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A methodology for structural health diagnosis and assessment using machine learning with noisy and incomplete data from self-powered wireless sensors

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ABSTRACT

This study presents a novel methodology for structural health monitoring (SHM), using a self-powered sensing concept, within the context of machine learning (ML) and pattern recognition (PR). The proposed method is based on the interpretation of data provided by a self-powered discrete analog wireless sensor used to measure the structural response along with an energy-efficient pulse switching technology employed for data communication. A system using such an energy-aware sensing technology demands dealing with power budgets for sensing and communication of binary data, resulting in missing and incomplete data received at the SHM processor. Numerical studies were conducted on an aircraft wing stabilizer subjected to dynamic loading to evaluate and verify the performance of the proposed methodology. Damage was simulated on a finite element model by decreasing stiffness in a region of the stabilizer's skin. Several features, i.e., patterns or images, were extracted from the strain response of the stabilizer. The obtained features were fed into a ML methodology incorporating low-rank matrix decomposition and PR for damage diagnosis of the wing. Different ML algorithms, including support vector machine, *k*-nearest neighbor, and artificial neural networks, were integrated within the learning methodology to assess the performance of the damage detection approach. Different levels of harvested energy were also considered to evaluate the robustness of the damage detection method with respect to such variations. Further, reliability of the proposed methodology was evaluated through an uncertainty analysis. Results demonstrate that the developed SHM methodology employing ML is efficient in detecting damage from a novel self-powered sensor network, even with noisy and incomplete binary data.

Keywords: Structural health monitoring, machine learning, pattern recognition, self-powered wireless sensors, time-delayed binary data

1. INTRODUCTION

Recent developments in energy-efficient wireless sensor networks for structural health monitoring (SHM) are leading to compatibly lean data generation that requires novel solutions for analysis and interpretation. This study presents one such case in which the structural health assessment and damage diagnosis is based on simulation of asynchronous time-delayed binary data. This type of data results from a pioneering SHM system, currently under development by the authors[1], that employs a network of self-powered sensors communicating data between sensor nodes by means of ultrasonic pulses through the substrate of the structure being monitored. The binary nature of the data follows from such communication scheme, termed pulse switching, which is motivated by the aim of minimizing the wireless sensor network's energy consumption. In regard to this, the occurrence of an event at a sensor node (based on local measurements, e.g., strains) is communicated as a pulse, rather than a data packet, to minimize power requirements. The time-delayed aspect of the data, on the other hand, follows form the fact that sensing and communication only occurs if sufficient energy can be harvested at the sensor node. The resulting data, therefore, possesses a unique type of degraded resolution. That is, the data merely implies the occurrence or absence of an event at a sensor node (1 or 0, respectively), the actual local demand value is unknown, it is temporally incomplete over the network, and is received with unique

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delay at the SHM processor. The innovative solution pursued by the authors to overcome these challenges is to learn from such low-resolution and incomplete data using machine learning.

The SHM platform presented in this research is based on a through-substrate wireless sensor network[1–3] that employs discrete floating-gate self-powered sensors[4]. The uniqueness of the analog wireless sensor, which uses piezoelectric transducers to empower an array of ultra-low power floating gate transistor computational circuits to integrate sensing, data storage and communication functions, is that it records discrete and asynchronous information. The communication part employs the pulse switching protocol by which a minimal number of ultrasonic pulses (i.e., compression stress waves transmitting through the material substrate) are used to denote event location and forwarding information. The through-substrate ultrasonic self-powered sensor network is shown in Figure 1. The significant property of such network is that it consists of a system of low-power through-substrate ultrasonic pulse networking (TUPN) units communicating with each other using the noted energy-lean pulse switching architecture, and are powered by energy harvested from the substrate's (i.e., structural) vibrations. Figure 1 illustrates how the event transportation network is formed on a bridge girder and an aircraft wing through the structure's substrate using cellular network abstraction. An ultrasonic pulse is generated by the TUPN detected event (based on a local measurement). The generated pulse is then transmitted via multi-hop communication between TUPNs to a data logger/sink node, where information received from sensor across the structure is accumulated. The pulse signals received at the sink indicate the occurrence of the corresponding event and its location of origin with a predefined-resolution. The resulting time-delayed discrete binary data is the one to be used for structural health diagnosis.

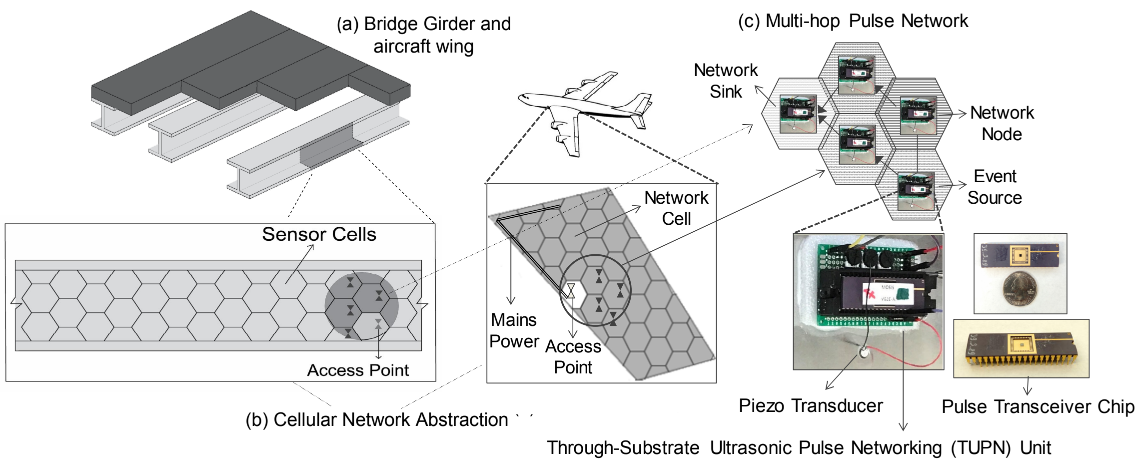

Figure 1. Structural health assessment and damage identification employing a through-substrate ultrasonic sensor network

