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# Fuzzy Control Model for Structural Health Monitoring of Civil Infrastructure Systems

Abayomi M. Ajofoyinbo and David O. Olowokere
*Department of Engineering, Texas Southern University, Houston, Texas77004, USA*

**Abstract:** This paper presents a Fuzzy Control Model for SHM (Structural Health Monitoring) of civil infrastructure systems. Two important considerations of this model are (a) effective control of structural mechanism to prevent damage of civil infrastructure systems, and (b) energy-efficient data transmissions. Fuzzy Logic is incorporated into the model to provide (a) capability for handling imprecision and non-statistical uncertainty associated with structural monitoring, and (b) framework for effective control of the mechanism of civil infrastructure systems. Moreover, wireless smart sensors are deployed in the model to measure dynamic response of civil infrastructure systems to structural excitation. The operation of these wireless smart sensors is characterized as discounted SMDP (Semi-Markov Decision Process) consisting of two states, namely: sensing/processing and transmitting/receiving. The objective of the SMDP-based measurement scheme is to choose policy that offers optimal energy-efficient transmission of measured value of vibration-based dynamic response. Depending on the net magnitude of measured dynamic responses to excitation signals, data may (or may not) be transmitted to the Fuzzy control segment for appropriate control of the mechanism of civil infrastructure systems. The efficacy of this model is tested via numerical analysis, which is implemented in MATLAB software. It is shown that this model can provide energy-efficient structural health monitoring and effective control of civil infrastructure systems.

**Keywords:** Structural health monitoring, fuzzy control, semi-Markov decision process, wireless sensors, civil infrastructure systems.

## 1. Introduction

A Fuzzy Set can be defined as a class of objects with a continuum of grades of membership and characterized by a membership function which assigns to each object a grade of membership ranging between 0 and 1. Fuzzy Logic defines modes of reasoning which are inexact rather than precise or exact. It is based on the notion of Fuzzy Sets Theory which provides a natural way of dealing with problems in which the source of imprecision is the lack of sharply defined criteria of class membership rather than the presence of randomness [1]. Fuzzy Sets Theory and Fuzzy Logic have been proven to have wide scope of applicability in engineering, oil and gas, medicine, biomedical instrumentation, decision analysis, etc. For example, in an earlier paper we presented the development of an embedded fuzzy controller for the case of triangular and Gaussian membership functions [2]. In another interesting contribution, we presented a new 3-layer Neuro Fuzzy network theory to detect the occurrence of off-specification gas in a natural gas supply/distribution network [3]. Moreover, Kamel [4] developed a new Fuzzy modeling and control strategy of random disturbances based on estimated margin of variations of state variables of a studied power system as affected by such random disturbances.

SHM (Structural Health Monitoring) of CIS (Civil Infrastructure Systems) provides a means for estimating structural state and detection of structural changes that affect the performance of civil infrastructure systems. Researchers have investigated challenges of SHM using WSSN (Wireless Smart Sensor Networks) with different objectives. For example, Sim et al. [5] developed an efficient means

**Corresponding author:** Abayomi M. Ajofoyinbo, Ph.D, research fields: intelligent control, embedded systems, wireless communications and wireless sensor networks. E-mail: ajofoyinboa@tsu.edu.

of autonomous long-term monitoring of cable tension using Imote2 Smart Sensors from MEMSIC Inc. The monitoring system featured autonomous operation, sustainable energy harvesting, power consumption, and remote access using the internet. Park et al. [6] developed a new displacement sensing system by incorporating wireless sensor technology with the multi-metric data-based algorithm. This system could address the difficulties and issues found in the traditional sensing system to realize a practical means of measuring displacement in full-scale bridge. In an interesting contribution, Li et al. [7] presented a post-sensing time synchronization scheme to reduce the latency of data collection while maintaining high accuracy of synchronization of collected data. A multi-hop bulk data transfer approach using multiple radio frequency channels was also implemented to achieve high data throughput. Moreover, Sim et al. [8] and Sim et al. [9] investigated decentralized RDT (Random Decrement Technique) for efficient data aggregation and system identification in wireless smart sensor networks. These papers presented a new decentralized data aggregation approach for system identification based on the random decrement technique. The efficacy of the RDT-based method was demonstrated experimentally in terms of the required data communication and accuracy of identified dynamic properties using the Imote2 smart sensor platform based on the Illinois SHM project service Toolsuite. An opened-source framework for SHM using the design principles of service-oriented architecture was developed by Rice et al. [10], which provides a suite of services implementing key middleware infrastructure necessary to provide high-quality sensor data and to transport it reliably across the sensor networks. Jo et al. [11] presented the development of hybrid wireless smart sensor network to achieve a full-scale SHM system for civil infrastructure monitoring. This hybrid system provides (a) power harvesting enabled for all sensor nodes, (b) improved sensing application, (c) decentralized data aggregation, and (d) environmental monitoring. For large civil infrastructure systems, SHM systems that are based on wireless smart sensors offered many advantages over the traditional wired sensor systems [12, 13]. The measurement of structural dynamic responses can be achieved with an instrumentation system handling the sensing. Acceleration, velocity and displacement are the most common types of measurement for dynamic response. Many features can be used to characterise a structure. For example, acceleration time history measured by accelerometers mounted on the civil infrastructure system can be used as a feature. SHM system is indeed a decision system that has sensors at the front-end and knowledge-base at the backend. On the one hand, the MDP (Markov Decision Process) models sequential decision making when outcomes are uncertain. Choosing an action in a state generates a reward and determines the state at the next decision epochs through a transition probability function. Policies are prescription of which action to choose at every future decision epoch. Moreover, decision epochs are points in time when a system executes action. On the other hand, in SMDP (Semi-Markov Decision Process), decision epochs follow each state transition and the times between decision epochs are exponentially distributed. Researchers have characterized systems process as MDP and SMDP models, and investigated optimal policies in different problem domains. For example, Kim et al. [14] investigated MDP-based admission control for multicast streaming services in wireless mobile networks. Moreover, Ajofoyinbo and Olowokere [15] characterized the operation of wireless smart sensors deployed in structural health monitoring of civil infrastructures as SMDP.

