ABSTRACT

The development of resilient extraterrestrial habitats necessitates a health management system (HMS) capable of accurately detecting and diagnosing faults while swiftly responding to hazardous disturbances, such as micrometeoroid impacts and fire scenarios. As a critical component of this system, structural health monitoring (SHM) enhances resilience and situational awareness, ensuring the habitat's safety and nominal operation. This work advances artificial intelligence (AI)-driven and physics-informed SHM technologies, with a focus on structural damage identification and sensor fault detection and accommodation, enhancing their applicability to real-world engineering challenges. A supervised damage detection approach is developed and integrated into a modular coupled virtual testbed (MCVT), where a finite element model (FEM) generates training data. However, accurately modeling real-world structures remains challenging due to model simplifications and uncertainties in material properties and boundary conditions. To address this limitation, an unsupervised anomaly detection framework is introduced. This framework integrates autoencoders (AEs) trained on continuous wavelet transforms (CWTs) and employs active sensing and information theory to enhance robustness against structural uncertainty and measurement noise. While unsupervised learning is effective for anomaly detection, it may struggle with precise damage localization. To overcome this issue, a physics-informed machine learning (PIML) approach is proposed, incorporating deep autoencoder-based anomaly detection followed by a physics-informed domain adaptation strategy. Physical constraints are enforced through a convolutional neural network (CNN) pre-trained to predict frequency response functions (FRFs), with the pre-trained CNN's weights used to initialize a discriminator-free adversarial learning network (DALN). This PIML framework serves as a robust digital twin of the actual structure, enhancing generalization and improving damage localization performance. High-quality sensor measurements are essential for the HMS to effectively perform fault detection and diagnosis. However, sensors in deep-space habitats may degrade or sustain damage due to the harsh operating environment. To mitigate this challenge, a convolutional autoencoder (CAE)-based approach is developed and integrated into the MCVT, enabling effective detection of temperature and pressure sensor faults under micrometeorite impact and fire sce-

narios. Furthermore, to impute missing data from faulty sensors, a time-frequency-informed stacked long short-term memory (LSTM)-based generative adversarial network (GAN) is proposed, enabling accurate reconstruction of missing data in both the time and frequency domains. The proposed artificial intelligence-driven and physics-informed SHM technologies offer a scalable and robust solution for SHM in extraterrestrial habitats, with potential applications in smart infrastructure monitoring on Earth.