To tackle the problems associated with discrete binary data, the authors previously proposed an SHM methodology for damage assessment within the context of pattern recognition (PR)[5,6]. An image-based PR approach for SHM assuming full data availability was developed, for which the effect of power budget was discarded. Different PR methods were then examined to interpret discrete binary data. Further, in order to take into account the effect of time delay due to the pulse switching protocol, the authors developed an algorithmic framework employing machine learning to learn from asynchronous time-delayed binary data for damage identification in aircraft structures[7]. Low-rank matrix decomposition was integrated with the *k*-nearest neighbor method for data recovery and classification. However, the effect of noise, variations in the harvested energy level, and different learning algorithms on the performance of the proposed machine learning framework were not studied, even though each of the aforementioned features could have a significant impact on the performance of such framework for SHM. To address these issues, this paper presents a methodology for damage assessment with low-resolution and incomplete time-delayed binary data, and its robustness with respect to harvested energy variations and measurement noise is evaluated. Another contribution of the present study is to explore the damage detection strategy's effectiveness using different learning algorithms. On this basis, support vector machine, artificial neural networks, and *k*-nearest neighbor methods were used within the machine learning methodology to determine damage identification accuracy, and to identify the most promising algorithm for SHM of an aircraft wing using timed-delayed binary data. It is noted that the integrated self-powered sensor with communication technology is under design and testing. Therefore, the focus of the present study is on evaluating the effectiveness of the proposed SHM methodology with event-based binary data generated through finite element simulations of an aircraft wing.

2. ENERGY-AWARE THROUGH-SUBSTRATE SENSOR NETWORK

In the energy-aware self-powered sensor network, the data forwarding protocol takes into consideration the energy availability and the pending event status in the event buffer to come up with optimal routing (optimal route selection and route diversity selection, i.e., how many redundant routes can be supported) and scheduling (i.e., when the event pulse should be transmitted) for every event delivery. The event pulse is then transmitted in the appropriate time within the frame structure. The actual pulse transmission can only happen when there is an event pending and sufficient energy to communicate such event. As a result, there can be a buffering time between the actual event generation and transmission (see Figure 2), which translates to a per-hop event delivery delay. This indicates that the measured event will be communicated with an unpredictable delay. It is to be noted that the length of the buffer at each node is the total number of sensor cells in the network.

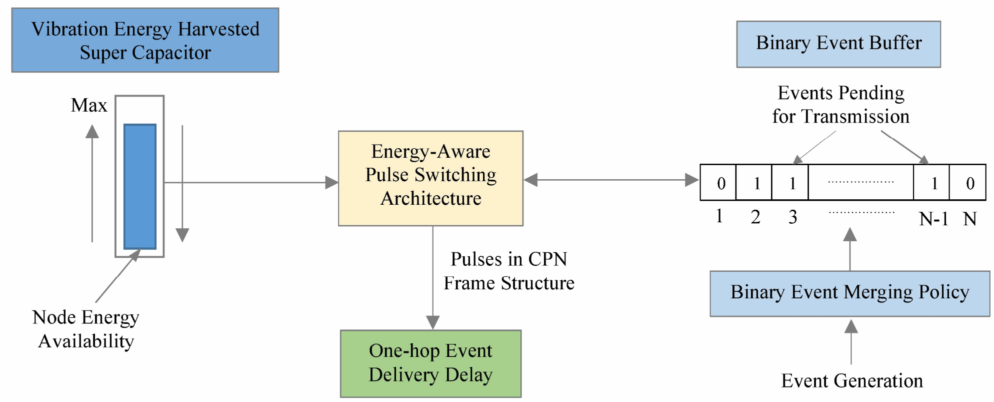

Figure 2. Factors affecting one-hop event delivery delay when using cellular pulse networking in energy-harvesting-powered WSNs

3. DAMAGE DETECTION METHODOLOGY FOR SHM USING MACHINE LEARNING

3.1 Finite element modeling of an aircraft stabilizer

The development and validation of the proposed damage detection procedure is based on data obtained through the structural response simulation of an aircraft horizontal stabilizer with the finite element method (FEM). The program ABAQUS[8] was used to conduct the simulations The model's geometry was simplified from that of the Boeing 737 horizontal stabilizer in a way that it represented the main structural components for the wing model to yield a realistic response. Shell elements with uniform thickness were used for modeling all parts. Additional stiffness from stringers was modeled by placing spars (beam elements) on the top edges of the leading and back stiffeners. The thickness of the shell elements, for the box structure and stiffeners, was 5 mm. This thickness value was determined to obtain realistic dynamic properties due to additional mass from non-structural components in the stabilizer. The spars were assumed to have circular cross sections of 20 mm in diameter. Material properties assigned to the model were those of aluminum 2024, with an elastic modulus of 73.1GPa, a Poisson ratio of 0.33 and density of 2780 kg/m^3. `