The rest of the paper is organized as follows. Related research is presented in Section 2. Motivation and problem formulation are presented in Section 3. Problem solution is discussed in Section 4. Numerical analysis and discussion of results as well as contributions of the research are presented in Section 5. Section 6 concludes the paper.

## 2. Related Research

He et al. [16] presented an IMPSO (inter-encoding multi-swarm particle swarm optimization) algorithm to place multi-axial sensors optimally on large structures for modal identification. The method merges a fitness function that considers the spatial correlation with an IMPSO algorithm for optimal multi-axial sensors placement for large structure. Park et al. [17] presented a WSSN-based decentralized processing scheme for damage detection of building structures. The paper adopted DI-ID (Damaged Induced Inter-story Deflection) proposed by Koo et al. [18] and extended the methodology to be used in a decentralized computing environment in the WSSN. Moreover, Fu et al. [19] investigated the problem of finding node locations to reliably diagnose the health of a structure while consuming minimum energy during data collection. Sendra et al. [20], also presented power saving and energy optimization techniques for wireless sensor networks. In an interesting contribution, Nagayama et al. [21] presented two complementary reliable multi-hop communication solutions for monitoring of civil infrastructure, namely: (1) the general purpose multi-hop, and (2) the single-sink multi-hop. Whereas the first is an adaptable any-to-any communication protocol, the second is an efficient many-to-one protocol utilizing all available radio frequency channels. Jo et al. [22] considered the problem of data congestion and excessive use of power while transmitting large amount of data generated by large array of wireless smart sensors due to limited bandwidth of wireless communication. Moreover, Nagayama et al. [23] demonstrated the use of a limited number of high-sensitivity reference sensors to reduce the effect of noise in estimation of cross-correlation functions. The global nature of the vibrational characteristics of interest to vibration-based SHM provides advantages compared to the other monitoring technique [24]. Modal parameters of the structure, such as natural frequency, damping, mode shape and its derivatives can also be used as features. The basic properties of vibration-based structural health monitoring are that changes of structural properties, such as mass, stiffness and damping, will affect the vibrational response of the structure. It is noted that the two aspects of vibration-based damage detection are (a) identification and extraction of vibration-related features, and (b) correlation of features to the structural properties. Two different states are compared, in which one state is defined as the “baseline” state. All subsequent states are compared to this “baseline” (or “undamaged”) state. Most SHM papers in the existing literature tend to focus on data collection, data aggregation and sensors placement. In this paper, a new approach is presented to address the challenges of energy efficiency in data transmissions in structural health monitoring and control of civil infrastructure systems.

## 3. Motivation and Problem Formulation

Motivations for this research and problem formulation are presented in Sections 3.1 and 3.2 respectively.

### *3.1 Motivations for this Research*

This research is motivated by the following factors:

(1) The need for decision framework which will result in energy-efficient transmissions of average power dissipated by measured signal.

(2) The need to use (1) as a basis for control of the mechanism of civil infrastructure systems, to prevent structural damage.

### *3.2 Problem Formulation*

The example of civil infrastructure systems considered in this paper is a Dam, in which wireless smart sensors are deployed on the barrier (Fig.1) to measure its structural response to excitation. Gateway nodes are strategically installed around the Dam (barrier) in a manner that the smart sensor nodes can transmit in single-hop to nearest gateway nodes. However, with the implementation of energy-efficient routing protocol [25], this framework can be applied to general wireless sensor network topologies and multi-hop transmissions.

Let $k_1(t)$ denotes the "baseline" structural response of the civil infrastructure system to excitation. Sensors measurement may come with useful and noise components. For the "baseline" response, useful response is denoted as $s_1(t)$ and noise component denoted as $n_1(t)$. Similarly, let $k_2(t)$ denotes subsequent dynamic response measured by a wireless smart sensor, which also consists of useful component $s_2(t)$ and associated noise component $n_2(t)$. Thus, the following models for baseline and subsequent measured dynamic responses are defined.

$$k_1(t) = s_1(t) + n_1(t). \tag{1}$$

$$k_2(t) = s_2(t) + n_2(t). \tag{2}$$

It is assumed in this paper that $n_1(t)$ and $n_2(t)$ are negligible, and may not significantly affect the actual measured signal. Hence, $n_1(t) = 0$ and $n_2(t) = 0$. The value of a signal can be modeled by the energy contained in that signal. Thus, the average power dissipated by signals $k_1(t)$ and $k_2(t)$ during the time interval $a \le t \le b$ can be defined as:

(i) Baseline signal (i.e., undamaged state of civil infrastructure systems)

$$h_1(t) = \frac{1}{(b-a)} \int_a^b |k_1(t)|^2\, dt. \tag{3}$$

(ii) Subsequent measured dynamic response to excitation

$$h_2(t) = \frac{1}{(b-a)} \int_a^b |k_2(t)|^2\, dt. \tag{4}$$

In Eqs. (3) and (4), $h_1(t) > 0$ and $h_2(t) > 0$ denotes average power dissipated by the baseline dynamic response and the subsequent measured dynamic responses to excitation respectively. Accordingly,

$$h_{net}(t) = h_2(t) - h_1(t) \quad ; \quad h_{net}(t) > 0. \tag{5}$$

where $h_{net}$(t) is the net average power dissipated by the signals.

