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Multi-Variable Markov Framework for Predicting Battery Depletion in Wireless Sensor Networks

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Abstract

Wireless Sensor Networks (WSNs) support intelligent data acquisition systems across environmental monitoring, industrial automation, and smart cities. As a fundamental enabler of the Internet of Things (IoT), WSNs rely heavily on battery-powered sensor nodes for sustained operation in dynamic and often remote environments. However, predicting battery lifetime in WSNs remains a critical challenge due to the complex interplay between environmental conditions and operational behaviors. Conventional energy models often fail to consider the simultaneous influence of temperature, humidity, and data traffic intensity on battery depletion rates. This study proposes a battery lifetime prediction model based on a Markov framework integrated with an exponential energy consumption function to address this issue. The model incorporates three primary variables—ambient temperature, relative humidity, and data movement to simulate energy usage dynamically. The framework calculates transition probabilities and energy load based on environmental states, enabling accurate forecasting. Additionally, the model evaluates the impact of different battery chemistries (Ni-MH, LiPo, Li-ion, and Alkaline) on lifespan performance across varying environmental scenarios. Simulation results reveal that temperature and humidity significantly influence energy depletion, while data transmission intensity plays a supporting role in high-traffic cases. LiPo and Li-ion batteries demonstrate superior performance and stability, especially under extreme environmental conditions. This study contributes a novel multi-variable model that bridges physical sensing environments with predictive battery analytics. The findings provide a foundation for strategic energy planning and adaptive deployment of WSNs in sustainability-critical applications.

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1. Introduction

Wireless Sensor Networks (WSNs) play a pivotal role in gathering intelligence regarding hostile surveillance zones, including the environmental assessment of rapidly occurring volcanic activities, wildfires, flooding events, and unpredictable ecological conditions [1]-[2]. The efficacy of WSNs is significantly impacted by the performance parameters of their power sources [3]-[4]. The energy derived from batteries constitutes the most critical resource within WSNs, and the longevity of the batteries utilized in WSNs is inherently unpredictable [5]. Consequently, the operational performance of WSNs is constrained, resulting in a markedly abbreviated lifespan, thereby rendering them inefficient and lacking in scalability [6]-[7]. WSNs are frequently deployed in inaccessible and high-stakes environments, occasionally in substantial numbers. Thus, the exact timing of battery depletion remains uncertain [8]. Therefore, precise forecasting of WSN battery longevity is essential for enhancing the overall performance of WSNs.

The WSNs performance is significantly affected by their operational lifespan [9]-[10]. The longevity of a WSN is quantitatively assessed based on the duration for which the batteries within the WSN can remain operational [11]. An extensive body of research has been conducted in recent years to enhance the longevity of WSNs. Various methodologies can be employed to prolong their lifespan, including 1) the selection of energy-efficient hardware components and the implementation of optimized algorithms and protocols [12]-[13]. 2) The minimization of data transmission requirements over the network through local processing and data aggregation at the sensor node level is capable of conserving critical energy resources [14]-[15]. 3) The incorporation of renewable energy sources, such as solar energy or vibrational energy, for recharging the battery nodes of sensors can substantially prolong the operational lifespan of WSNs [16]. Furthermore, applying adaptive power management strategies, which involve modulating communication frequencies according to necessity or placing sensor nodes into a low-power state during idle periods, can also contribute to energy efficiency. However, not all the methods that have been explained still can predict battery life significantly.

The deployment of WSNs in the IoT environment has brought numerous advantages, particularly in intelligent monitoring and data collection for various applications [17]-[18]. However, these networks face significant challenges, primarily due to security vulnerabilities and limited energy resources in sensor nodes. This research has developed a lightweight authentication protocol to mitigate security risks using PUF technology. Implemented on the Node-MCU ESP8266, this protocol optimizes memory usage, making it suitable for IoT devices with constrained capabilities, such as WSN nodes [19]-[20]. Additionally, ZigBee WSNs have demonstrated significant contributions to the IoT ecosystem, particularly for low power and cost-effective applications. Despite ZigBee's efficiency in energy management and routing, challenges associated with IoT security remain unresolved, emphasizing the need for secure deployment strategies.

To improve the efficiency of WSNs, researchers have explored various data aggregation and network management strategies. One such effort is the introduction of the E2S-DRL algorithm, which aims to reduce latency and prolong network lifespa [21]. This algorithm comprises three phases: clustering with the zBC scheme, duty cycling through DRL, and routing using Ant Colony Optimization (ACO) and Firefly Algorithm (FFA). The simulation outcomes showed that E2S-DRL reduced energy consumption, lowered latency, and increased network throughput and lifespan compared to prior methodologies. Another researcher proposed an energy-efficient data aggregation strategy using fuzzy logic. This strategy allows autonomous data collection and classification while reducing energy usage and extending network lifetime [22].