In this study, a simple pilot-type local rule for binary event generation was defined in terms of a strain threshold (R1) at the sensor nodes (i.e., corresponding FE model mesh nodes). Thus, a binary event was generated if the maximum principal strain at the sensor node was larger than R1. The threshold R1 (80 micro-strains) was empirically chosen, based on the FE simulations, to ensure that binary events representing damage could be generated. Damage in the FE model was simulated by decreasing the element's stiffness in a region of the stabilizer skin. The geometry of the aircraft wing stabilizer, the layout of the self-powered sensor nodes, and the region of simulated damage in the FE model are shown in Figure 3.

The lift pressure distribution across the wing chord length is illustrated in Figure 4(a). The loading pressure was applied to the model as an incremental ramp with a noise perturbation of 10% over a time domain of 4000 sec. The simulated demand neglected the rigid-body flight dynamics of the plane and thus it captured only the relative response of the stabilizer wing. The dynamic analysis was conducted with an implicit solver and time histories of transverse accelerations at the model's top surface nodes were extracted. A surface contour plot of the average absolute acceleration at the top surface nodes is shown in Figure 4(b). As expected, nodes at the tip experience greater acceleration on average than the nodes at the mid span of the stabilizer.

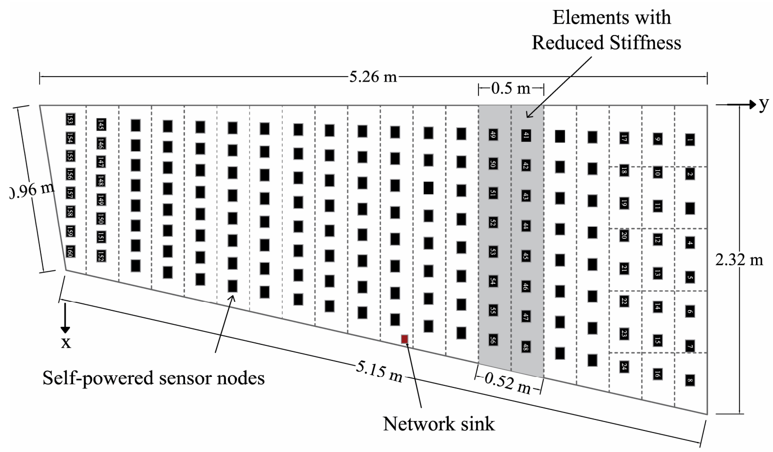

Figure 3. Wing stabilizer geometry and self-powered sensor configuration

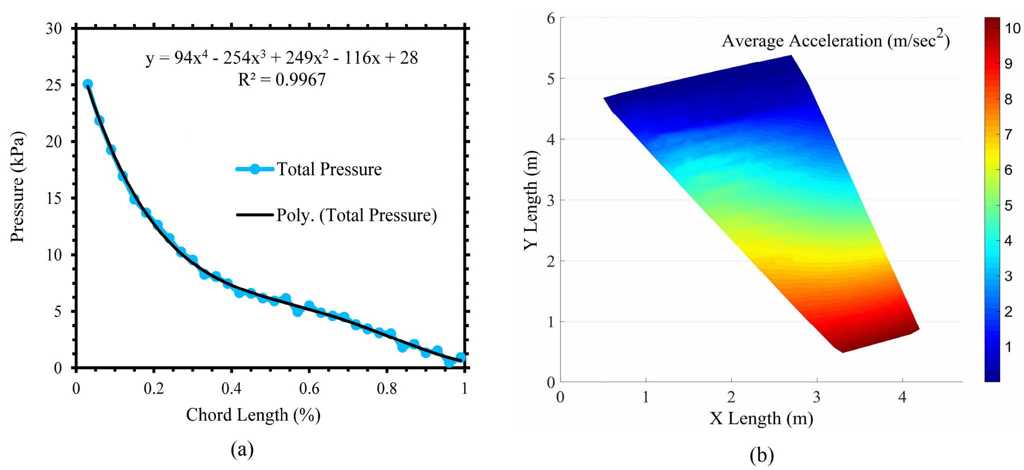

Figure 4. (a) Total pressure profile and simplified triangular pressure vs. chord length, (b) Average acceleration based on node coordinates on bottom of the plan-view of the stabilizer

3.2 Data processing and uncertainty analysis

Acceleration and maximum principal strain responses at the stabilizer sensor nodes were extracted from the FE model. The strain response was used to generate binary events using a threshold concept, while the acceleration response was used for determining harvested energy. The acceleration response and binary events were then fed to a simulated through-substrate sensor network employing an energy-aware pulse switching protocol to generate the delivery delayed event data. Finally, the time-delayed binary data was introduced as input to the SHM methodology employing machine learning for damage detection. To establish the reliability of the proposed damage detection methodology to measurement noise, various levels of noise were added to the numerical input vectors. To this aim, the calibrating/training, validation, and test data sets from the original self-powered sensor signal were polluted with random noise using Eq. (1):

$$x_{noisy} = x_{original} + \alpha \cdot \ rand \cdot \ x_{original} \tag{1}$$

where α is the noise level in %, $x_{original}$ is the input signal vector, x_{noisy} is the noise-contaminated signal, and *rand* is a MATLAB[9] function that generates random values. Performance evaluation with variations in harvested energy