The schematic diagram of the operational sequence of the SHM system is presented in Fig. 2. Moreover, the operational sequence of the structural health monitoring and control model consists of two segments, namely: (a) SMDP, and (b) Fuzzy control and actuation of the mechanism of civil infrastructure systems. Wireless smart sensors are deployed in the SMDP segment to measure the response of civil infrastructure systems to excitation. Thereafter, the embedded computing element of the smart sensor nodes compute average power dissipated by the

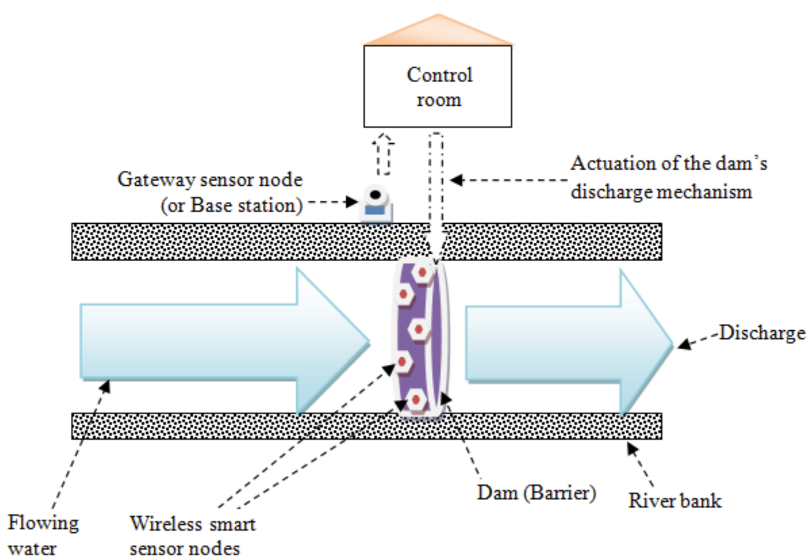


**Fig. 1 Schematic representation of sample sensors deployment on a Dam.**

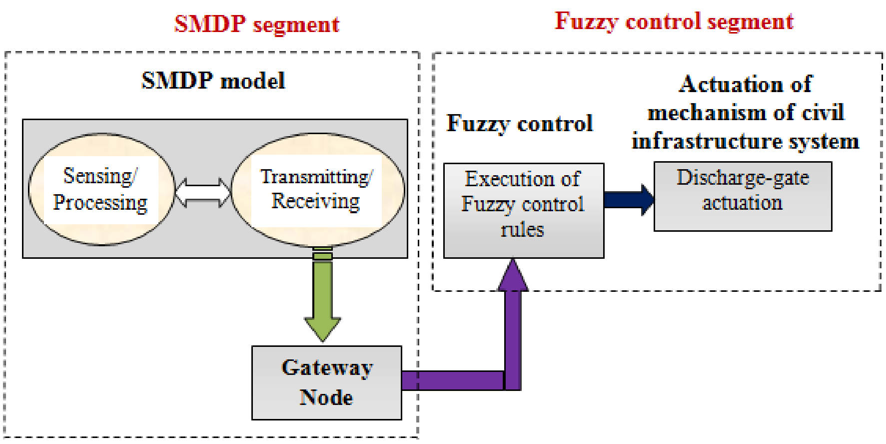


**Fig. 2 Schematic diagram of the operations of the SHM system.**

measured signals. Next, the measured signal is compared with baseline dynamic response. Wireless smart sensors subsequently make decision on whether transmission of measure data to a gateway node (or base station) is necessary. In order to achieve continuous monitoring, large amount of data may be generated by the wireless smart sensors; but not all data generated by these instrumentation systems at all times are high enough to require transmission across networks. SHM applications for civil infrastructure systems should progressively escalate when measurement values exceed baseline value. It is noted that wireless smart sensor nodes consist of radio, embedded computing, data storage and local power modules. The radio subsystem however consumes more energy than the other subsystems.

3.2.1 SMDP Model

The operation of the wireless smart sensor nodes is characterized as discounted SMDP. SMDP is an example of a continuous-time Markov decision model. In this model, decision epochs follow each state transition and the times between decision epochs are exponentially distributed [26, 27]. SMDP model typically consists of five elements, namely: (a) decision epochs, (b) states space, (c) action space, (d) transition probability, and (e) rewards. Table 1 shows the characterization of the wireless smart sensors as constituting SMDP. SMDP can be described mathematically as:

$$SMDP = \{T, S, A_s, p_t(j \mid s,a), r_t(s,a)\}; \quad t \in T, s \in S, a \in A_s \,. \tag{6}$$

The transition rate diagram for this SMDP-based SHM model is presented in Fig. 3. Whereas $\lambda$ denotes positive rate parameter for the sojourn time distribution during the “forward-pass” sequence, $\mu$-denotes positive rate parameter for the sojourn time distribution during the “return-pass” sequence. In SMDP models, exponential distribution is normally used to model the sojourn time in each state. Depending on the computed magnitude of $h_{net}(t)$ at the *processing* stage, the SMDP-based SHM system makes decision to (i) discard the measured signal and remain in current state or (ii) transit to next state and transmit measured signal. Thus, a decision framework is provided as follows:

$$h_{net}(t)\begin{cases} 0 < h_{net}(t) < v_1 & ; \quad discard\ data \\ v_1 \le h_{net}(t) \le v_2 & ; \quad transmit\ data \end{cases} \tag{7}$$

where, $v_1$ and $v_2$ define the range of values of $h_{net}(t)$ for purpose of decision making on data transmissions. Recall that $h_{net}(t)$ is the net average power dissipated by the signals $k_1(t)$ and $k_2(t)$.

