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Health Monitoring and Control of Civil Infrastructures using Wireless Smart Sensors

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Abstract

This paper investigates health monitoring and control (HMC) of civil infrastructures using wireless smart sensor networks. Two important requirements are (i) energy efficiency, and (ii) effective control to prevent damage of civil infrastructures. Fuzzy control scheme is incorporated in the system model to provide capability for addressing problems of imprecision and uncertainty that can be associated with values of dynamic response. Moreover, operation of wireless smart sensor networks is characterized as discounted Semi-Markov Decision Process (SMDP) consisting of four states, namely: sleep, sense, store, and transmit. The objective is to choose policy that offers optimal energy-efficient transmission of vibration-based dynamic response, and subsequently activate appropriate control. Relevant mathematical representations are formulated for this model and its efficacy tested via numerical analysis, which is implemented in MATLAB software. It is shown by the results obtained that this HMC model can provide effective control and increase energy efficiency.

Keywords: *health, monitoring, control, Markov decision, sensors*

1. Introduction

Over the years, researchers have investigated challenges of Structural Health Monitoring (SHM) using Wireless Smart Sensor Networks (WSSN), with different objectives. For example, Sim et al [1] developed an efficient means of autonomous long-term monitoring of cable tension using MEMSIC's Imote2 Smart Sensors. A new displacement sensing system was developed by Park et al [2], by incorporating wireless sensor technology with the multi-metric data-based algorithm. He et al [3] presented an inter-encoding multi-swarm particle swarm optimization (IMPSO) algorithm to place multi-axial sensors optimally on large structures for modal identification. In an interesting contribution, Li et al [4] presented a post-sensing time synchronization scheme to reduce the latency of data collection while maintaining high accuracy of synchronization of collected data. Sim et al [5] and Sim et al [6] investigated decentralized random decrement technique (RDT) for efficient data aggregation and system identification in wireless smart sensor networks. Rice et al [7] developed an opened-source framework for structural health monitoring using the design principles of service-oriented architecture, 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. Moreover, Jo et al [8] presented the development of hybrid wireless smart sensor network to achieve a full-scale SHM system for civil infrastructure monitoring. In their contribution, Nagayama et al [9] presented two complementary reliable multi-hop communication solutions for monitoring of civil infrastructures, namely: (1) the general purpose multi-hop and (2) the single-sink multi-hop. For large civil infrastructure systems, SHM systems that are based on wireless smart sensors offered many advantages over the traditional wired sensor systems (Rice et al [10], Jang et al [11]). Many features can be used to characterise civil structure. For example, acceleration time history measured by accelerometers mounted on the structure 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. A Markov Decision Process (MDP) 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

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prescription of which action to choose at every future decision epoch, and decision epochs are points in time when a system executes action. In Semi-Markov Decision Process (SMDP), decision epochs follow each state transition and the times between decision epochs are exponentially distributed [12],[13]. A Fuzzy set is 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 formalizes modes of reasoning which are approximate 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 absence of sharply defined criteria of class membership rather than the presence of randomness (Zadeh [14]). Over the years, Fuzzy sets theory and Fuzzy logic have proven to have wide scope of applicability in engineering, oil exploration, medicine, biomedical instrumentation, decision analysis, etc. For example, Olunloyo et al [15] presented the development of an embedded Fuzzy controller for the case of triangular and Gaussian membership functions.

The rest of the paper is organized as follows. Related research is presented in Section 2. We present motivation and problem formulation in Section 3. Problem solution is discussed in Section 4. Results of numerical analysis and discussion of results as well as contribution of the research are presented in Section 5. Section 6 concludes the paper.

2. Related Research

Park et al [16] presented a WSSN-based decentralized processing scheme for damage detection of building structures. The paper adopted Damaged Induced Inter-story Deflection (DI-ID) proposed by Koo et al [17] and extended it to be used in a decentralized computing environment in the WSSN. Fu et al [18] considered the problem of finding node locations to reliably diagnose the health of a structure while consuming minimum energy during data collection. In their contribution, Sendra et al [19] presented power saving and energy optimization techniques for wireless sensor networks. Jo et al [20] investigated 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 [21] 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 (Karbhari et al [22]). The two aspects of vibration-based damage detection are (i) identification and extraction of vibration-related features, and (ii) 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 [22].