Energy conversion efficiency in the self-powered sensor network is primarily a function of the sensor modules' electromechanical coupling constant (ECC). Erratic vibrations and conversion efficiency can lead to variability in the energy harvesting potential. Such variability in the harvesting capacity can manifest in the network's performance in terms of variable data delivery delay from the same source node to the sink in different situations. To demonstrate the robustness of the proposed damage identification strategy against such variations in data delivery delay, the damage detection performance for a range of energy availability situations was evaluated. The inconsistency in energy availability was simulated by using different ECC values for the piezos on the associated TUPN units in separate tests. Four different electromechanical coupling constant values, indicated by 0.55*Θ, 0.75*Θ, 0.9*Θ, 1.0*Θ, were considered to create a variable energy harvesting potential. The value Θ indicates a coupling constant of 1.96×10^{-4} Coulomb/m, which is a reasonably high value for piezo transducers. Thus, different fractions (0.55, 0.75, 0.9, etc.) of the coupling constant were used to simulate the variability in energy harvesting conditions from low to high.

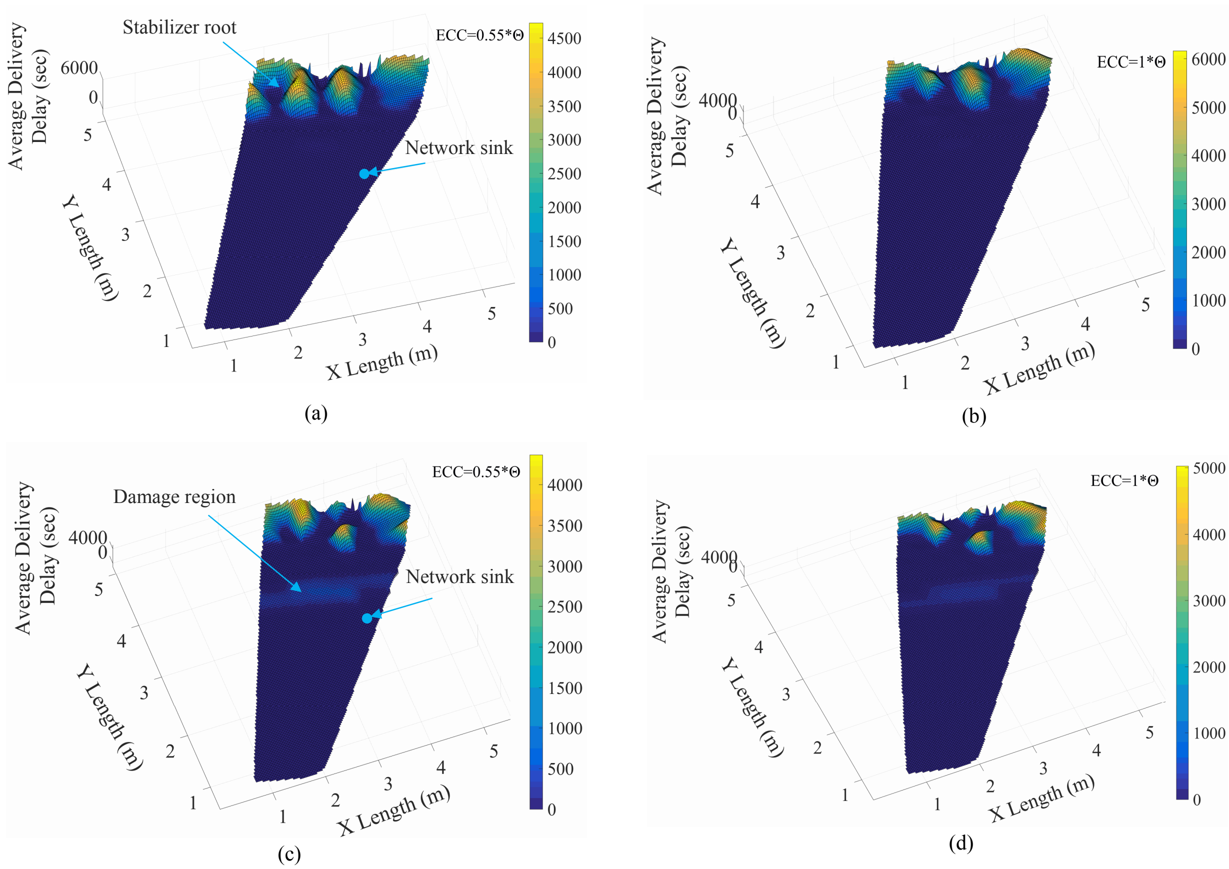

Figure 5. Average delivery delay response of sensor nodes for different harvested energy levels: (a) & (b) Intact stabilizer, (c) & (d) Damaged stabilizer

Average delivery delay times from the sensing nodes for ECC values of 0.55*Θ and 1.0*Θ (i.e., lowest and highest harvested energy levels) for healthy and damaged stabilizers were computed, and the surface plot of these values are shown in Figure 5. As can be seen, for the undamaged stabilizer (Figure 5(a) and (b)), the average delivery delay of the sensor nodes in the critical region of the stabilizer (see Figure 3) is zero and only sensor nodes close to the root of the stabilizer show delivery delay variations, which is because of the binary event generation in this area. For the damaged stabilizer (Figure 5(c) and (d)), unlike the healthy stabilizer, sensor nodes close to the damage region also have delivery delay since binary events are generated due to damage. Preliminary results demonstrate that variations in harvested energy, i.e., different ECC values did not significantly influence the delivery delay values received at the sink, confirming that the variation in harvested energy does not have a notable effect on the damage detection accuracy. An interesting point regarding these results is that the average time delivery delay of sensor nodes in the damage region is much lower than that of sensor nodes near to the wing root. This is because such sensor nodes are very close to the network sink, thus decreasing delivery delay. Therefore, the delivery delay values received at the sink would not affect the damage identification performance.

