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Actively Managed Battery Degradation of Wireless Sensors for Structural Health Monitoring

Tahsin Afroz Hoque Nishat *[a], Jong-Hyun Jeong[a], Hongki Jo[a], Qiang Zhou[b], Jian Liu[b]
[a]Dept. of Civil and Architectural Engineering and Mechanics, University of Arizona, AZ, USA;
[b]Dept. of System and Industrial Engineering, University of Arizona, AZ, USA

ABSTRACT

The battery-powered wireless sensor network (WSN) is a promising solution for structural health monitoring (SHM) applications because of its low cost and easy installation capability. However, the long-term WSN operation suffers from various concerns related to uneven battery degradation of wireless sensors, associated battery management, and replacement requirement, and ensuring desired quality of service (QoS) of the WSN in practice. The battery life is one of the biggest limiting factors for long-term WSN operation. Considering the costly maintenance trips for battery replacement, a lack of effective battery degradation management at the system level can lead to a failure in WSN operation. Moreover, the QoS needs to be ensured under various practical uncertainties. Optimal selection with a maximal number of nodes in WSN under uncertainties is a critical task to ensure the desired QoS. This study proposes a reinforcement learning (RL) based framework for active control of the battery degradation at the WSN system level with the aim of the battery group replacement while extending the service life and ensuring the QoS of WSN. A comprehensive simulation environment was developed in a real-life WSN setup, i.e. WSN for a cable-stayed bridge SHM, considering various practical uncertainties. The RL agent was trained under a developed RL environment to learn optimal nodes and duty cycles, meanwhile managing battery health at the network level. In this study, a mode shape-based quality index is proposed for the demonstration. The training and test results showed the prominence of the proposed framework in achieving effective battery health management of the WSN for SHM.

Keywords: Wireless Sensor Network (WSN), Structural Health Monitoring (SHM), Battery Health Management, Quality of Service (QoS), Reinforcement Learning (RL)

1. INTRODUCTION

A major evolution from wired to wireless sensing technology in structural health monitoring (SHM) has occurred in recent decades due to the advancements in the Internet of Things (IoT). Battery-powered wireless sensor network (WSN) has the advantages of being a low-cost solution and having easy installation capability for SHM in comparison to wired methods. However, the limited battery life, even for rechargeable solutions, hinders the widespread use of WSNs in real practice. Indeed, effective battery management becomes one of the most important control factors in the long-term operation of the WSNs. Battery depletion can vary depending on various factors such as usage patterns, environmental conditions, and faulty operation of sensor/battery/charger which impacts the reliability and sustainability of the WSNs. An advanced battery management strategy is needed to ensure the desired and longer operation of WSNs in a cost-effective manner.

There has been substantial research going on in battery health management for WSNs. Analytical battery modeling approaches have been studied to predict the batteries' state of health (SoH) and state of charge (SoC) based on the number of charge or discharge cycles, internal resistance, voltage, temperature, etc., [1],[2]. Battery health has been monitored in real-time by measuring the battery's voltage or current and estimating SoH and SoC to provide an alert when it's time for replacement [3],[4],[5]. Battery optimization techniques have been investigated to increase the lifetime of batteries and to reduce energy consumption by controlling the duty cycle, sensor topology, energy harvesting scheme, etc. [6],[7],[8]. Implementation of solar energy harvesting WSN with a duty cycle strategy (i.e. low-power sleep mode, idle mode, or fully active mode with maximal power usage) has been proven to increase the functionality of the network with longevity.

The end-of-life time of each sensor's battery can differ depending on the assigned workloads, battery charging rate, communication uncertainties, spatial location of the sensor node in the network, etc. The batteries that reached their end-of-life time need to be replaced in a timely manner to maintain the desired operation of the WSNs. However, it poses a great challenge during its replacement. The replacement of batteries requires huge efforts (i.e. traveling, scheduling, and logistics of equipment and personnel), particularly for WSNs deployed in remote and hard-to-reach locations. To reduce

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such expensive efforts, group replacement of batteries is often a preferred option, i.e. replacing all batteries in one maintenance trip instead of replacing one or just a few depleted batteries. Previous studies on battery health management mostly focus on improving individual-level battery health rather than system-level battery management. There has not been a systematic study on system-level battery management aiming for such group replacement.