In this paper, a new approach is presented for monitoring health of civil infrastructures and effecting appropriate control mechanism to prevent damage or disaster.

3. Motivation and Problem Formulation

3.1. Motivation for this Research

This research is motivated by the following reasons:

(a) The need for a systematic approach to determine dissimilarity between the baseline dynamic response and subsequent measured dynamic response.
(b) The need to use (a) as a basis for decision making at decision epochs as to ensure energy-efficient data transmission.
(c) The need to effectively control operations of civil infrastructures based on (a) and (b).

3.2. Problem Formulation

A Dam is the civil infrastructure considered in this paper wherein wireless smart sensors are deployed on the barrier (Figure 1). Gateway nodes are assumed to be strategically installed at the river bank such that all nodes can transmit in single-hop to nearest gateway node. Let $z_1(t)$ denotes the “baseline” structural response of the civil infrastructure to excitation. Sensors measurement comes with useful and noise components. For the “baseline” response, useful response is denoted as $x(t)$ and noise component as $n_1(t)$. Moreover, let $z_2(t)$ denotes subsequent dynamic response sensed by a wireless smart sensor, which also consists of useful component $y(t)$ and its associated noise component $n_2(t)$.

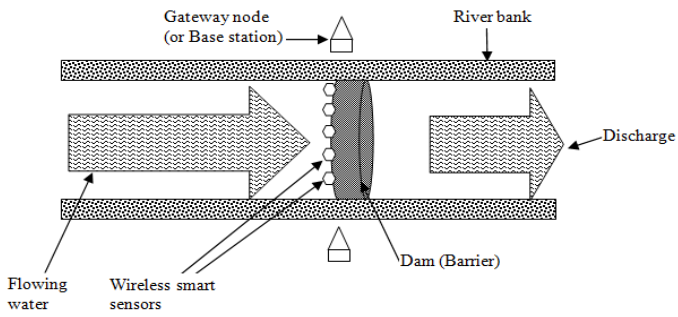

Figure 1. Schematic representation of typical wireless smart sensors deployment on a Dam

Thus, we define the following models for "baseline" and subsequent measured dynamic responses.

$$z_1(t) = x(t) + n_1(t). \tag{1}$$

$$z_2(t) = y(t) + n_2(t). \tag{2}$$

The value of a signal can be modeled by the energy contained in that signal. Thus, the total energy over time interval $a \le t \le b$ in continuous-time signals $z_1(t)$ and $z_2(t)$ denoted as E_1 and E_2 respectively, are defined as

$$E_1 = \int_a^b | z_1(t) |^2 \, dt. \tag{3}$$

And

$$E_2 = \int_a^b | z_2(t) |^2 \, dt. \tag{4}$$

The average power dissipated by signals $z_1(t)$ and $z_2(t)$ during the time interval $a \le t \le b$ are defined as

$$P_1 = \frac{1}{(b-a)} \int_a^b | z_1(t) |^2 \, dt. \tag{5}$$

and

$$P_2 = \frac{1}{(b-a)} \int_a^b | z_2(t) |^2 \, dt. \tag{6}$$

Let D denotes the magnitude of the difference between P_1 and P_2. It follows that

$$D = P_2 - P_1 \quad ; \qquad D \geq 0. \tag{7}$$

(i) Discounted SMDP Modelling

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 (Howard [12]; Puterman [13]). SMDP model typically consists of five elements, namely: (i) decision epochs, (ii) states space, (iii) action space, (iv) transition probability, and (v) rewards. Table 1 shows the characterization of the HMC system as constituting SMDP. Mathematically, SMDP can be described as:

$$SMDP = \{T, S, A_s, p_t(j \mid s,a), r_t(s,a)\}; \quad t \in T, s \in S, a \in A_s \ . \tag{8}$$