3.2.2 Fuzzy Control

Fuzzy control is a methodology of representing and implementing human’s knowledge in relation to control of a system or an operation. It is based on the Fuzzy Sets Theory and Fuzzy Logic. On the one hand,

**Table 1 Characterization of the operation of wireless smart sensors as SMDP.**

| Elements | Characterization |
|---|---|
| Decision epochs | Decision epochs are points in time when the SHM system executes actions. In this paper, decision epochs are: T = $\{t_1, t_2, t_3, \ldots\}$. |
| State space | The states are: State 1 (*sensing/processing*), and State 2 (*transmitting/receiving*). Thus, s = $\{s_1, s_2\}$. |
| Action space | In every state *s* and decision epoch *t*, action *a* in action set *A* is chosen. Thus, A = $\{a_{i,j}, a_{j,i}\}$.<br>$a_{i,j}$: transition from states $s_i$ to $s_j$.<br>$a_{j,i}$: transition from states $s_j$ to $s_i$.<br>where $s_i$ denotes current state and $s_j$ denotes a next state. |
| Transition probability | Based on choosing an action *a* in current state s, (i.e., $a \in A_s$), at current decision epoch *t*, the system state *j* at the next decision epoch is determined by the probability distribution:<br>*p(j\|s,a)*. |
| Rewards | The immediate discounted rewards function, *r(s,a)*, is given by:<br>$r(s,a) = k(s,a) + \int_0^\infty \sum_{j \in S} \left[ \int_0^\beta e^{-\alpha t} c\left(j', s, a\right) p\left(j' \mid t, s, a\right) dt \right] F(\beta \mid s,a)\, d\beta$<br>*c(j',s,a)* is the continuous reward rate and *p(j'\|t,s,a)* is the transition probability of the natural process. *F(β\|s,a)* is the sojourn time distribution in state *s*, and *k(s,a)* is the lump sum reward in state *s*. In addition, α denotes the discount rate. |
| Objective<br>The objective is to compute the sum of expected total discounted reward in every state, given that the process occupies state *s* at current decision epoch; and then determine the optimal policy. The optimal policy maximizes rewards from efficient energy utilization by the wireless smart sensor nodes for data transmission over infinite horizon. | |

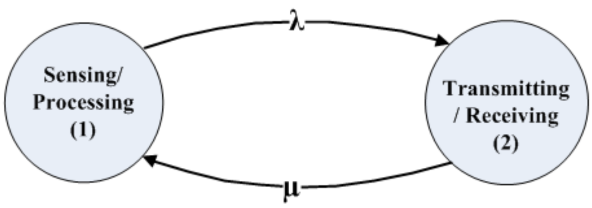


**Fig. 3 Transition rate diagram.**

Fuzzy sets theory provides a means of dealing with problems in which the source of imprecision is the lack of sharply defined criteria of class membership but not the presence of randomness. On the other hand, Fuzzy Logic maps an input space to an output space using linguistic variables and the mechanism of fuzzy rules. For example, let *X* denotes the input space and its elements $x_0, x_1, \cdots, x_n$ denote values of average power dissipated by signals. Thus, the Fuzzy set *A* in *X* is defined as a set of ordered pairs.

$$A = \{x_i, \mu_A(x_i) \mid x_i \in X\}; \quad i = 0,1,\ldots,n. \quad (8)$$

where, $\mu_A(x)$ is the membership function of *x* in A. It maps each element of *X* to a membership value between 0 and 1.

In the current paper, fuzzy control is based on the Mamdani Fuzzy Inference System [28] in which the output membership functions are Fuzzy Sets. Since the aggregation process yields fuzzy set for each output variable, there is a need for defuzzification to obtain single value for each output fuzzy set. The single value obtained is then used for actuation of control mechanism of the civil infrastructure system.

## 4. Problem Solution

### *4.1 SMDP Segment*

In SMDP-based models, decision epochs follow each state transition and the times between decision epochs are exponentially distributed. Upon choosing action $a \in A_s$ in a current state, the next decision epoch in the SMDP-based model occurs at or before time *t*, and the system state at that decision epoch is *j*, with probability *Q(t,j|s,a)*. Thus,

$$Q(t, j \mid s,a) = p(j \mid s,a) F(t \mid s,a). \quad (9)$$

where, *Q(t,j|s,a)* is the joint probability that the state at the next decision epoch equals *j* and that the next decision epoch occurs at or before time *t* when action *a* is chosen in state *s* at the present decision epoch [26]. Furthermore, *p(j|s,a)* is the probability that the embedded Markov decision process occupies state *j* at next decision epoch given that action *a* was chosen in state *s* at the current decision epoch *t*. *F(t|s,a)* is the probability that the next decision epoch occurs within *t* time units of the current decision epoch, given that action *a* is chosen in state *s* at the current decision epoch. This probability is defined as:

$$F(t \mid s,a) \leq 1-\gamma;\ 0 \leq \gamma < 1; t \geq 0. \tag{10}$$

Decision rules in this paper are Markovian (M) because the decision rules are only based on the current state of the SHM system's process; and deterministic (D) since decision rules indicate specific action to be taken by the SHM system at any given decision epoch. Whereas a decision rule prescribes a procedure for action selection in each state at specified decision epochs, a policy $\pi$ is the sequence of decision rules $d_1, d_2, \ldots$ in the infinite horizon decision epochs. Since the decision rule is MD, it follows that the policy is also MD and stationary. It is a stationary policy because it does not vary from decision epoch to decision epoch.

4.1.1 Rewards System

Rewards in this paper represent energy utilization for data transmission by the wireless sensor nodes deployed on the Dam (barrier) to measure structural response of the civil infrastructure system to excitation. Negative reward represents loss due to inefficient utilization of limited energy resources by the wireless smart sensors, while positive reward represents gain due to efficient utilization of limited energy resources. The immediate reward, *r(s,a)* received in a current state consists of the (a) lump sum reward, *k(s,a)*, and (b) accumulated rewards at continuous reward rates, *c(j',s,a)*. The total discounted reward in current states is computed by

$$\begin{aligned} r(s,a) &= k(s,a) \\ &+ \int_0^\infty \sum_{j\in S} \left[ \int_0^\beta e^{-\alpha t} c\left(j', s, a\right) p(j' \mid t, s, a) dt \right] F\left(\beta \mid s,a\right) d\beta. \end{aligned} \tag{11}$$

where, *p(j'|t,s,a)* is the transition probability of the natural process, *F(β|s,a)* is the sojourn time distribution in state *s* of the SMDP model and $\alpha$ denotes discount rate. The natural process does not change state until the next decision epoch, hence *p(j'|t,s,a)=1*. Thus, Eq. (11) can be expressed as:

$$\begin{aligned} r(s,a) &= k(s,a) \\ &+ c\left(j', s, a\right) \int_0^\infty \sum_{j\in S} \int_0^\beta e^{-\alpha t} dt\, F\left(\beta \mid s,a\right) d\beta. \end{aligned} \tag{12}$$