In recent years, reinforcement learning (RL) based system-level energy management (e.g. optimal resource allocation, energy-efficient communication, routing selection, etc.) in WSNs are being explored due to its prominence compared to other traditional approaches [9],[10],[11]. RL is an area of machine learning where an intelligent agent takes actions in a simulated environment and learns the optimal policy by trial-and-error process over time. In the context of battery health management of WSNs in SHM, an agent can learn the optimal battery charging and discharging policies by considering the battery's state (e.g. remaining battery life, energy harvesting rate, etc.,) and operational requirements (i.e. quality of service). A new RL agent has been proposed as a centralized power manager in a solar energy harvesting WSN [12]. In the study, a comprehensive simulated environment has been developed to model the harvested and consumed energy at each node, wireless connectivity for a WSN, and the agent is trained to utilize a double deep-Q network (DDQN) algorithm. Even though the DDQN agent showed improved performance over 'greedy' and 'eno' agents, focusing on extending the lifetime of as many as batteries, the group replacement of batteries or the quality of service (QoS) of the sensor network has not been considered in the study.

The efficacy of a WSN depends on how well it meets the user specific desired QoS needs in a cost-efficient manner. A practical WSN deployed in the field is expected to maintain the minimal QoS for different node configurations which are achieved either through hardware or algorithms or both. Various definitions of the QoS can be made depending on the WSN applications, For SHM applications for critical civil structures, the WSN-measured structural response data can be used to identify the dynamic characteristics (e.g., natural frequencies, mode shapes, damping, etc.,) of the structure. Indeed the quality of such identified information from the WSN can define a QoS index. Of course, depending on the number and location of the active sensor nodes, the accuracy/quality of the identified system properties can vary. While adaptively controlling the duty cycle of the sensor nodes, maintaining the desired QoS throughout the service life of the network regardless of such uncertain sensor node configuration is crucial.

This study investigates to develop a reinforcement learning (RL) based framework for active control of the battery degradation for WSN at the system level with the aim of the battery group replacement while extending the service life and ensuring the desired QoS of WSN.

2. WIRELESS SENSOR NETWORK MODELING

In this study, a realistic sensor configuration is simulated. For this purpose, the Jindo bridge (a twin cable-stayed bridge situated in South Korea) is considered. It consists of 113 sensor nodes with high-sensitive accelerometers (SHM-H), strain sensors (SHM-S), and anemometers (SHM-DAQ). The south side of the bridge (i.e., Jindo side) has a total of 57 sensors whereas the north side (i.e., Haenam side) has 56 sensors. Preliminarily, only 30 sensors on the deck of the Jindo side of the bridge have been considered for simplicity. Figure 1 shows the full configuration of the WSN of the bridge.

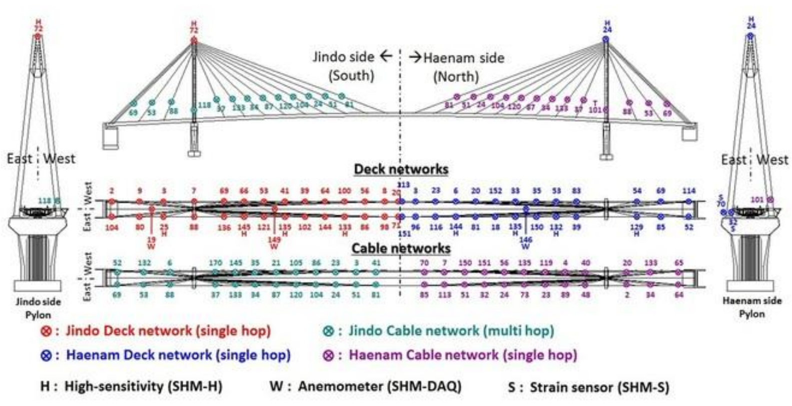


Figure 1 Sensor locations of Jindo Bridge [13]

Each of the sensor nodes consists of a means of harvesting solar energy, a physical sensor, a rechargeable battery, a radio, and a processor. Battery health at each node depends on the harvested energy, consumed energy, communication between different channels, operational status, etc. To model battery level at a particular time step, each of the parameters needs to be defined. A detailed description of all the parameters and quality of service index is provided in the following sections.