Table 1. Characterization of the HMC system as SMDP

Elements	Characterization
Decision epochs	Decision epochs are points in time when the HMC system executes actions. As shown in Figure 2, decision epochs are: T = {t_1, t_2, t_3, t_4}.
State space	The states are: state 1 (*sleep*), state 2 (*sense*), state 3 (*store*), state 4 (*transmit*). Thus, s = {s_1, s_2, s_3, s_4}.
Action space	In every states *s* and decision epoch *t*, action *a* in action set *A* is chosen. That is, A = {$a_{i,j}$, $a_{i,h}$}.
Transition probability	Based on choosing an action *a* in current state *s* at current decision epoch *t*, the system state *j* at the next decision epoch is determined by the probability distribution: *p (j |s, a).*
Rewards	The immediate discounted rewards function, $r(s,a)$, is given by: $$r(s,a) = x(s,a) + \int_0^{\infty} \sum_{j \in S} \left[\int_0^{v} e^{-\alpha t} c(j,s,a) p(j \mid t,s,a) dt \right] F(v \mid s,a)\, dv$$
<u>Objective</u>: 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 earnings from efficient energy utilization for data transmission over infinite horizon.	

The corresponding transition rate diagram for this SMDP-based HMC model is presented in Figure 2. Whereas λ denotes rate parameter for the sojourn time distribution during the "forward-pass", β denotes positive rate parameter for the sojourn time distribution during the "return-pass".

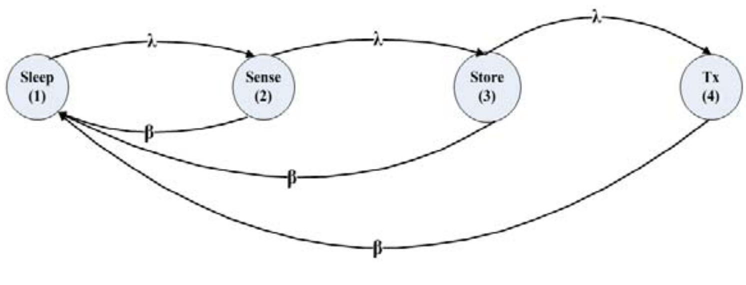

Figure 2. Transition rate diagram

In SMDP models, exponential distribution is normally used to model the sojourn time in each state.

(ii) Fuzzy Control

Uncertainty and imprecision due to absence of sharply defined criteria of class membership for values of measured dynamic response informed the adoption of Fuzzy sets theory and Fuzzy logic control. We define dynamic-response (DR) as a linguistic variable with linguistic values *High*, *Very-High*, and *Too-High* (Figure 3). Let X denotes the universe of discourse and its elements $x_0, x_1, \cdots, x_n$ denote values of dynamic response. The Fuzzy set A in X is defined as a set of ordered pairs.

$$A = \{x_i, \mu_A(x_i) \mid x_i \in X\}; \quad i = 0,1,...,n. \tag{9}$$

In Eq. (9), $\mu_A(x)$ is the membership function of x in A. It maps each element of X to a membership value between 0 and 1. In Figure 3, k_1, k_2, k_3, and k_4, denote sample values of dynamic response.

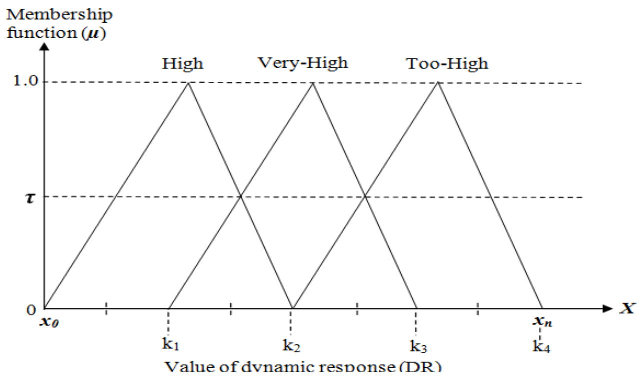

Figure 3. Fuzzification of values of dynamic response (i.e., input) in Fuzzy plane