3.3 Machine learning for damage detection model

Machine learning (ML) is a major subfield in artificial intelligence dealing with the study, design, and development of algorithms that can learn from the data itself and make predictions on the data[10]. Essentially, ML refers to the capability of computers to learn without being explicitly programmed. ML in the context of structural health monitoring (SHM) is expressed as creating knowledge from previous experiences, learning the model parameters, and then focusing on predicting new input data. Different ML algorithms, including artificial neural networks (ANN)[11,12], support vector machines (SVM)[11], and *k*-nearest neighbor method (*k*-NN)[7], are attractive for structural damage identification due to their effectiveness and robustness while dealing with insufficient information, noise, and uncertainty. Diverse research studies have shown the importance of ML in SHM. It is postulated that incomplete/missing and delayed binary event data obtained from a through-substrate self-powered sensor network employing energy-aware pulse-switching protocol can be recovered by means of matrix decomposition, where the classification of the recovered noisy features is performed using PR. In regard to this, an imaged-based PR framework proposed in a previous study[7] was integrated with low-rank matrix completion and data fusion models to recover the missing data. Detailed information regarding the imputation and classification phases has been previously reported by the authors[7]. The main contribution of this study is to investigate the effect of different harvested energy and measurement noise levels, as well as various learning algorithms on the SHM approach. In this context, four harvested energy levels (see Section 3.4) were considered. The methodology and learning algorithms were implemented thru a custom program in MATLAB[9].

4. RESULTS OF DAMAGE IDENTIFICATION WITH SMART SELF-POWERED SENSING TECHNOLOGY

The FE simulation of the stabilizer wing consisted of a linear-elastic implicit dynamic analysis for 4,000 seconds with a time step of 0.1; therefore, the size of dataset was 40,000. The dataset (patterns) were then classified to 7 classes using *k*-means clustering. Classes 1 and 2 represented patterns due to normal condition of the stabilizer, classes 3 to 5 denoted the noisy patterns, and classes 6 and 7 represented patterns due to damage simulated in the stabilizer. In the present study, 85% of the data was used for training/validation and 15% was used for testing the pattern classifiers. Further, 10-fold cross validation was performed for the validation phase. Different learning algorithms, i.e., SVM, *k*-NN, and ANN were integrated within the ML methodology to assess performance of the SHM approach. A polynomial kernel was selected for the SVM analysis. Preliminary results determined the following optimum values for the SVM hyperparameters: $d = 15$, $C = 10$, and $\gamma = 20$. For the *k*-NN analysis, the optimum value of k was found to be 5, and the optimum distance was Spearman. For the ANN analysis, a three-layer (i.e., two-hidden-layers, each with 10 neurons) feed-forward neural network was considered for the simulations.

According to the proposed imputation algorithm, once the data delay matrix X is observed at the sink/data logger, the mask matrix M is computed from the original matrix, i.e., full-data matrix, using the spatial-temporal data fusion system shown in[7]. In order to determine the mask matrix, the maximum, minimum, average, and median values for the time steps at which the neighbors of sensor S_i reported a value of 1, given that the values of sensor S_i itself is 1, are computed and used to determine the four mask matrices $M1$, $M2$, $M3$, and $M4$ based on the fused information. Once the mask matrices are determined, the observed delayed matrix reported at the sink are reconstructed ($RX1$, $RX2$, $RX3$, and $RX4$) using the corresponding mask matrices ($M1$, $M2$, $M3$, and $M4$). The optimal mask matrix M and reconstructed matrix RX are the ones with the highest classification accuracy.