2.1 Harvested energy

Each battery is rechargeable with solar power. The harvested solar energy varies each day of the year depending on the weather, location of the WSN, and geometry of the network. To incorporate solar power variability in the developed environment depending on weather, the solar profile is generated from 2016 to 2020 using System Advisor Model (SAM). This data is generated for the Jindo bridge region with 0 deg. tilt and 3-Watt maximal power storage capability of solar panels using 3 hours time intervals. To incorporate solar power variability due to spatial variations of the nodes, the harvested energy at a particular node can be expressed as the following function of averaged harvested energy ($E\mu_{t_k}$ found from SAM model) and perturbation of the random field at the location of a particular sensor at time t_k.

$$Eh_{t_k} = E\mu_{t_k}(1 + Y) \tag{1}$$

A detailed description of the harvested energy can be found in [12]. Using the equation, the solar harvesting variation (with 15% uncertainty) has been modeled for 30 sensor nodes as shown in Figure 2.

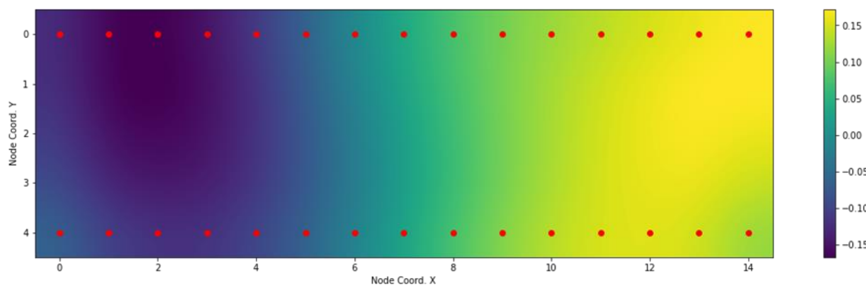


Figure 2 Solar harvesting variability for 30 nodes

2.2 Wireless connectivity

Local peer-to-peer communication between the two channels has some uncertainties which need to be included in the model. Without a connection being successful, the node status change command cannot be performed. The soft geometric model described in [14] provides a realistic model of network connectivity. The connection probability (H_{ij}) between the i and j node can be expressed as a function of a distance-independent parameter β (usually 1), Euclidean distance(r_{ij}) between node i and j, range parameter (r_0) and signal decay over distance (η).

$$H_{ij} = \beta.exp(-(\frac{r_{ij}}{r_0})^{\eta}) \tag{2}$$

2.3 Energy consumption

Each node has a fixed and identical battery capacity which can be denoted as B_{max}= 3000 mW. For a discrete time interval of 3 hours, each time slice can be denoted as t_k for which the node status is X_i (here, i=0 for active mode, i=1 for idle mode, and i=2 for sleep mode). Depending on the node status, the power consumption of each node varies. The consumed power is selected based on the power consumption rate of the MEMS accelerometer. The consumption rates are 0.4 mW, 170.2 mW, and 425.5 mW respectively during sleep, idle, and active mode. The battery level ($B_{t_{k+1}}$) at time t_{k+1} can be calculated as a function of remaining battery (B_{t_k}), harvested energy (Eh_{t_k}), and consumed energy (Ec_{t_k}) at t_k.

$$B_{t_{k+1}} = B_{t_k} + Eh_{t_k} - Ec_{t_k} \tag{3}$$

2.4 Rain flow counting

A rain flow cycle counting algorithm [15] is incorporated into the model. The algorithm is commonly used to calculate the fatigue life of a component under sequentially varying stress. In this study, this algorithm is used to calculate the life cycle of batteries and to ensure a uniform life cycle based on the cycle count.

