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Entropy-Based Stochastic Analysis of Wireless Sensor Networks

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Abstract: Wireless sensor networks operate in highly dynamic environments, where channel conditions are continuously influenced by several factors. Accurate characterization of channel state dynamics is therefore essential for evaluating network reliability, communication efficiency, and overall system performance. An entropy-based stochastic framework was proposed for the statistical analysis of channel state information derived from wireless sensor networks. The link quality of an individual sensor node was modeled as a discrete random variable with four mutually exclusive channel states representing outage (deep fade), marginal connection, stable communication, and line-of-sight operation, corresponding respectively to complete packet loss, elevated retransmission rates, nominal communication performance, and maximum achievable data throughput. The information of each communication channel state was quantified through link information, whereas the uncertainty associated with the link quality was measured using link entropy. Because wireless communication environments exhibit inherent temporal variability, repeated observations of sensor states were collected to construct empirical probability distributions. Based on these empirical distributions, the maximum uncertainty point, expected channel state, entropy, information elasticity coefficient, and unpredictability coefficient were systematically derived to quantify the statistical characteristics of channel-state variability. Consequently, different channel-state samples were objectively classified according to their statistical properties, thereby facilitating quantitative assessment of network stability, communication quality, and operational robustness under dynamic environmental conditions. The proposed framework provides a rigorous and computationally efficient methodology for entropy-based characterization of wireless sensor network behavior and establishes a general analytical foundation for reliability assessment, adaptive network management, and information-driven optimization of wireless sensing systems.

Keywords: Wireless sensor networks; Channel state information; Entropy; Stochastic modeling; Empirical probability distribution; Information elasticity coefficient; Unpredictability coefficient; Channel state analysis

1 Introduction

The dawn of the Internet of Things and pervasive computing has fueled the mass deployment of wireless sensor networks. These networks consist of spatially distributed, autonomous devices utilizing sensors to cooperatively monitor physical or environmental conditions [1]. Early research in wireless sensor networks focused primarily on the hardware constraints of the nodes, such as limited computational power, and restricted battery life [2]. However, as deployments scale from dozens to millions of nodes, the primary challenge shifts from managing the physical hardware to managing the information itself. Sensor networks are no longer viewed merely as collections of static hardware, but as complex, evolving systems characterized by high mathematical fluidity. The fluid exchange, aggregation, and degradation of data across a network is known as information dynamics. Understanding how information flows, mutates, and stabilizes across these networks is crucial for optimizing everything from data accuracy to energy efficiency.

In reality, wireless sensor networks are plagued by three constraints that govern their information dynamics:

(i) Data flood vs. channel bandwidth: Sensors generate massive amounts of local data. If every node transmits its raw readings, the wireless medium quickly becomes congested, leading to packet collisions and information loss.

(ii) Energy consumption vs. information fidelity: The "viscosity" of data in a network is inextricably linked to power. Transmitting data consumes significantly more energy than processing it.

(iii) Network topology and evolution: Wireless sensor networks are rarely static. New nodes are added, and environmental obstructions alter communication links. This changing physical topology alters the pathways through which information can flow [3].

By adjusting some classical mathematical models, engineers can predict how rapidly a piece of information, or a malicious data-injection attack, will saturate a network [4]. But, in general, while the performance analysis of many aspects of the stochastic service systems has been conducted [5–8], analytical models based on system information and system entropy analysis are largely absent. Thus, there exists only the famous and very exploited information theoretic approach based on entropy maximization given certain constraints [9–18].

In this work, depending on the basic concepts of information i and entropy $S = E(i)$ of a given sensor node in a wireless sensor network, where the link quality category of the sensor node (being a discrete random variable) is represented by four states (i.e., deep fade/outage, poor/marginal connection, good/stable communication, and excellent/line-of-sight operation), this study promotes a stochastic framework for wireless sensor network analysis. The quantity of information i possessed by a sensor node link (i.e., carried out by the communication channel) is an essential characteristic of the particular link states and, by definition, the entropy $S = E(i)$ is the uncertainty, associated with the link quality. This study applies the Gibbs' formula for entropy [19], and its adaptation to random variables, proposed firstly by Shannon [20] (focusing only on the discrete case).