The Fuzzy control rules are defined as follow:

(a) IF $(x_i \le k_1)$ and $(\mu(x_i) \le 1)$ THEN *Low-discharge*

(b) IF $((x_i > k_1)$ and $(x_i \le k_2))$ and $(\mu(x_i) \le \tau)$ THEN *Low-discharge*

(c) IF $((x_i > k_1)$ and $(x_i \le k_2))$ and $(\mu(x_i) > \tau)$ THEN *High-discharge*

(d) IF $((x_i > k_2)$ and $(x_i \le k_3))$ and $(\mu(x_i) \le \tau)$ THEN *High-discharge*

(e) IF $((x_i > k_2)$ and $(x_i \le k_3))$ and $((\mu(x_i) > \tau)$ THEN *Maximum-discharge*

(f) IF $((x_i > k_3)$ and $(x_i \le k_4))$ and $(\mu(x_i) \le 1)$ THEN *Maximum-discharge*

The schematic representation of the operational sequence of the HMC system is presented in Figure 4.

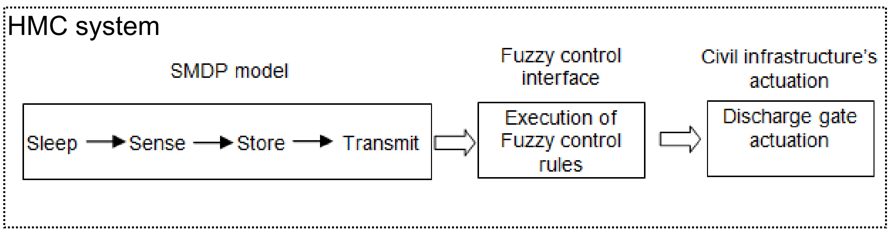

Figure 4. Schematic representation of the operation of the HMC system

4. Problem Solution

Upon choosing action $a \in A_s$ in a current state, the next decision epoch in the SMDP-based HMC model occurs at or before time *t*, and the system state at that decision epoch is *j,* with probability $Q(t, j \mid s, a)$. Thus,

$$Q(t, j \mid s,a) = p(j \mid s,a)F(t \mid s,a). \tag{10}$$

$Q(t, j \mid s,a)$ 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 (Puterman [13]). $p(j \mid s,a)$ 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 . $F(t \mid s,a)$ 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

$$F(t \mid s,a) \le 1-\gamma ; \quad 0 \le \gamma < 1; t \ge 0. \tag{11}$$

4.1 Rewards System

In this paper, negative reward represents a loss due to inefficient utilization of limited energy resources in wireless smart sensor networks, while positive reward indicates revenue earned by efficient utilization of limited energy resources. Rewards are subsequently specified in terms of earning (or loss) from data transmission in the SMDP-based HMC system as follows: Lump sum reward (revenue/earning) associated with the *sleep* state is equal to 2. The system process accumulates rewards (revenue/earning) between the decision epochs at continuous reward rate of 5 (or loss at continuous reward rate of -10). Lump sum reward (revenue/earning) associated with the *sense* state is equal to 15, and system process accumulates rewards (revenue/earning) between decision epochs at continuous reward rate of 20 (or loss at continuous reward rate of -40). Lump sum reward (revenue/earning) associated with the *store* state is equal to 15, and system process accumulates rewards (revenue/earning) between decision epochs at continuous reward rate of 20 (or loss at continuous reward rate of -40). Lump sum reward (revenue/earning) associated with the *transmit* state is equal to 20, and the system process accumulates rewards (revenue/earning) between decision epochs at continuous reward rate of 20 (or loss at continuous reward rate of -40). Immediate reward, $r(s,a)$, received in a current state consists of (i) lump sum reward, $x(s,a)$ and (ii) accumulated rewards at continuous reward rates, $c(j,s,a)$. In the SMDP model, the natural process does not change state until the next decision epoch. Therefore, $p(j \mid t,s,a)=1$. Consequently, the total discounted reward in current state is computed by

$$r(s,a) = x(s,a) + c(j,s,a)\int_0^\infty \sum_{j \in S} \int_0^v e^{-\eta t} dt\, F(v \mid s,a) dv. \tag{12}$$