By invoking Eq. (9), the infinite horizon total discounted reward in a current state under policy $\pi$ is given by:

$$\begin{aligned} v_\alpha^\pi(s) &= r(s,a) \\ &+ \sum_{j\in S} p(j \mid s,a) \int_0^\infty e^{-\alpha t}\, F(t \mid s,a)\, dt\; v_\alpha^\pi(j). \end{aligned} \tag{13}$$

For illustration purpose, the unit of rewards is mJ. Rewards are subsequently specified as follows:

(1) Efficient energy utilization

Lump-sum reward in State 1 is equal to 2 mJ, and the system's process accumulates reward between decision epochs at continuous reward rate of 10 mJ. Moreover, lump-sum reward in State 2 is equal to 3 mJ, and the system's process accumulates rewards between decision epochs at continuous reward rate of 5 mJ.

(2) Inefficient energy utilization

Lump-sum reward in State 1 is equal to 2 mJ, and the system's process accumulates rewards between decision epochs at continuous reward rate of -10 mJ. Moreover, lump-sum reward in State 2 is equal to -3 mJ, and the system's process accumulates cost between decision epochs at continuous reward rate of -5 mJ.

4.1.2 Determination of Energy-Efficient Policy

The objective is to identify policy that maximizes the sum of $r(s,a)$ and the expected discounted rewards in the SMDP-based model. To achieve this objective, the SHM system chooses action $a \in A_s$ in current states to make the expression in Eq. (13) as large as possible. In order to find such an action, the system must evaluate this equation for each $a \in A_s$

and then determine the maximum value of sum of expected total discounted rewards starting from state 1. Thus, the optimal value of sum of expected total discounted reward following policy $\pi$ in current states is given by

$$v_\alpha^*(s) = \underbrace{\max}_{a \in A_s} \left\{ \begin{aligned} & r(s,a) \\ & + \sum_{j \in S} p(j \mid s,a) \int_0^\infty e^{-\alpha t} F(t \mid s,a)\, dt\, v_\alpha(j) \end{aligned} \right\}. \quad (14)$$

It is noted that the integrations in Eqs. (11)-(14) are over the domain of sojourn time in current states. It is also noted that the SHM's system process transits from state to state and continues to operate in this manner over infinite horizon as end-point cannot be pre-determined. Over the infinite horizon, it can be proved that the optimal value of sum of total discounted reward in a current state converges to $v_\alpha^\pi(s)$.

Theorem: If the SHM system's process operates over infinite horizon consisting of $m$ cycles (i.e., a cycle: $s_1$-$s_2$-$s_1$) where $m=1,2,3, \ldots, \infty$, then the average optimal value of sum of expected total discounted rewards in current states starting from State 1 can be obtained by:

$$v_a^\pi(s) = v_\alpha^*(s). \quad (15)$$

Proof: Let $k$ denotes indexing variable for the cycles and $v_a^\pi(s)$ denotes the average optimal value of sum of expected total discounted rewards in current states, starting from State 1. It can be proved that

$$v_a^\pi(s) = \underbrace{\lim}_{m \to \infty} \left\{ \frac{1}{m} \sum_{k=1}^{m} \left( v_\alpha^*(s) \right)_k \right\}. \quad (16)$$

$$v_a^\pi(s) = \underbrace{\lim}_{m \to \infty} \left\{ \frac{m \left( v_\alpha^*(s) \right)}{m} \right\}. \quad (17)$$

Therefore,

$$v_a^\pi(s) = v_\alpha^*(s). \quad (18)$$

*4.2 Fuzzy Control Segment*

Recall from Section 3.2 that $h_2(t)$ is the average power dissipated by signals $k_2(t)$. In this fuzzy model, $h_2(t)$ is the linguistic variable with linguistic values Low, High and Very-high. The Fuzzification of the input variable is shown in Fig. 4.

Fuzzy rules are subsequently defined as follow:

IF $h_2(t)$ == Low THEN discharge = low

IF $h_2(t)$ == High THEN discharge = high

IF $h_2(t)$ == Very-high THEN discharge = max

With the Mamdani-type inference system, output membership functions are Fuzzy Sets. Moreover, Fuzzy sets representing the output of each Fuzzy rule are aggregated into a single fuzzy set. By using the centroid method, the aggregated fuzzy set is subsequently defuzzified to obtain a single output value.

## 5. Results and Discussion of Results

For purpose of numerical illustration, the maximum value of accelerometer measurement is 4 g. In addition, $h_1(t) < 0.1$ and $h_2(t) >= 0.1$. The results of numerical analysis to determine optimal values in the SMDP-based SHM model are presented in Tables 2-3, and Figs. 5-6.