Entropy-based link quality indicators provide the most value in highly dynamic, unpredictable, and interference-prone network environments. Conventional monitoring, such as moving averages of the received signal strength indicator, or packet delivery ratio, treats link quality as a static or smoothly changing value. It fails in conditions where the variability of the channel matters more than its average strength. The specific network conditions where entropy indicators excel are:

(i) High-interference environments: Conventional metrics smooth out the short-term spikes, showing a deceptive "decent average" quality. Entropy captures the high randomness (high entropy) of the bursts, warning routing protocols that the link is secretly highly volatile.

(ii) Mobile mesh networks: A communication link may transition rapidly from a high-quality connection to a complete outage within a short time interval. Entropy measures the uncertainty and captures the information elasticity and unpredictability of these transitions. Low entropy means the link behavior is stable (even if poor), while high entropy flags an erratic, untrustworthy route.

(iii) Edge-of-coverage zones: Instead of waiting for a threshold to drop and trigger a disconnected state, entropy detects the sudden spike in state-switching uncertainty early, allowing the network to proactively reroute traffic.

Therefore, conventional metrics (e.g., the received signal strength indicator, or packet delivery ratio), which measure the average signal strength or throughput over time, are best for static, stable environments with linear degradation, and fail in bursty/dynamic conditions (where spikes are masked as a "good average"). On the other hand, entropy-based metrics, which measure uncertainty, randomness, and statistical stability, are best for highly volatile, unpredictable, or interference-heavy networks, and fail in purely static environments (with unnecessary computation added).

The rest of this study is organized as follows. Section 2 gives the system model and introduces the performance measures in the methodology. Section 3 illustrates the methodology for three scenarios (i.e., stable environment with low entropy dynamics, unstable environment with medium entropy dynamics, and dynamic/obstructed environment with high entropy dynamics) and presents a discussion of the obtained results. Section 4 is a conclusion of the study.

2 System Model

This study considers a sensor network, targeting the channel state information/link quality indicators. In real-world wireless sensor networks or telecommunication mesh networks, hardware sensors continuously evaluate the physical environment. Instead of transmitting volatile, noisy continuous metrics, the sensor's firmware automatically classifies the radio environment into a stable, discrete operational state to optimize routing protocols.

Let N be a discrete random variable, representing the link quality category of a specific sensor node. The firmware map converts hardware measurements (like the received signal strength indicator) into strict, finite set of discrete states, $n = \{0, 1, 2, 3\}$, defined explicitly as:

$$N = \begin{cases} n = 0: \ \text{Deep Fade / Outage} & \text{(Packet drops entirely)} \\ n = 1: \ \text{Poor / Marginal connection} & \text{(High retransmission rate)} \\ n = 2: \ \text{Good / Stable communication} & \text{(Standard nominal operation)} \\ n = 3: \ \text{Excellent / Line - of - sight operation} & \text{(Maximum data throughput)} \end{cases}$$

At regular intervals (e.g., every second or every minute), the sensor logs one of these four integers. This creates a clean, discrete time series ready for information-theoretic profiling.

2.1 Methodology Basics

Because a network's environment changes dynamically (due to physical obstructions, weather, or malicious radio jamming), this study calculates block measures over a sliding window of m temporal observations (e.g., $m = 60$ observations, representing 1 hour of minute-by-minute sensor tracking). The empirical probability of the sensor node in state n within the current window is:

$$p_n = \frac{1}{m} \cdot \sum_{i=1}^{m} I[N(i) = n], \text{for } n \in \{0, 1, 2, 3\} \tag{1}$$

where,

$$I[X = n] = \begin{cases} 1, & \text{if } X = n, \\ 0, & \text{if } X \neq n. \end{cases}$$

Staying in any of its particular states n, with $n \in \{0, 1, 2, 3\}$ a sensor node possesses (i.e., the random variable N carries out) a quantity of information i_N with possible values $i_n, n \in \{0, 1, 2, 3\}$, and its expected value, i.e., entropy S,

$$i_n \overset{\text{def}}{=} -\ln p_n, \quad n = 0, 1, 2, 3 \tag{2}$$

$$S = E(i) \overset{\text{def}}{=} \sum_{n=0}^{3} i_n \cdot p_n = -\sum_{n=0}^{3} p_n \cdot \ln p_n \tag{3}$$

The entropy is an average information dynamics metric, representing the uncertainty associated with the sensor node. The empirical relation in Eq. (1) can be written in the form as follows:

$$\frac{p_n}{p_0} = a_n, \quad a_n > 0; \quad n = 0, 1, 2, 3$$

$$p_0 = \frac{1}{f_3}, \quad f_3 = \sum_{n=0}^{3} \frac{p_n}{p_0} = \sum_{n=0}^{3} a_n \tag{4}$$

where, $a_0 = 1$, and a_n, with $n = 1, 2, 3$, are calculated as the corresponding frequencies.