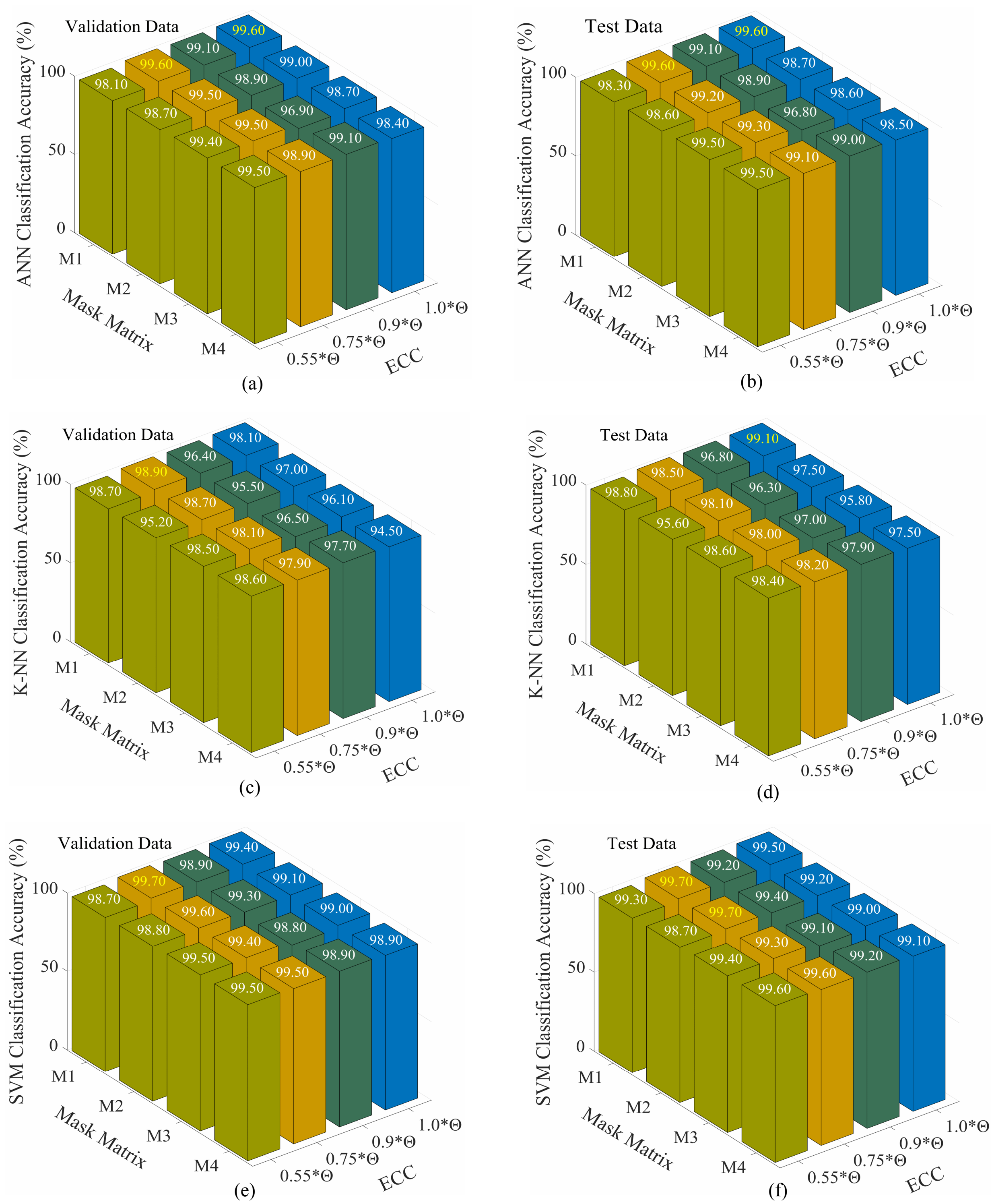

Figure 6. Damage detection accuracy for varying mask matrices and harvested energy levels on validation and test data: (a) & (b) ANN method, (c) & (d) *k*-NN method, (e) & (f) SVM method

As discussed before, the robustness of the damage detection strategy was evaluated with respect to variations in harvested energy levels using different electromechanical coupling constant (ECC) values (0.55*Θ, 0.75*Θ, 0.9*Θ, 1.0*Θ) for the piezo as part of the TUPN unit mounted on the aircraft stabilizer. To further explore the proposed SHM methodology, results of the ANN, *k*-NN, and SVM pattern classification methods with various mask matrices and harvested energy levels were determined and shown in Figure 6 for the validation and test data. A confusion matrix containing information about actual and predicted classification results using different learning algorithms was also determined and shown in Figure 7.

For the majority of the cases (see Figure 6) the minimum and average mask matrices, i.e., *M*1 and *M*2, led to the highest classification accuracies for different levels of harvested energy for all the learning algorithms. As an example, for the ANN analysis the maximum accuracies for ECC values of 0.75*Θ, 0.9*Θ, and 1.0*Θ were 99.60%, 99.10%, and 99.60% on test data, respectively, which were based on mask matrix *M*1, i.e., the minimum mask matrix (Figure 6(b)). Similarly, for the *k*-NN analysis (Figure 6(d)) the maximum classification accuracies were 98.80%, 98.50%, and 99.10% for ECC values 0.50*Θ, 0.75*Θ, and 1.0*Θ, respectively. Similar results were obtained for the SVM classification method, confirming that mask matrices *M*1 and *M*2 were the optimal mask matrices. Therefore, the confusion matrices were determined for the noted mask matrices based on the highest harvested energy level (i.e., 1.0*Θ) and shown in Figure 7.

Results indicate that the highest damage classification accuracy was based on the noted matrices, i.e., 99.60% on validation and test data for the ANN method, 98.90% and 99.10% on validation and test data for the *k*-NN method, and 99.70% for the SVM method on both datasets. Results based on ANN and *k*-NN algorithms show that the best classification accuracies on test data were 99.6% and 99.10% (based on mask matrix *M*1), respectively, for which the classification error for class 7 (damaged stabilizer) was 0.8% for both algorithms (see

Figure 7(a) and (c)). Results of the SVM algorithm, on the other hand, reveal that the highest classification accuracy on test data based on the minimum mask matrix was 99.50%, for which the classification error was 1.7% (see

Figure 7(e)). Thus, the results show that all the three ML algorithms resulted in good pattern classification accuracy, such that the highest accuracy based on SVM was 99.70% compared to the ANN (99.60%) and *k*-NN (99.10%). The pattern classification results demonstrate the good performance of the proposed damage detection strategy employing different learning algorithms in terms of identifying damage with missing and noisy features.