For stationary policy, and by invoking Eq. (10), the infinite horizon total discounted reward in a current state under policy π is given by

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

4.2 Energy-efficient Policies

For stationary policy, the optimal value of following policy π in current state s is obtained by

$$v_{\eta}^{*}(s)=\underbrace{\max}_{a\in A_s}\left\{r(s,a)+\sum_{j\in S}p(j\,|\,s,a)\int_{0}^{\infty}e^{-\eta t}F\left(t\,|\,s,a\right)dt\,v_{\eta}^{*}(j)\right\}. \tag{14}$$

It is important to note in Eqs. (12), …, (14) that the integrations are over the domain of sojourn time in current states.

4.3 Notes on Convergence of Infinite Horizon Process

It can be shown that the average optimal value in infinite horizon converges to the optimal value in Eq. (14).

Theorem: If the HMC system's process run over infinite horizon consisting of *n* cycles, where n=1,2,3,..,∞, then the average optimal value of sum of expected total future discounted rewards in current states starting from state 1, $v_{avg}(s)$, is equal to $v_{\eta}^{*}(s)$. That is, $v_{avg}(s)=v_{\eta}^{*}(s)$.

Proof: Let *w* denotes indexing variable and $v_{avg}(s)$ denotes the average optimal value of sum of expected total future discounted rewards in current states starting from state 1.

$$v_{avg}(s)=\underbrace{\lim}_{n\to\infty}\left\{\frac{1}{n}\sum_{w=1}^{n}v_{\eta}^{*}(s)_{w}\right\}. \tag{15}$$

$$v_{avg}(s)=\underbrace{\lim}_{n\to\infty}\left\{\frac{n\left(v_{\eta}^{*}(s)\right)}{n}\right\}. \tag{16}$$

$$v_{avg}(s)=\underbrace{\lim}_{n\to\infty}\left\{\frac{\frac{n}{n}\left(v_{\eta}^{*}(s)\right)}{\frac{n}{n}}\right\}. \tag{17}$$

$$v_{avg}(s)=v_{\eta}^{*}(s). \tag{18}$$

4.4 Fuzzy Control

MATLAB Fuzzy Logic Toolkit is used to implement the Fuzzy logic control scheme, wherein the Fuzzy inference system was based on the Mamdani Fuzzy inference system. For this inference system, the output membership functions result in Fuzzy sets. After the aggregation process, there is therefore a Fuzzy set for each output variable; hence the need for defuzzification.

5. Results of Numerical Analysis and Discussion of Results

The results of numerical analysis to determine optimal values in the SMDP based HMC model are presented in Tables 2 -5, and Figure 5 - 12.

Table 2. Total discounted rewards in states at decision epochs [D = 2]

v(s)	Options	1	2	3	4	Total	Optimal value
$v_1(s)$	A	9.98	3.29	1.27	18.13	32.67	118.6
	B	60.12	20.95	19.4	18.13	118.6	
$v_2(s)$	A		3.29	1.27	18.13	22.69	58.48
	B		20.95	19.4	18.13	58.48	
$v_3(s)$	A			1.27	18.13	19.4	37.53
	B			19.4	18.13	37.53	
$v_4(s)$	A				18.13	18.13	18.13
	B				18.13	18.13	

Table 3. Total discounted rewards in states at decision epochs [D = 4]

v(s)	Options	1	2	3	4	Total	Optimal value
$v_1(s)$	A	37.28	30.6	1.27	18.13	87.28	173.74
	B	49.94	86.27	19.4	18.13	173.74	
$v_2(s)$	A		30.6	1.27	18.13	50.0	123.8
	B		86.27	19.4	18.13	123.8	
$v_3(s)$	A			1.27	18.13	19.4	37.53
	B			19.4	18.13	37.53	
$v_4(s)$	A				18.13	18.13	18.13
	B				18.13	18.13	