2.5 Quality of service index for SHM

The quality of the estimated mode shape from the response data of the active sensors of the WSN is considered a system-level quality index. The first quality indicator of mode shape is the modal assurance criteria (MAC) to measure the consistency (i.e. degree of linearity) between the estimated and expected mode shape. The second quality indicator is the modal scale factor (MSF) to provide a measure of bias considering the magnitude and phase difference of mode shape. MAC and MSF can be obtained from mode shape vectors by using the following equation (4) and (5).

$$MAC\ (r,s) = \frac{\left|\sum_{L=1}^{p}(\varphi_L^r)(\varphi_L^s)^*\right|^2}{(\sum_{L=1}^{p}(\varphi_L^r)(\varphi_L^r)^*)(\sum_{L=1}^{p}(\varphi_L^s)(\varphi_L^s)^*)} \tag{4}$$

$$MSF_{cd}^r = \frac{\sum_{L=1}^{p}(\varphi_{cL}^r)(\varphi_{cL}^r)^*}{(\sum_{L=1}^{p}(\varphi_{dL}^r)(\varphi_{dL}^r)^*)} \tag{5}$$

Here, φ^r and φ^s denote r^{th} and s^{th} mode shape vectors respectively, p is the degrees of freedom, c is the estimated mode vector and d is the reference mode vector.

To make a comparison in terms of MAC and MSF for a particular sensor configuration, a reference mode shape needs to be obtained first. For this study, simulated acceleration response data from 30 sensor nodes (15 on either side) is used. The response is obtained from a numerical model of a simply supported bridge which is 80 feet long and 20 feet wide. Each of the 15 sensors is evenly spaced at 5 feet distance. The considered moment of inertia is 100 in^4, the modulus of elasticity is $6.58x10^6$ psi and the mass density per unit length is $lb.sec^2/in/in$. Acceleration response is simulated from a random excitation (i.e. ambient vibration) for a 180-second duration with a 512 Hz sampling rate. 5% measurement noise is added to the signal. Then an output-based modal analysis is carried out to obtain the reference mode shape from 15 nodes. Up to mode shape vector 5 is considered for the analysis.

Using equations (4) and (5), 5x5 MAC and 5x5 MSF matrix can be obtained from the reference and an estimated mode shape Here, the diagonal elements denote the correlation between the same mode no. and the values need to be close to 1. The off-diagonal elements denote the correlation between different mode no. and the values should be close to 0. The more accurate the estimated mode shape is, the more accurate values we get from the MAC and MSF matrix. Accuracy in the estimation depends on the number and location of the active sensors.

To decide on the desired threshold of the MAC and MSF values, rigorous modal analysis is carried out. For a particular number of sensors, an optimal configuration of the active nodes can be obtained by using the traditional iterative effective independence (EI) algorithm [16]. Using different sensor configurations and comparing them with an optimal sensor configuration, it is found that diagonal elements of the MAC matrix are close to 0.95 and off-diagonal elements are close to 0.01. On the other hand, the average error in diagonal elements of the MSF matrix is close to 0.06 and the average error in off-diagonal elements is close to 0.1. Based on the analysis, the desired thresholds for diagonal elements of the MAC and MSF matrix are selected to be 0.95 and 0.9 respectively. In other words, if we can achieve this threshold with a sensor configuration, that configuration is an optimal or expected sensor configuration.

3. REINFORCEMENT LEARNING ALGORITHM

A reinforcement Learning (RL) based framework is developed for the described WSN to actively control the battery health of each sensor node. A formal RL is modeled as Markov Decision Process (MDP) [17] which consists of an agent or learner, an environment the agent interacts with, a transition model the agent follows to take an action, and a reward function the agent observes upon taking an action. In this model-based algorithm, an agent can make predictions of the next state and the next reward by learning the model of the environment. The goal of this framework is to make the agent learn the optimal policy by maximizing the rewards. However, in the real world, the dynamics of the environment may not be known beforehand. In this case, we need to use a model-free algorithm.