In order to evaluate the reliability of the proposed energy-lean SHM strategy, the validation and test data were contaminated with random noise. Noise levels of 5% to 20%, in 5% increments, were considered. The classification results using ANN, *k*-NN, and SVM methods with various noise levels for the optimal mask matrix *M*1 are presented in Figure 8. Results suggest that the damage detection model's performance on the validation and test data was affected by the increase in noise level, such that for the ANN method the minimum accuracies (90%) were achieved for all the considered ECC values when the noise level was 20%, see Figure 8(d). As can be seen from Figure 8(e), the minimum accuracy based on the *k*-NN algorithm and the same noise level was 87% for the ECC value of 0.90*Θ. Similar results were obtained for the SVM analysis, in which the minimum classification accuracy on test data was 91% (see Figure 8(f)). Results indicate that although the damage detection accuracy gradually decreased with increasing noise level, the proposed damage detection approach is still capable of identifying the damage phase even with high noise levels.

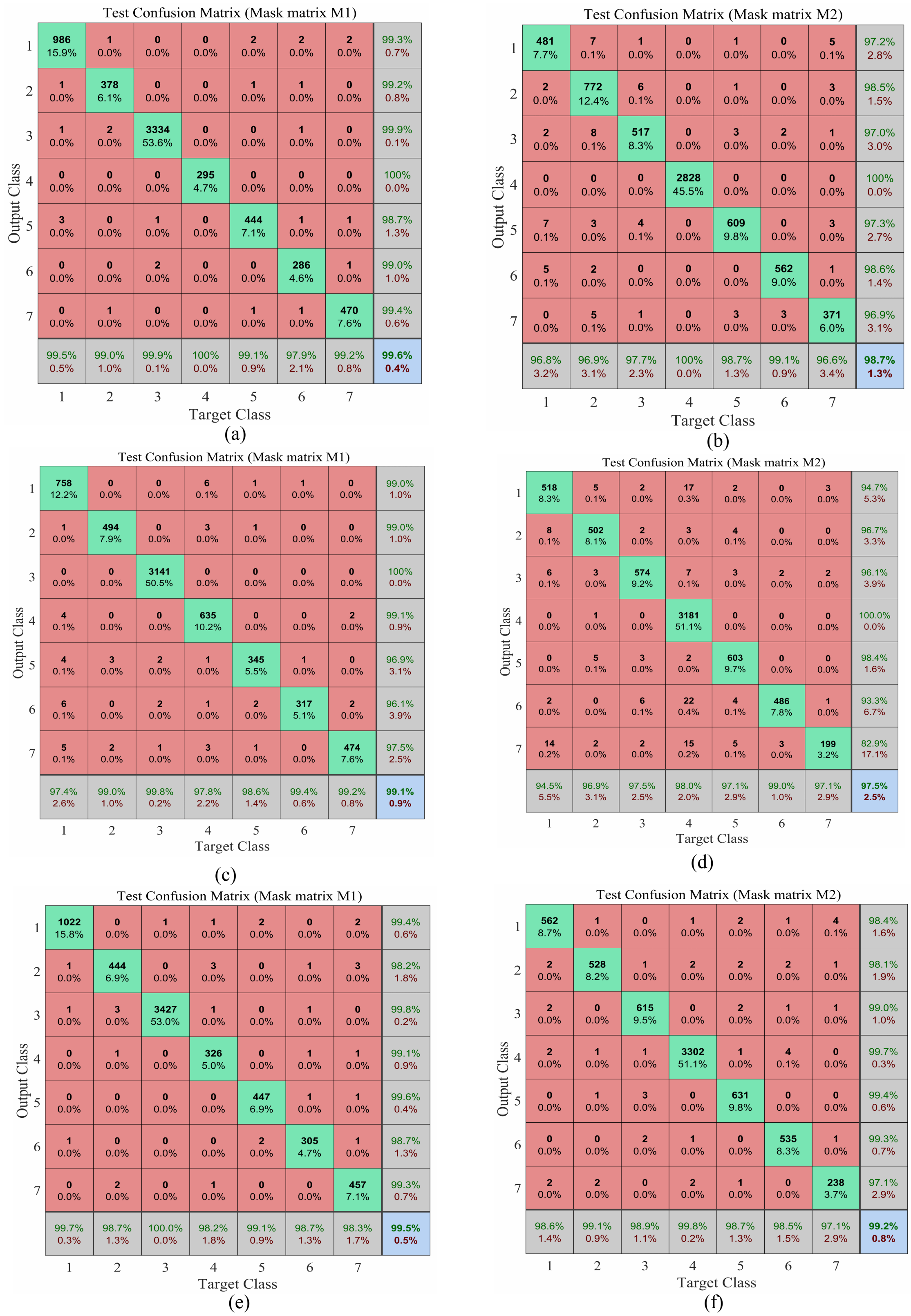

Figure 7. Confusion matrix for test data based on optimum mask matrices M1 and M2: (a) & (b) ANN method, (c) & (d) *k*-NN method, (e) & (f) SVM method