The steady-state probability distribution of a birth-death process of size $M + 1$ is determined by the probability continuity law (i.e., global balance equations) and probability conservation law (i.e., normalization factor) [21–23]. It is expressed with respect to the utilization parameter ρ (i.e., the birth-death ratio) as follows:

$$\frac{p_n(\rho)}{p_0(\rho)} = a_n \rho^n, \quad n = 0, 1, \ldots, M,$$

$$p_0(\rho) = \frac{1}{f_M(\rho)}, \quad f_M(\rho) = 1 + \sum_{n=1}^{M} a_n \rho^n, \quad \rho > 0 \tag{5}$$

The relations in Eq. (4) could now be considered as a special case of the standard probability mass function of a birth-death process of size $M = 3$, with an assumption that the birth-death process resides in the point $\rho = 1$. Then, the calculation of the information $i_N(\rho)$ through Eq. (2) and Eq. (5) leads to:

$$i_n(\rho) = i_0(\rho) + (-\ln \rho)n + (-\ln a_n), \quad n = 1, 2, \ldots, M, \quad \rho > 0 \tag{6}$$

The calculation of the entropy $S(\rho)$ through Eq. (3) and Eq. (5) leads to:

$$S(\rho) = \ln f_M(\rho) - (\ln \rho) \cdot \overline{N}(\rho) - \frac{1}{f_M(\rho)} \cdot \sum_{n=1}^{M} (a_n \cdot \ln a_n) \cdot \rho^n, \quad \rho > 0 \tag{7}$$

Eq. (7) also presents the relationship between the entropy $S(\rho)$ and the mean state $\overline{N}(\rho)$ of the birth-death process. The calculation of the function $\overline{N}(\rho)$ through Eq. (5) is given by:

$$\overline{N}(\rho) \overset{\text{def}}{=} \sum_{n=1}^{M} n \cdot p_n(\rho) = \rho \cdot \frac{f'_M(\rho)}{f_M(\rho)} = \frac{\sum_{n=1}^{M} n \cdot a_n \cdot \rho^n}{\sum_{n=0}^{M} a_n \cdot \rho^n}, \quad \rho > 0 \tag{8}$$

The function $S(\rho) \to 0$, as $\rho \to 0^+$ or $\rho \to +\infty$. Furthermore, the significant maximum uncertainty point $\rho_{M,\max}$, at which system entropy $S(\rho)$ has a maximum value, is the solution of the equation, obtained as $S'(\rho) = 0$ as follows:

$$\mathrm{cov}(N, i_N) = 0, \quad \text{i.e.,}$$

$$\sum_{n=0}^{M} \left[n - \overline{N}(\rho)\right] \cdot (a_n \cdot \rho^n) \cdot \ln(a_n \cdot \rho^n) = 0 \tag{9}$$

When $p_n = \mathrm{Prob}\{N = n\}$ obeys a uniform distribution, then $S = S_{\max}$. In the concrete scenario, because the sensor node has four states, then $p_n = 1/4$, with $n = 0, 1, 2, 3$, the maximum possible entropy is $S_{\max} = \ln(4)$, representing absolute chaos/randomness, and the minimum is $S_{\min} \to 0$, representing absolute certainty/static environment.

Remark 1. Considering, for example, a wireless system as a population of users, where the quantity N represents the current number of users, then besides the standard user mean $\overline{N} = E(N)$ and entropy $S = E(i_N)$ observed by an outside observer, the mean and entropy observed by arriving and departing users can also be analyzed and compared. Furthermore, these measures, seen from all three points of view, are equal only in the case of a system linear in information (i.e., when $a_N = 1$; that is the case when N obeys a truncated geometrical distribution). These three risk types allow us to distinguish two systems obeying the same probability distribution observed by an outside observer, such as the Erlang loss system compared to the system with discouraged user arrivals.