In Tables 2-3, Option *A* represents the approach presented in this paper wherein the system's process starts at decision epoch 1 (in State 1), and can either

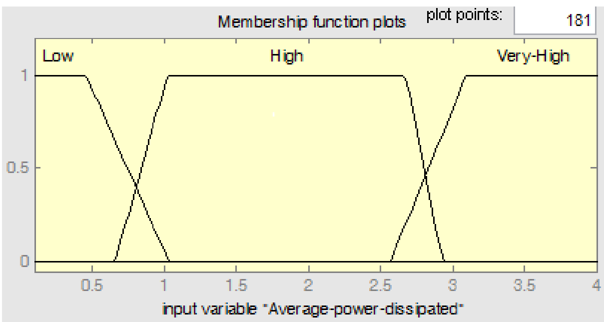


**Fig. 4 Fuzzification of the input variable.**

**Table 2 Total discounted rewards in states at decision epochs [$h_2(t)$= 0.1].**

| v(s) | Options | 1 | 2 | Total | Optimal value |
|---|---|---|---|---|---|
| $v_1(s)$ | A | 135.7 | 8.4 | 144.1 | 144.1 |
| | B | -172.4 | -11.0 | -183.0 | |
| $v_2(s)$ | A | | 8.4 | 8.4 | 8.4 |
| | B | | -11.0 | -11.0 | |

**Table 3 Total discounted rewards in states at decision epochs [$h_2(t)$ = 3.0].**

| v(s) | Options | 1 | 2 | Total | Optimal value |
|---|---|---|---|---|---|
| $v_1(s)$ | A | 421.9 | 26.3 | 448.2 | 448.2 |
| | B | 412.1 | 25.9 | 438 | |
| $v_2(s)$ | A | | 26.3 | 26.3 | 26.3 |
| | B | | 25.9 | 25.9 | |

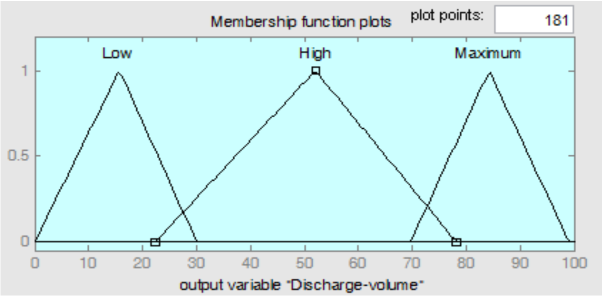


**Fig. 5 Output Fuzzy Sets.**

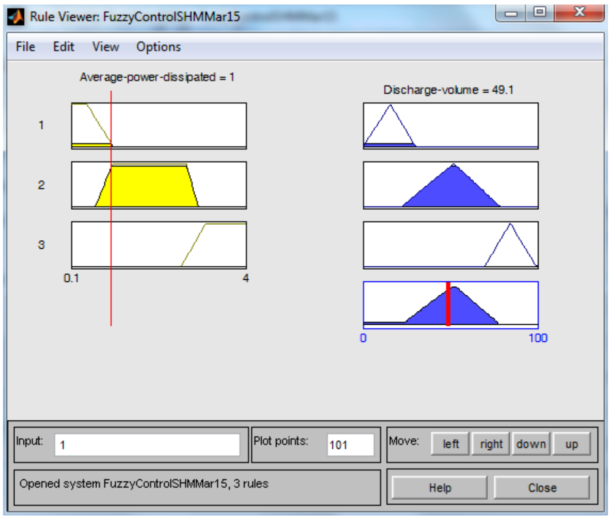


**Fig 6 Activation of Fuzzy Rules [ $h_2(t)$ = 1.0].**

transit to State 2 or discard the value of average power dissipated by the measured signal. If the system's process transit to State 2, then the system transmits the value of average power dissipated by measured signal to the nearest gateway node, and thereafter transits back to State 1. This cycle continues infinitely. Option *B* represents the case wherein the SHM system's process starts in State 1 (at decision epoch 1), and transits to State 2 for data transmission to nearest gateway node at all times.

The total discounted rewards in states at decision epochs are presented in Tables 2-3. For example, whereas Option *A* in Table 2 yields total discounted rewards of 135.7 mJ in current state starting in State 1 and 8.4 mJ in current state starting in State 2, Option *B* yields total discounted cost of -172.4 mJ in State 1 and -11.0 mJ in State 2. In Table 3, whereas Option *A* earns total discounted reward of 421.9 mJ in current states starting in State 1 and 26.3 mJ in current states starting in State 2, Option *B* earns total discounted reward of 412 mJ in State 1 and 25.9 mJ in current states starting in State 2.

The Fuzzy Control Model for SHM of civil infrastructure systems was implemented using MATLAB Fuzzy Logic Toolkit. The output Fuzzy sets are presented in Fig. 5, where the linguistic variable is discharge-volume with linguistic values Low, High, and Maximum.

Whereas sample activation of the Fuzzy Rules for $h_2(t)$ = 1.0 is shown in Fig. 6, sample activation of the Fuzzy rules for $h_2(t)$ = 3.0 is shown in Fig. 7.

In Fig. 6 for example, an average power dissipated value of 1.0 corresponds to a control signal that results in discharge volume of 49.1% of the maximum discharge volume. Similarly, an average power dissipated value of 3.0 (Fig. 7) corresponds to a control signal that results in discharge volume of 84.4% of the maximum discharge volume.

The sums of expected total discounted rewards are presented graphically in Figs. 8-9 for different values of average power dissipated by signals. Option *A* yields higher values of sum of total discounted rewards in current states than Option *B*. For example, whereas Option *A* earns 144.1 mJ starting in State 1 (at decision epoch 1 where $h_2(t)$ = 0.1) in Fig. 8, Option *B* earns -183.0 mJ. Similarly, whereas Option *A* earns 448.2 mJ starting in State 1 (at decision epoch 1 where $h_2(t)$ = 3.0) in Fig. 9, Option *B* earns 438 mJ.

From the foregoing, the optimal analysis generally shows that Option *A* yields optimal value of rewards at every decision epoch. This implies higher level of energy efficiency in data transmissions by the SHM model presented in this paper.