Table 4. Total discounted rewards in states at decision epochs [D = 7]

v(s)	Options	1	2	3	4	Total	Optimal value
$v_1(s)$	A	1558	1551	312.08	55.74	3477.0	3563.6
	B	1571	1569	367.82	55.74	3563.6	
$v_2(s)$	A		1551	312.08	55.74	1918.80	1992.6
	B		1569	367.82	55.74	1992.6	
$v_3(s)$	A			312.08	55.74	367.82	423.56
	B			367.82	55.74	423.56	
$v_4(s)$	A				55.74	55.74	55.74
	B				55.74	55.74	

Table 5. Input (dynamic response) and output (discharge status)

Input (Defuzzified)	0.1	0.5	1	2	2.5	3	3.5	4	4.5	5	5.5	6	6.5	7	7.9
Output (Defuzzified)	1.5	1.5	1.5	1.5	2.11	2.5	2.89	3.5	4.45	4.95	5.4	6	6	6	6

In order to achieve continuous monitoring, large amount of dynamic data are normally generated by wireless smart sensors. But not all data generated by the instrumentation systems at all times are high enough to necessarily require transmission across networks. When measured dynamic response falls within defined ranges, the SMDP-based HMC system makes decision to (i) discard, (ii) store, or (iii) transmit the dynamic response information. The maximum output range of the accelerometers (i.e., the wireless smart sensors) is set to 8g. Thus subsequent measured dynamic response is in the range, $0 < x_{(.)} < 8$. We compare two options, *Options A* and *B*, to test the efficacy of the SMDP-based HMC model. In Tables 2, 3, and 4, Option A represents the case wherein the HMC system's process starts at state 1 (*sleep*), receives external excitation (i.e., *sense*), *stores* the dynamic response, and *transmits* information to nearest gateway node. Option B represents the approach presented in this paper wherein the system's process starts at decision epoch 1 in state 1 (*sleep*), *senses* excitation and can either (i) transit to next state (*i.e., store*) or (ii) *discard* the sensed dynamic response and transit to state 1. At state 3 (i.e., *store*), the system can either (i) *store* the sensed dynamic response in non-volatile flash memory, and transit to the *sleep* state, or (ii) transit to the next state and *transmit* the dynamic response information to the nearest gateway node. At state 4 (i.e., *Tx*), the system transmits dynamic response information, and thereafter transits to a next state (i.e. *sleep*).

The sum of expected total future discounted rewards are presented graphically in Figure 5, 7, and 9 for different values of dynamic response. For example, whereas Option A in Figure 5 yields sum of expected total future discounted rewards of 32.67 units in state 1 and 19.4 units in state 3, Option B yields 118.6 units in state 1 and 37.53 units in state 3. Similar explanations are applicable to the other states in Figure 5, and graphs in Figure 7 and 9. Furthermore, the graphs for total discounted rewards in current states starting from state 1 (*sleep*) are presented in Figure 6, 8, and 10 for different values of dynamic response. At every state, Option B yields higher values than Option A. For example, whereas Option A achieves 1558 units at decision epoch 1 in Figure 10, Option B earns 1571 units. Option B generally shows higher earnings at every decision epoch. This implies higher level of energy efficiency in transmission of dynamic response by the HMC system. Similar explanations are applicable to other states in Figure 10, and graphs in Figure 6 and 8.