There are mainly three types of model-free algorithms: value-based (e.g. Q-learning), policy-based (e.g. Policy gradient), and both (e.g. Actor critic). A value-based algorithm learns the optimal policy by estimating the value function at each state whereas a policy-based algorithm explicitly represents a policy from a state-action pair at each step. An actor-critic can exploit the benefit of both value-based and policy-based algorithms and is faster and more robust. This algorithm is adopted in the current study due to its recent success in network optimization [18],[19],[20].

The model can be defined by a set of states (S), a set of actions (A), and a reward model (R). For example, the agent can earn a reward (R_a) while transitioning from one state (s) to another (s') by taking a certain action (a). The states at each node observed are the remaining battery percentage, current node status, percent battery difference at the current time step, and battery cycle. The actions are defined as active, idle, and sleep status. Finally, the reward function is modeled as the following equation:

$$Reward = 0.9 \times (average\ diagonal\ MSF\ magnitude) + average\ diagonal\ MAC - 0.06 \times standard\ deviation\ of\ active\ node\ counts \tag{6}$$

The reward function modeled is critical to ensure uniform battery degradation and desired quality of service in terms of MAC and MSF scores.

4. RESULTS

The developed model is trained for 5000 episodes with each episode consisting of 240 steps. Each time step is a 3 hours time slice which means each episode consists of 30 days of data. The solar profile data from 2016 to 2019 is used during training whereas the 2020 data is separated to use for testing the model. The training results are shown in the following sections:

4.1 Episode score

The learning curve of the agent is shown in Figure 3. The defined performance metric is the episode score (i.e., cumulative rewards) throughout episodes. As the training progresses, the episode score increases which indicates the improved performance of the agent.

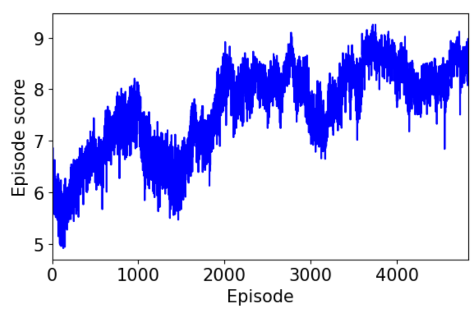
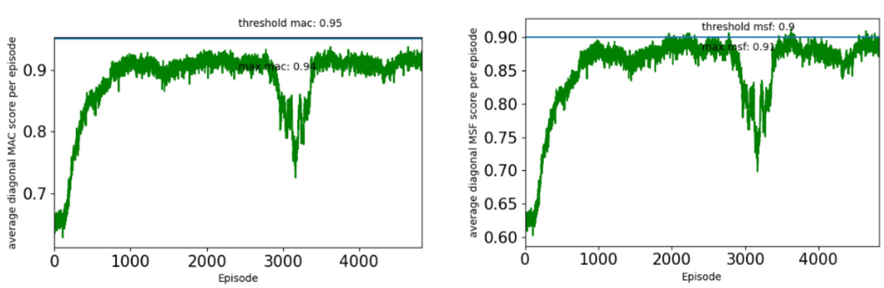


Figure 3 Episode score vs. episode

4.2 MAC and MSF score

The MAC and MSF scores are indices to evaluate the quality of service of the network selected at a particular time step. The RMS average of diagonal MAC and MSF (magnitude) at each episode (i.e. 240 time steps) are plotted in Figure 4. It is found that the score is increasing over the episodes which means the improved quality of the network. The desired MAC score for a particular network is 0.95 whereas the obtained MAC score at the last episode is 0.94. On the other hand, the desired MSF score is 0.9 whereas the obtained MSF score at the last episode is 0.91.



a. MAC score b. MSF score

Figure 4 MAC and MSF score vs Episode

4.3 Node count

The node count at the last episode for all channels at different statuses in Figure 5 shows the variation of duty cycle among 30 channels. The goal during training was to minimize the standard deviation among these node counts which will ensure uniform duty cycle and uniform battery life among all channels. The obtained standard deviation of active node counts at 30 channels is 0.06 during the last episode.