2.2 Information Elasticity and Unpredictability

The entropy in Eq. (7) can be written as:

$$S(\rho) = S_{\text{reg}}(\rho) + S_{\text{syn}}(\rho)$$

where,

$$S_{reg}(\rho) = i_0(\rho) + S_{el}(\rho) = i_0(\rho) + \left(-\ln \frac{\rho}{\rho_{M,\max}}\right) \cdot \overline{N}(\rho), \quad \rho > 0 \tag{10}$$

and

$$S_{\text{syn}}(\rho) = -\frac{1}{f_M(\rho)} \cdot \sum_{n=1}^{M} \left[a_n \cdot \ln\left(a_n \cdot \rho_{M,\max}^n\right)\right] \cdot \rho^n, \rho > 0 \tag{11}$$

Following the proposed approach, the relative magnitude and connectivity between the elastic part S_{el} and the ground part i_0 of the entropy S is quantified using the coefficient of information elasticity $\zeta(\rho)$, defined as follows:

$$\zeta(\rho) \stackrel{\text{def}}{=} \frac{S_{el}(\rho)}{i_0(\rho) + S_{el}(\rho)} = \frac{1}{1 + \frac{i_0(\rho)}{S_{el}(\rho)}}, \rho > 0 \tag{12}$$

This is a measure of the degree of information elasticity (i.e., information simplicity). If $\zeta(\rho) = 0$ (i.e., $\rho = \rho_{M,\max}$), then the sensor node is an information inelastic system, indicating complex system behavior. It can be noted that $\zeta(\rho) \to 1$, as $\rho \to 0^+$and as $\rho \to +\infty$. To express the relative magnitude and connectivity between the synchronization part S_{syn} and the regular part S_{reg} of the entropy S, this study uses another important coefficient of unpredictability $\eta(\rho)$, as follows:

$$\eta(\rho) \stackrel{\text{def}}{=} \frac{|S_{\text{syn}}(\rho)|}{S_{\text{reg}}(\rho) + |S_{\text{syn}}(\rho)|} = \frac{1}{1 + \frac{S_{\text{reg}}(\rho)}{|S_{\text{syn}}(\rho)|}}, \rho > 0 \tag{13}$$

This measures the degree of unpredictability (i.e., non-uniformity in the synchronization sensor/environment). Particularly, if $\zeta(\rho) = 0$ (i.e., $\rho = \rho_{M,\max}$), there exists a non-uniform adaptation sensor/environment. It can be noted that $\eta(\rho) \to 0$, as $\rho \to 0^+$and as $\rho \to +\infty$. The concepts of predictability and information linearity are equivalent; that is, a sensor is an information non-linear sensor, if and only if the synchronization sensor/environment is non-uniform.

2.3 Empirical Distribution Case

Considering the empirical distribution in Eq. (4) of a sensor node with $M+1=4$ states (i.e., experimentally obtained one), where this study examines the sensor node as in the point $\rho=1$ (but, the point $\rho_{M,\max}$, depending on the size M, is given through Eq. (9)).

In this case, for the entropy $S(1)$ and the mean state $\overline{N}(1)$, the following equations can be derived:

$$S(1)=\ln\left(\sum_{n=0}^{M}a_n\right)-\frac{1}{\sum_{n=0}^{M}a_n}\cdot\sum_{n=1}^{M}(a_n\cdot\ln a_n) \tag{14}$$

$$\overline{N}(1)=\frac{\sum_{n=1}^{M}n\cdot a_n}{\sum_{n=0}^{M}a_n} \tag{15}$$

In this case, Eq. (12) and Eq. (13) are used:

(i) If $\rho_{M,\max}\in[1,+\infty)$, then the sensor operates in an information-elastic manner, and

$$\zeta(1)=\frac{1}{1+\frac{\left(\sum_{n=0}^{M}a_n\right)\cdot\ln\left(\sum_{n=0}^{M}a_n\right)}{(\ln\rho_{M,\max})\cdot\sum_{n=1}^{M}n\cdot a_n}} \tag{16}$$

$$\eta(1)=\frac{1}{1+\frac{\left(\sum_{n=0}^{M}a_n\right)\cdot\ln\left(\sum_{n=0}^{M}a_n\right)+(\ln\rho_{M,\max})\cdot\sum_{n=1}^{M}n\cdot a_n}{\left|\sum_{n=1}^{M}a_n\cdot\ln[a_n\cdot(\rho_{M,\max})^n]\right|}} \tag{17}$$