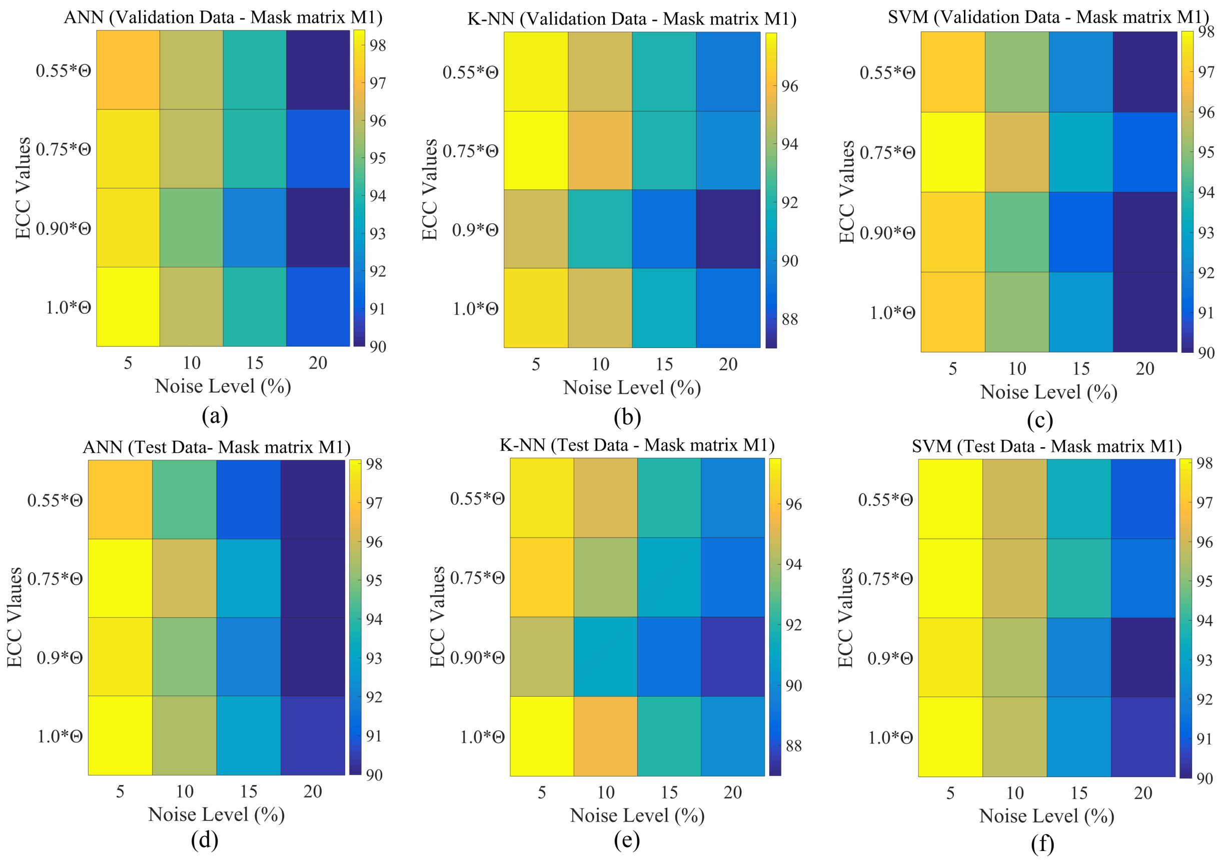

Figure 8. Damage detection accuracy for varying noise levels based on minimum mask matrix M1 and different learning algorithms: (a) to (c) Validation data, (d) to (f) Test data

5. CONCLUSIONS

This paper presented a novel methodology for structural health monitoring (SHM) employing machine learning (ML) for damage assessment in aircraft structures. The applicability of the methodology was demonstrated based on the simulation of asynchronous time-delayed and incomplete binary data from a through-substrate ultrasonic self-powered wireless sensor network employing an energy-efficient pulse switching protocol. Different ML algorithms, including support vector machine (SVM), artificial neural networks (ANN), and *k*-nearest neighbor (*k*-NN) were incorporated with the proposed learning methodology to explore the performance of the SHM approach. In addition, different levels of harvested energy and measurement noise were considered to further investigate the detection model's performance. The following conclusions were reached from the study:

1) Imputation and classification results indicate that among different mask matrices constructed within the ML methodology, the minimum and average mask matrices resulted in the highest accuracy, such that the best classification accuracy on the test data was 99.7% based on the minimum mask matrix.

2) Results suggest that the proposed energy-lean SHM method is robust with respect to varying harvested energy levels, as the delivery delay values of the sensor nodes received at the sink were not considerably affected by such variations.

3) Accuracy of the damage detection model was investigated using ANN, *k*-NN, and SVM algorithms, and damage classification results showed that all the noted algorithms led to acceptable accuracy using data with noisy and missing features.

The presented study demonstrated the applicability and effectiveness of a damage detection method employing ML and various learning algorithms for health monitoring of an aircraft horizontal stabilizer with time-delayed data. It is noted that the focus of the presented study was on the performance evaluation of the learning algorithms in terms of damage classification accuracy. Nevertheless, the reliability of the proposed SHM approach with respect to other aspects needs to be investigated in future studies. Further, the focus of on-going studies is the verification of the proposed methodology in full-scale experiments using an integrated self-powered sensor with the energy-aware pulse switching protocol.

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