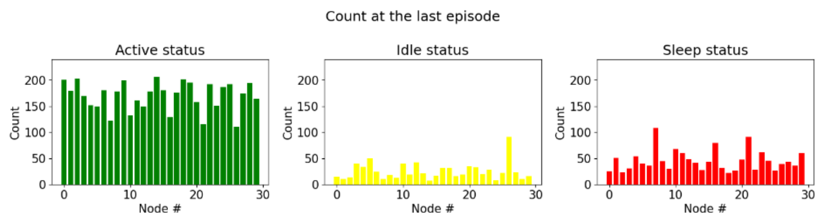


Figure 5 Node status count at the last episode

4.4 Battery level

The maximum battery level for each node is 3000 mW and the minimum allowed battery level beyond which a sensor should not operate is 400 mW. After reaching the maximum battery level, the battery should degrade uniformly. Figure 6 shows the battery level variation of sensor node 3 in the last episode. It can be seen the battery level, for most of the duration, degrades uniformly over time.

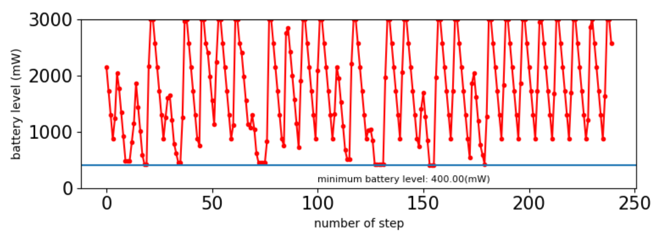


Figure 6 Battery level for node 3 at the last episode

4.5 Mode shape at the last step

Figure 7 shows the obtained sensor node configuration for 30 nodes in the last episode. Based on the number of active nodes and locations, the third mode shape of the simulated simply supported bridge is obtained. The obtained mode shape is shown in Figure 8.

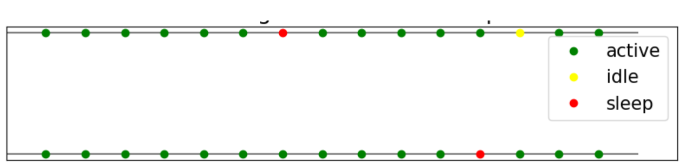


Figure 7 Sensor node configuration at the last step

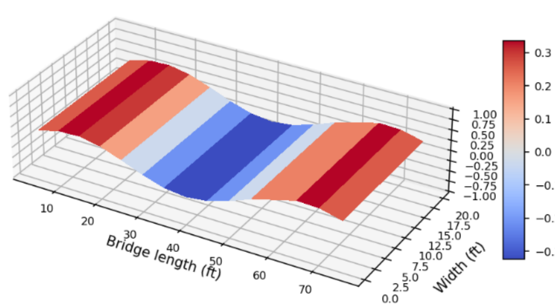


Figure 8 Obtained mode 3 from the active node configuration at the last step

5. CONCLUSIONS

This study proposes an RL framework to actively control the battery health of a WSN, focusing on SHM applications. The main goal is to make group replacements of batteries feasible to minimize associated maintenance efforts while ensuring the desired quality of service in terms of the mode shapes of the target structure. A realistic WSN environment is simulated in the model considering solar energy harvesting variability due to weather conditions and spatial variation, wireless connectivity uncertainty. Moreover, MAC and MSF threshold is defined to ensure the desired quality of the identified mode shapes. The actor-critic RL algorithm is selected to train the model. The training result shows the improved performance of the agent over the episodes. It is found that the MAC and MSF scores are close to the desired threshold, and the standard deviation of the active nodes at the last episode is around 0.06. approximately uniform battery degradation happens in the last episode.

The results obtained show the prominence of the developed framework in managing battery health with a sufficient quality of service. Future research will be carried out to improve the performance of the agent by updating the reward function or observed states, by adding more layers to the neural network with an increased period of training. The full WSN configuration of the Jindo bridge will also be included in the model.

The prospect of the developed framework is that it can become economically feasible by achieving similar end-of-life times for all the batteries and by activating only optimal sensor nodes. The framework, although developed based on structural health monitoring applications, can be implemented in varieties of wireless IoT applications.

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