(ii) If $\rho_{M,\max}\in(0,1]$, then the sensor operates in an information-anti-elastic manner, and

$$\zeta(1)=\frac{1}{1+\frac{\left(\sum_{n=0}^{M}a_n\right)\cdot\ln\left(\frac{\sum_{m=0}^{M}a_n}{a_M\cdot\rho_{M,\max}^{M}}\right)}{(-\ln\rho_{M,\max})\cdot\sum_{n=0}^{M}(M-n)\cdot a_n}} \tag{18}$$

$$\eta(1)=\frac{1}{1+\frac{\left(\sum_{n=0}^{M}a_n\right)\cdot\ln\left(\frac{\sum_{n=0}^{M}a_n}{a_M\cdot\rho_{M,\max}}\right)+(\ln\rho_{M,\max})\cdot\sum_{n=1}^{M}n\cdot a_n}{\left|\sum_{n=1}^{M}a_n\cdot\ln[a_n\cdot(\rho_{M,\max})^n]+\left(\sum_{n=0}^{M}a_n\right)\cdot\ln\left(a_M\cdot\rho_{M,\max}^{M}\right)\right|}} \tag{19}$$

3 Application Data

3.1 Test Scenario Results

Three representative real-world deployment scenarios are here considered based on some illustrative test cases, and are arranged in ascending order of entropy. All output metrics for a sensor node are given in Table 1. The scenario probabilities are considered illustrative examples, representing conceptual test cases by some synthetic samples. In each scenario, this study takes into account two close empirical distributions (with Scenarios A and B yielding the same entropy and Scenario C yielding the same mean).

Table 1. Output sensor measures under three deployment scenarios with sensor states $N\in\{0,1,2,3\}$

Scenario	$\overline{N}(1)$	M	$\overline{N}(1)/M$	$S(1)$	$S_{\max}$	$S(1)/S_{\max}$	$\rho_{M,\max}$	$\zeta(1)$	$\eta(1)$
A (1)	1.85	3	61.67%	0.914	1.386	65.95%	0.304	18.90%	44.97%
A (2)	1.95	3	65%	0.914	1.386	65.95%	0.312	18.49%	45.32%
B (1)	1.70	3	56.67%	1.089	1.386	78.57%	0.496	17.14%	39.31%
B (2)	1.90	3	63.30%	1.089	1.386	78.57%	0.512	16.91%	36.93%
C (1)	1.50	3	50%	1.194	1.386	86.10%	1	0%	32.51%
C (2)	1.50	3	50%	1.366	1.386	98.56%	1	0%	13.13%
Maximum	1.50	3	50%	1.386	1.386	100%	1	0%	0%

Note: A, B, and C denote the three deployment scenarios, while numbers in parentheses indicate different empirical probability distributions within each scenario. ζ and η represent the information elasticity and unpredictability coefficients, respectively.

(i) Scenario A: Stable sensor network environment (low entropy dynamics)

The sensor node is fixed inside a climate-controlled smart factory warehouse with zero structural changes. The radio link is highly stable. As an empirical observation vector is obtained over 60 intervals, the sensor records state 2 almost exclusively, with occasional jumps to 3 and 1, and rarely to 0. The corresponding empirical state probabilities are:

- Case 1: $p_0 = 0.05,\ p_1 = 0.15,\ p_2 = 0.7,\ p_3 = 0.1$; and
- Case 2: $p_0 = 0.05,\ p_1 = 0.1, p_2 = 0.7,\ p_3 = 0.15$.

The low entropy value proves high information stability. The network path is highly predictable, meaning routing protocols do not need to waste computational overhead recalculating paths.

(ii) Scenario B: Unstable environment (medium entropy dynamics)

The sensor node is deployed in an outdoor network, or some localized signal interference occurs. As an empirical observation vector is obtained over 60 intervals, the link quality shifts back and forth from time to time as the line of sight is less/more clear. The corresponding empirical state probabilities are:

- Case 1: $p_0 = 0.1,\ p_1 = 0.2,\ p_2 = 0.6,\ p_3 = 0.1$; and
- Case 2: $p_0 = 0.1,\ p_1 = 0.1,\ p_2 = 0.6,\ p_3 = 0.2$.

The medium entropy value presents moderate information stability. The network is experiencing some environmental volatility, notifying the network path with some unpredictability.

(iii) Scenario C: Dynamic/obstructed environment (high entropy dynamics)

The sensor node is deployed in an outdoor urban mesh network or an automated shipping yard. Heavy machinery moves back and forth, or active localized signal interference occurs. As an empirical observation vector is obtained over 60 intervals, the link quality violently shifts back and forth as physical obstacles block the line of sight. The corresponding empirical state probabilities are:

- Case 1: $p_0 = 0.1,\ p_1 = 0.4,\ p_2 = 0.4,\ p_3 = 0.1$; and
- Case 2: $p_0 = 0.2,\ p_1 = 0.3,\ p_2 = 0.3,\ p_3 = 0.2$.

