentation. The constructed dataset was randomized and the 15% of the data was completely excluded from the process of designing the ROM (train/cross validate/test) and was used for further testing the ability of ROM to predict the system response from new data.

By following the approach of using the simulations dataset without augmentation using 85 experiments, after an iterative process, an ANN with two hidden layers of size 26 for the first hidden layer and size 7 for the second hidden layer has exhibited the best performance for the train/cross-validate/test data set. However, after testing on the test dataset, the ANN exhibits overfitting due to the large number of parameters compared to the available dataset. This is a problem already described in literature (A. Rasheed et al, 2020), and it is suggested that this method can be used to interpolate and not extrapolate in the context of accelerating the analytical solution. On the other hand, when the simulations dataset was provided as input to a sparse autoencoder with 4 hidden layers and a linear transfer function for the decoder, the dataset was augmented with by generating new and diverse instances of the initial values. The approach is shown in Fig.7. The augmented dataset provided to the same ANN and the prediction performance on the test dataset is significantly better. The performance of the two approaches, in terms of Mean Square Error compared to the test strain data set, are summarized in Fig. 8.

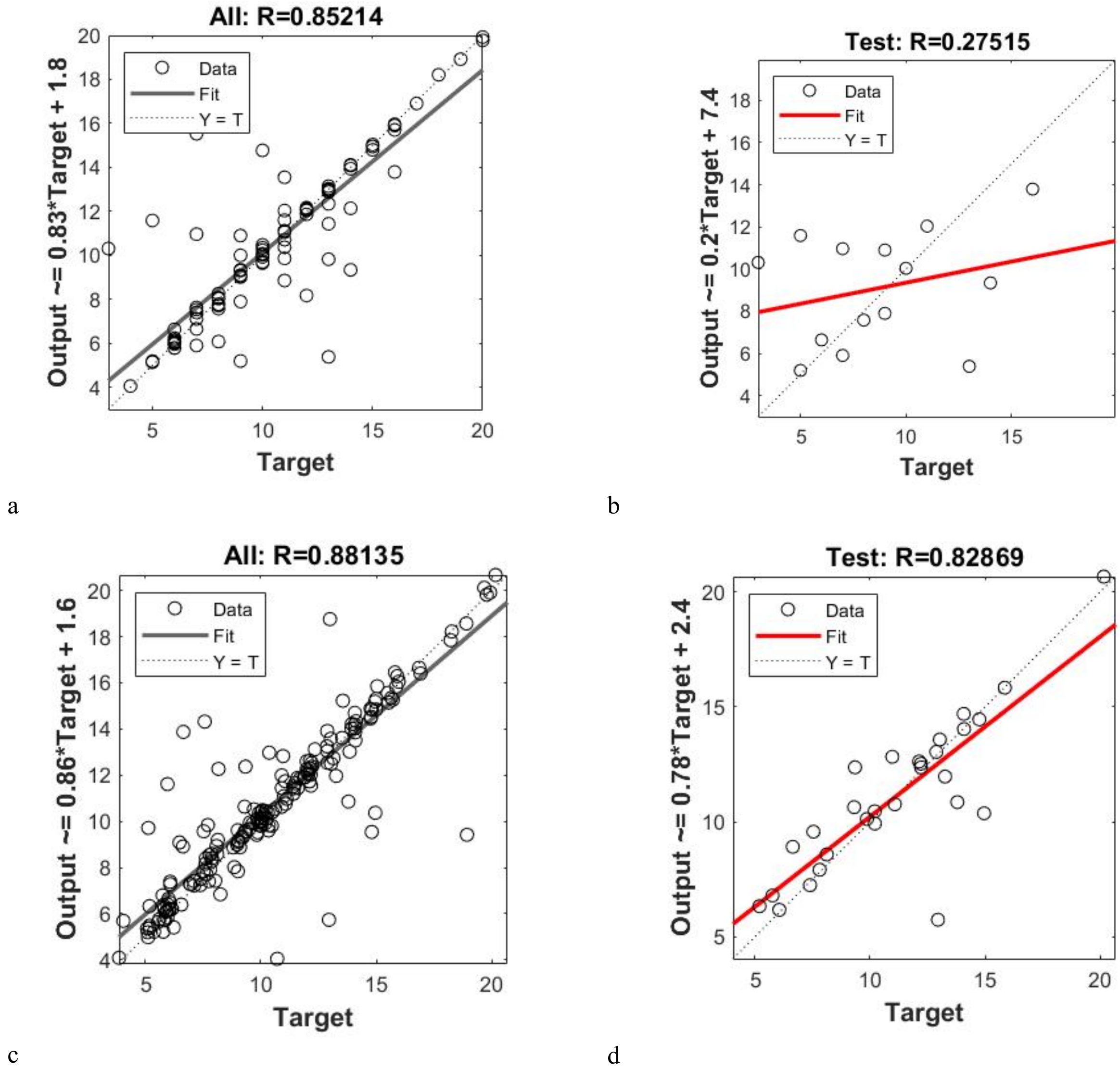


Fig 8. Training performance of ANN without (a) and with (c) data augmentation and test performance without (b) and with (d) data augmentation.

Conclusions

This paper presents a digital twin assisted conceptual framework for measuring pavement strain. Three important aspects of this framework are described: (i) computational model, (ii) uncertainty quantification via stochastic model, and (iii) hardware for data collection from the physical twin. To enhance the computational strategy and allow real-time computations, a physics-based computational model is combined with machine learning to construct a digital twin that would be connected to the physical counterpart and support decisions. The simulated structure analyzed enabled to construct a digital twin, and to understand its characteristics. Several conditions regarding properties variation and loading were tested aiming to validate the capacity of the digital twin to predict the measured strain value in different scenarios. The physics-based computational model is important in such structures to assure interpretability and to explore different damage conditions that could not be assessed with the physical twin. Due to the fact that the physics-based simulations of such complicated problems are time consuming, training a machine learning algorithm allows a fast evaluation of the physical twin in a real time operation. Future research should include detailed correlation between the field tests and finite element simulations. This correlation will allow a digital twin that can handle both experimental and numerical data sets and provide strain predictions. This will allow prognosis of failure using the on-site measurements and the Digital Twin.

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