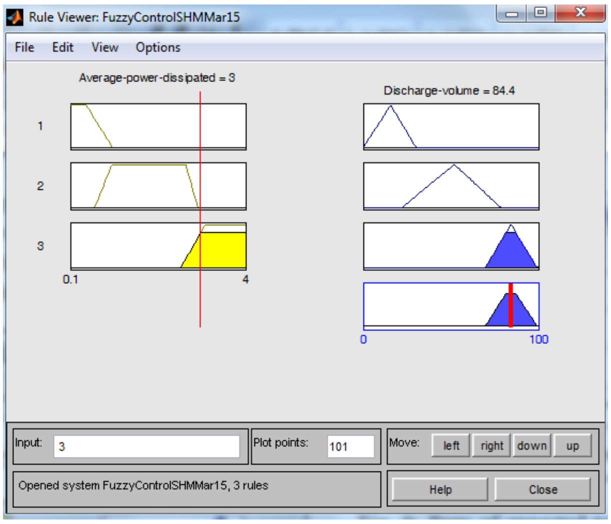


**Fig 7 Activation of Fuzzy Rules [$h_2(t)$ = 3.0].**


**Fig. 8 Sum of expected total future discounted reward [$h_2(t)$=0.1]. Discount rate = 5%.**

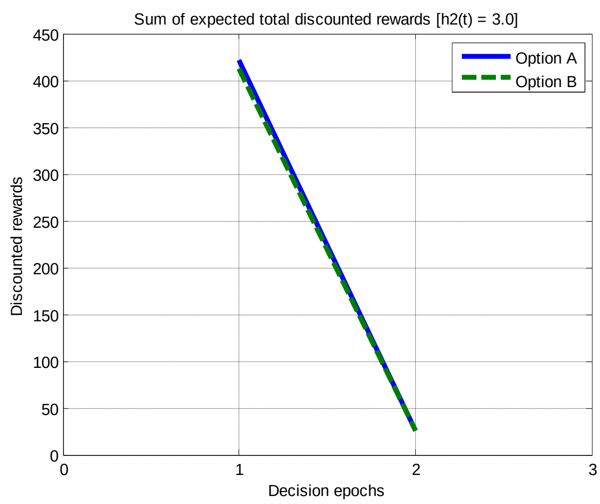


**Fig. 9 Sum of expected total future discounted reward [$h_2(t)$=3.0]. Discount rate = 5%.**

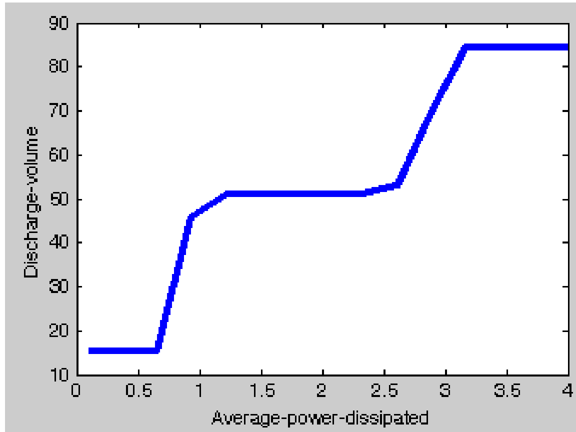


**Fig. 10 Discharge-status based on results of defuzzification of aggregated output.**

The discharge status based on results of defuzzification of the aggregated output fuzzy set is presented graphically in Fig. 10. The graph relates average values of measured structural response to excitation with the corresponding discharge volumes. For example, average values of measured structural responses of 1.5, 2.5, 2.7, and 3.0 correspond to 50.9, 50.9, 56.9, and 84.4 percents of the maximum discharge volumes respectively.

The results presented in Tables 2-3, and Figs. 5-10, generally show that the approach presented in this paper can provide a basis for design and implementation of energy-efficient structural health monitoring and effective control of civil infrastructure systems.

The main contributions of this research are as follow:

(1) It provides a decision framework that will guarantee energy-efficient data transmissions.

(2) It provides a basis for effective actuation of mechanism of civil infrastructure systems, thereby preventing structural damage.

## 6. Conclusion

In this paper, we investigated the challenges of energy utilization in structural health monitoring systems and control of mechanism of civil infrastructure systems. A Dam was considered as an example of civil infrastructure systems, in which wireless smart sensors are deployed on the barrier. The operation of these wireless smart sensors was characterized as SMDP consisting of two states, namely: sensing/processing and transmitting/ receiving. Fuzzy control scheme was incorporated in the model to provide robust control capability for addressing problems of imprecision and uncertainty in structural health monitoring. The efficacy of the approach presented in this paper was tested under two different Options. Moreover, the numerical analysis was implemented in MATLAB software, and the results were presented in Tables 2-3, and Figs. 5-10. The results obtained show that the new approach provides (1) a decision framework that will guarantee energy-efficient data transmissions, and (2) a basis for effective actuation of mechanism of civil infrastructure systems, thereby preventing structural damage.

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## References

[1] Zadeh, L. A. 1965. "Fuzzy Sets." *Information and Control* 8: 338-53.

[2] Olunloyo ,V. O. S., Ajofoyinbo, A. M., and Ibidapo-Obe. O. 2011. "On Development of Fuzzy Controller: The Case of Gaussian and Triangular Membership Functions." *Journal of Signal and Information Processing* 2: 257-65.

[3] Olunloyo, V. O. S., Ajofoyinbo, A. M., and Badiru, A. B. 2014. "Neuro Fuzzy Mathematical Model for Monitoring Flow Parameters of Natural Gas." *Applied Mathematics and Computation* 149 (3): 747-70.

[4] Kamel, J. 2014. "New Approach for Modeling Random Disturbances." *Journal of Control Science and Engineering* 2: 16-27.

[5] Sim, S. H., Li, J., Jo, H., Park, J. W., Cho, S., Spencer, J. B. F., and Jung, H. J. 2014. "A Wireless Smart Sensor Network for Automated Monitoring of Cable Tension." *Journal of Smart Materials and Structures* 23 (2). doi: 10.1088/0964-1726/23/2/025006.

[6] Park, J. W., Sim, S. H., and Jung, H. J. 2014. "Wireless Displacement Sensing System for Bridges Using Multi-sensor Fusion." *Journal of Smart Materials and Structures* 23 (4). doi:10.1088/0964-1726/23/4/045022.