The entropy approaches its theoretical maximum (which is $S_{\text{max}} = \ln(M + 1) = \ln(4) = 1.386$, when $p_n = 1/(M + 1) = 1/4, n = 0, 1, 2, 3$). This flags an information dynamics disruption event. The network is experiencing severe environmental volatility, notifying the system architecture to dynamically reroute data packets through alternate, lower-entropy paths.

3.2 Discussion

The monitoring of the entropy of a discrete variable is superior to that of traditional methods, since for the raw link tracking metrics, the traditional approach checks thresholds only (with patterns missing) and the entropic approach measures entropy shift (with environment chaos tracking). The research gap is that traditional networks observe instantaneous link drops. However, they fail to measure the rate of environment destabilization. The value proposition shows that by calculating the entropy of the discrete state variable, this framework quantifies the information elasticity and unpredictability of the physical environment itself. As an engineering takeaway, the results suggest that network routing protocols should not only consider "strong" signals, but also prioritize low-entropy links, which may help reduce battery consumption and mitigate packet dropouts under dynamic conditions.

Considering the output values in Table 1, it can be concluded as follows:

(i) If two observed samples of node states give the same entropy value, but then this study calculates different values for the maximum uncertainty point $\rho_{M,\max}$, which means they come from different families of distributions. Furthermore, although the same uncertainty S is associated to both samples, the data samples (i.e., sensor data) can be distinguished by slightly diverse values for the coefficients of information elasticity ζ and of unpredictability η.

(ii) If for two observed samples of node states, different but symmetrical empirical distributions are obtained. Then, for both samples, state mean $\overline{N} = M/2$, and $\rho_{M,\max} = 1$, which yields $\zeta = 0$.

(iii) Finally, if an observed sample of node states is approaching a uniform distribution (i.e., each state is almost equally likely), then both $\zeta \to 0$ and $\eta \to 0$, and $S \to S_{\text{max}} = \ln(M + 1)$.

As a comparative discussion in regard of the main differences among the Scenarios A to C, as entropy increases, the point $\rho_{M,\max}$ approaches the value of 1. Then, the link has no information elasticity (i.e., $\zeta = 0$), that is, the indicator ζ is more sensitive to the environmental changes. Furthermore, as S approaches S_{max} , the link becomes more predictable (i.e., η obtains smaller values). Finally, when $S = S_{\text{max}}$, then the link is totally predictable (i.e., $\eta = 0$).

Remark 2. It is worth mentioning that, with some observations on the current number N of users (i.e., a sample with some size), the estimation of the utilization parameter ρ using the maximum likelihood estimation does not take the non-linearity in information into account for parameter estimation (i.e., it does not consider the information noise). In this direction, an entropy-based estimation of the parameter ρ, which takes the population features into account using the whole entropy for a given sample for the quantity N, has been introduced [24] and further examined [25], demonstrating that the maximum likelihood estimation can be successfully applied only to the distribution linear in information. Regarding the entropy-based estimation, a transcendental equation with respect to the parameter is obtained (which needs to be solved numerically; and, usually, two solutions are obtained), compared to the maximum likelihood estimation, where the procedure is reduced to a linear algebraic equation (giving just one solution somewhere between the previous two solutions).

4 Conclusions

This study considers a wireless sensor network, where a sensor node with four possible states is investigated (that is, deep fade/outage, poor/marginal connection, good/stable, and excellent/line-of-sight), i.e., the current state N can take any integer value in the range $N \in \{0, 1, 2, 3\}$ and analyze the amount of information i_N carried by the random variable N, and also the entropy $S = E(i_N)$. Taking a number of temporal observations on sensor state N, because of the dynamically changing network environment (due to weather, signal transmission interference, or malicious signal interdiction), this study obtains an empirical distribution of the quantity N and then calculates the maximum uncertainty point of the corresponding family of empirical distributions, mean state, entropy, and the coefficients of information elasticity and of unpredictability. All these measures serve to classify the different samples of sensor states.

While the current framework assumes a four-state discretization model and fixed observation windows to establish a tractable baseline, these parameters can be adaptively scaled. Future extensions could naturally expand the system to larger, more granular state spaces to capture subtle channel variations, or transition toward real-time, sliding-window monitoring settings. Implementing these adaptive approaches would allow the network to dynamically quantify entropy, information elasticity, and unpredictability in response to instantaneous environmental shifts.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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