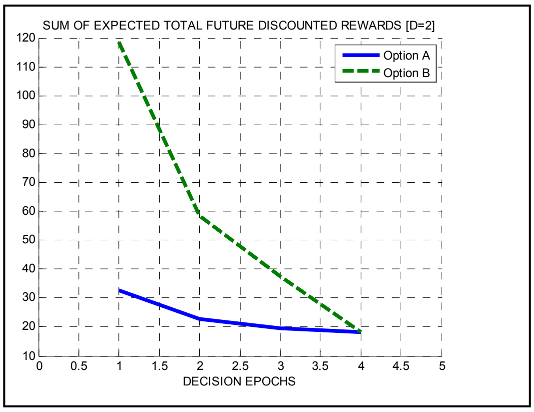

Figure 5. Sum of expected total future discounted reward

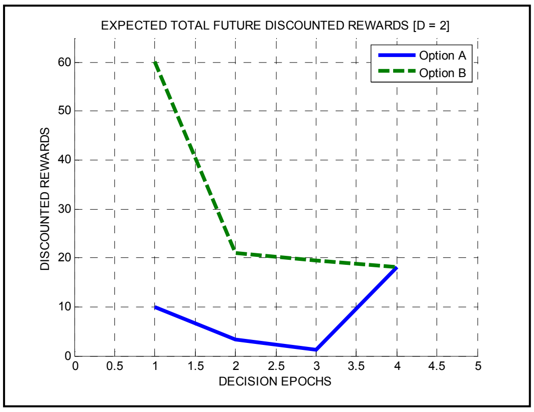

Figure 6. Expected total discounted rewards in current states, starting at state 1 [D =2]

Defuzzified input and output values are presented in Table 5. It is noted that values of dynamic response of 0 and 8 corresponding to the *Low-Discharge* and *Maximum-Discharge* Fuzzy sets respectively, have grade of membership of zero. The plot of discharge-status in Figure 12 is based on results of defuzzification of aggregated output in Table 5. Whereas input values from 4.5 to 7.9, yield output values of 4.45 to 6 which indicate maximum-discharge of water from the Dam to prevent damage, defuzzified input values from 0.5 to 3, result in output values of 1.5 to 2.5 which indicates low-discharge of water from the Dam. The advantage of incorporating the Fuzzy logic control scheme is its inherent capability to manage smooth transition between adjoining classes with unsharply defined criteria of class membership.

The results generally show that the discounted SMDP and Fuzzy logic control based approach presented in this paper can provide a basis for design and implementation of robust energy-efficient health monitoring and control systems for civil infrastructures using wireless smart sensor networks.

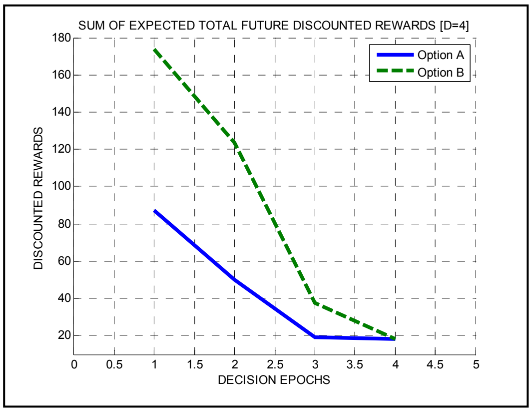

Figure 7. Sum of expected total future discounted rewards

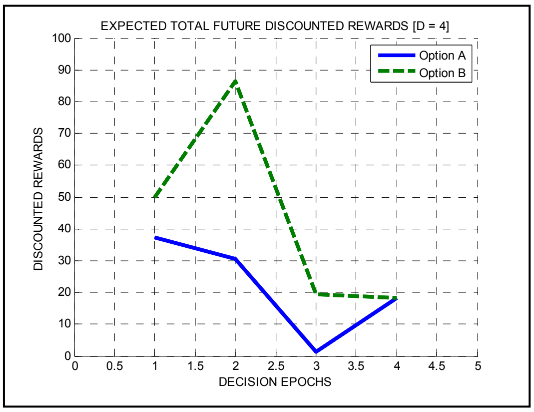

Figure 8. Expected total discounted rewards in current states, starting at state 1 [D =4]