[7] Li, J., Nagayama, T., Mechitov, K. A., and Spencer J. B. F. 2012. "Efficient Campaign-type Structural Health Monitoring Using Wireless Smart Sensors." In *Proceedings of SPIE 8345, Sensors and Smart Structures for Civil, Mechanical and Aerospace Systems*.

[8] Sim, S., Carbonell, M. J., Spencer, J. B. F., and Jo, H. 2011. "Decentralized Random Decrement Technique for Efficient Data Aggregation and System Identification in Wireless Smart Sensor Networks." *Journal of Probabilistic Engineering Mechanics* 26: 81-91.

[9] Sim, S. H., Spencer, J. B. F., Zhang, M., and Xie, H. 2010. "Automated Decentralised Modal Analysis Using Smart Sensors." *Journal of Structural Control and Health Monitoring* doi:10.1002/stc.348.

[10] Rice, J. A., Mechitov, K. A., Sim, S. H., and Spencer, J. B. F. 2011. "Enabling Framework for Structural Health Monitoring Using Smart Sensors." *Journal of Structural Control and Health Monitoring* 28 (5): 574-87.

[11] Jo, H., Sim, S., Mechitov, K. A., Kim, R., Li, J., Moinzadeh, P., Spencer, B. F. J., Park J. W., Cho, S., Jung, H., Yun, C., Rice, J. A., and Nagayama, T. 2011. "Hybrid Wireless Smart Sensor Network for Full-scale Structural Health Monitoring of a Cable-stayed Bridge." In *Proceedings of The SPIE Conference*.

[12] Rice, J. A., Mechitov, K., Sim, S. H., Nagayama, T., Jang, S., Kim, R., Spencer, B. F. J., Agha, G., and Fujino, Y. 2010. "Flexible Smart Sensor Framework for Autonomous Structural Health Monitoring." *Journal of Smart Structures and Systems* 6 (5-6): 423-38.

[13] Jang, S., Jo, H., Cho, S., Mechitov, K. A., Rice, J. A., Sim, S. H., Jung, H. J., Yun, C. B., Spencer, J. B. F. and Agha, G. A. 2010. "Structural Health Monitoring of a Cable-stayed Bridge Using Smart Sensor Technology: Deployment and Evaluation." *Journal of Smart Structures and Systems* 6 (5-6): 439-59.

[14] Kim, T. O., Alfa, A. S., and Choi, B. D. 2012. "MDP-based Admission Control for Multicast Streaming Services in Wireless Mobile Networks." In *the Proceedings of IEEE International Conference on Communications.*

[15] Ajofoyinbo, A. M., and Olowokere, D. O. 2014. "Health Monitoring and Control of Civil Infrastructures using Wireless Smart Sensors." *Bulletin of Electrical Engineering and Informatics* 3 (3):201-12.

[16] He, L., Lian, J., Ma, B., and Wang, H. 2014. "Optimal Multiaxial Sensor Placement for Modal Identification of Large Structures." *Journal of Structural Control and Health Monitoring* 21: 61-79.

[17] Park, J. W., Sim, S. H., and Jung, H. J. 2013. "Wireless Sensor Network for Decentralized Damage Detection of Building Structures." *Journal of Smart Structures and*

*Systems* 12 (3-4): 399-414.

[18] Koo, K., Sung, S., and Jung, H. 2011. "Damage Quantification of Sheer Building Using Deflections Obtained by Modal Flexibility." *Journal of Smart Materials and Structures* 20 (4). doi:10.1088/0964-1726/20/4/045010

[19] Fu, T. S., Gosh, A., Johnson, E. A., and Krishnamachari, B. 2012. "Energy-efficient Deployment Strategies in Structural Health Monitoring Using Wireless Sensor Network." *Journal of structural control and health monitoring*: 1-15.

[20] Sendra, S., Lioret, J., Garca, M., and Toledo, J. F. 2011. "Power Saving and Energy Optimization Techniques for Wireless Sensor Networks." *Journal of communications* 6 (6): 439-59.

[21] Nagayama, T., Moinzadeh, P., Mechitov, K., Ushita, M., Makihata, N., Leiri, M., Agha, G., Spencer, J. B. F., Fujino, Y., and Seo, J. 2010. "Reliable Multi-hop communication for Structural Health Monitoring." *Journal of Smart Structures and Systems* 6 (5-6): 481-504.

[22] Jo, H., Sim, S., Nagayama, T., and Spencer, J. B. F. 2010. "Decentralised Stochastic Modal Identification Using High Sensitivity Wireless Smart Sensors." In *the Proceedings of 5th world conference on structural control and monitoring*.

[23] Nagayama, T., Ushita, M., Fujino, Y., Leiri, M. and Makihata, N. 2010. "The Combineduse of low-cost smart Sensors and High Accuracy Sensors Apprehend Structural Behavior." In *Proceedings of SPIE Smart Structures/NDE*.

[24] Karbhari, V. M., Guan, H. and Sikorsky, C. 2009. "Operational Modal Analysis for Vibration-based Structural Health Monitoring of Civil Structures." *Journal Structural Health Monitoring of Civil Infrastructure Systems*: 213-59.

[25] Pantazis, N. A., Nikolidaskis, S. A., and Vergados, D. D. 2013. "Energy-efficient Routing Protocol in Wireless Sensor Networks: A Survey." *IEEE Communications Surveys & Tutorials* 15 (2): 551-91.

[26] Puterman, M. L. 2005. "Markov Decision Process: Discrete Stochastic Dynamic Programming." *Wiley series in Probability and Statistics*, Wiley-Interscience.

[27] Howard, R. A. 1960. "Dynamic Programming and Markov Process." New York: The Massachusetts Institute of Technology and John Wiley & Sons.

[28] Mamdani, E. H., and Assilian, S. 1975. "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller." *International Journal of Man-Machine Studies* 7 (1): 1-13.