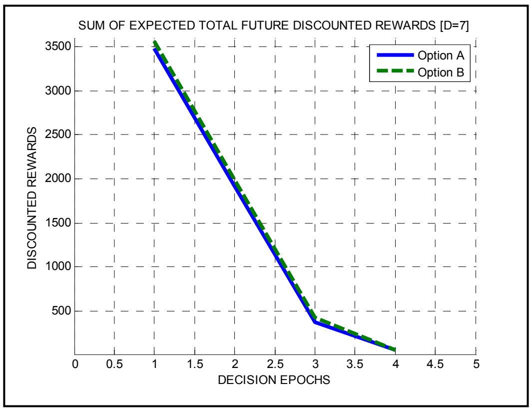

Figure 9. Sum of expected total future discounted reward

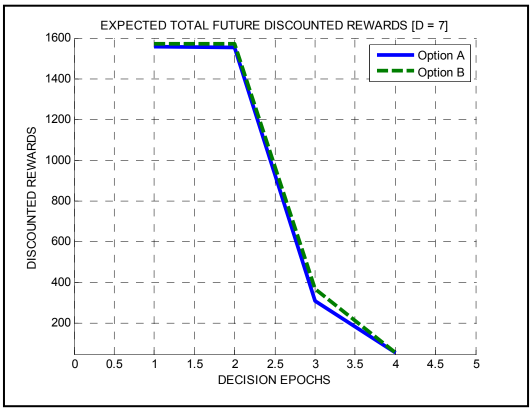

Figure 10. Expected total discounted rewards in current states, starting at state 1 [D = 7]

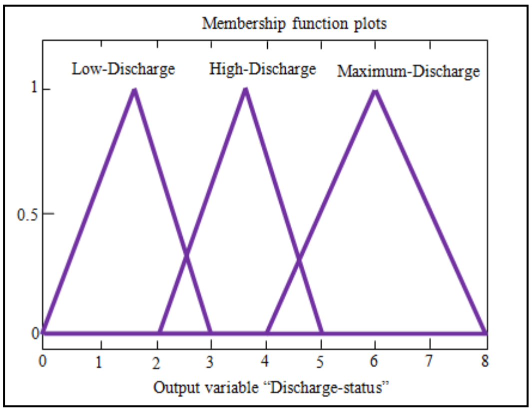

Figure 11. Fuzzification of output (i.e., discharge-status)

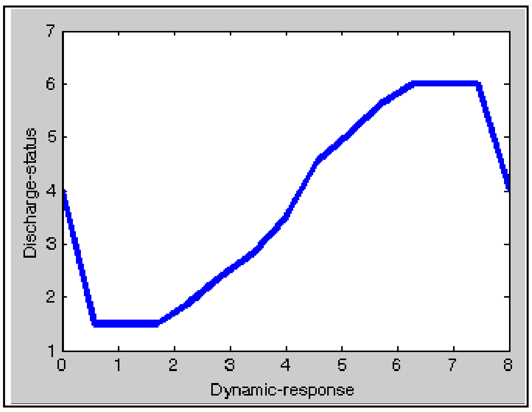

Figure 12. Discharge-status based on results of defuzzification of aggregated output

The main contributions of this research are:
(a) It provides robust control scheme and energy-efficient design framework for HMC system for civil infrastructures using wireless smart sensor networks. This has potential for averting damage and resultant destruction of the environment.
(b) It provides energy-efficient decision model for HMC applications using wireless smart sensor networks.

6. Conclusion

In this paper, we investigated the problem of energy utilization and control of health monitoring system for civil infrastructures using wireless smart sensor networks. We considered a Dam wherein wireless smart sensors are deployed on the barrier. The HMC system was characterized as SMDP, and subsequently obtained relevant mathematical representations for decision making in this model. Fuzzy logic control scheme was incorporated in the HMC model to provide robust control capable of addressing concerns for imprecision and uncertainty in the system's dynamic responses. The efficacy of the approach was tested under different scenarios of dynamic responses, via numerical analysis which was implemented in MATLAB software. The results in Tables 2 - 5 and Figure 5 - 12 show that the discounted SMDP and Fuzzy logic control based approach can provide a basis for design and implementation of robust energy-efficient HMC systems for civil infrastructures using wireless smart sensor networks.

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