Meanwhile, energy-harvesting techniques have emerged as a viable solution to prolong the lifespan of battery-dependent WSNs by harnessing ambient energy [23]. Researchers in energy harvesting have evaluated various energy harvesting prediction methods within WSNs, introducing the iPro-Energy model, which has shown superior prediction accuracy and throughput in short- to medium-term forecasts. While ASIM offered lower complexity, iPro-Energy outperformed in terms of prediction capabilities, establishing it as a valuable tool in energy management for WSNs. These methodologies, alongside advancements in ultra-low power consumption strategies for EHWSNs, demonstrate the ongoing focus on improving network longevity through enhanced power management [24]. Still, challenges remain in optimizing the recharge cycles and battery health within the WSN ecosystem.

Despite advancements in security, energy efficiency, and data management, the specific longevity of WSN batteries under varying environmental conditions, such as temperature, humidity, and data transmission rates, has received limited attention. This study addresses this gap by proposing a predictive model for WSN battery lifespan influenced by ambient environmental factors. By incorporating Markov Model predictions, this research quantifies the impact of temperature, humidity, and data transmission dynamics on WSN battery longevity, providing an analytical framework for accurately forecasting network sustainability.

2. Methodology

The Markov model constitutes a statistical framework employed to forecast the likelihood of an event transpiring [25]. Using Markov models facilitates the anticipation of the subsequent state based on the individual's prior state. Consequently, energy consumption can be ascertained in advance, enabling the implementation of appropriate measures according to the requirements of WSN. Within the Markov prediction model context, a state signifies a specific condition under which an event may occur within a defined temporal interval. The likelihood associated with a state is the probability of a state transition. Each state possesses an associated transition probability to alternate states, thereby allowing for the formulation of a transition probability matrix by the specified equation:

$$p = \begin{bmatrix} p_{11}\, p_{12} \cdots p_{1n} \\ p_{21}\, p_{22} \cdots p_{2n} \\ . \quad . \quad . \quad . \\ . \quad . \quad . \quad . \\ . \quad . \quad . \quad . \\ p_{n1}\, p_{n2} \cdots p_{nn} \end{bmatrix} \tag{1}$$

P_{11} examines the likelihood of transitioning from state 1 to state 1. For instance, this analysis considers scenarios where the wireless sensor network (WSN) battery is fully charged, completely depleted, or at a 50% charge level. A fully charged battery is represented by the numeral 1, whereas a fully depleted battery is denoted by the numeral 0. The probability of encountering a depleted battery is designated as P. In contrast, the probability of a fully charged battery is represented as 1-P, indicating that the variations in battery consumption are contingent upon the preceding state P [26]. The battery power consumption within a WSN typically correlates with the specific WSN unit employed. Nevertheless, it is generally observed that the WSN units engaged predominantly utilize battery energy, as illustrated in Table 1.

Table 1: Current Consumption

CPU Mode	Current	Radio Mode	Current
active	8.0 mA	Rx	7.0 mA
Idle	3.2 mA	Tx (-20 dBm)	3.7 mA
ADC noise reduction	1.0 mA	Tx (-19 dBm)	5.2 mA
Power down	103 µA	Tx (-15 dBm)	5.4 mA
Power Save	110 µA	Tx (- dBm)	6.5 mA
Standby	216 µA	Tx (- dBm)	5.4 mA
Extended Standby	223 µA	Tx (dBm)	8.5 mA
Internal Oscillator	0.93 µA	Tx (+ dBm)	11.6 mA
LEDs	2.2 mA	Tx (+ dBm)	13.8 mA
Sensor Board	0.7 mA	Tx (+ dBm)	17.4 mA
EEPROM Access		Tx (+10 dBm)	21.5 mA
Read	6.2 mA		
Read Time	565 µS		
Write	18.4 mA		
Write Time	12.69 mS		

Utilizing Table 1, one can formulate a straightforward mathematical expression to ascertain energy consumption in Wireless Sensor Networks (WSNs) through the subsequent equation:

$$\begin{aligned} EUIcom &= E_{mc} + E_{Im} + E_{S1} + E_{s2} - E_{D} \\ EUIAct &= E_{S} + E_{L} + E_{e} + E_{EDP} + E_{CTR} - E_{D}. \end{aligned} \tag{2}$$

EUI_{com} = Energy Use Index, E_{mc} = Energy Consumed by Microcontroller, E_{s1} = Energy Consumed by sensor 1, E_{s2} = Energy Consumed by sensor 2, E_D = Energy Depletion, EUI_{Act} = Energy Use Index Action, E_S = Energy for sensing, E_L = Energy for Localization, E_e = Energy for Encryptions, E_{EDP}= Energy for data processing, E_{CTR} = Energy for Communication (Transmitting, Receiving).

The energy depletion assessed in this investigation is derived from the performance metrics of WSNs, including variables such as temperature (t), humidity (c), and data transmission (τ_n). Discrepancies in the battery temperature data recorded in antecedent research indicated that each battery experienced surface temperature fluctuations of 0.02, 0.03, and 0.05 degrees Celsius [27]. Consequently, predictive calculations can be executed for each sequence of inputs to ascertain the WSN's anticipated energy consumption. In this context, the likelihood of each trained Markov model producing a particular sequence of inputs is evaluated using state-space and Autoregressive Exogenous (ARX) algorithms. Each model is specifically trained to correspond with a distinct energy consumption label. The model exhibiting the highest likelihood will be chosen, and the energy associated with the label will be regarded as estimated energy consumption.

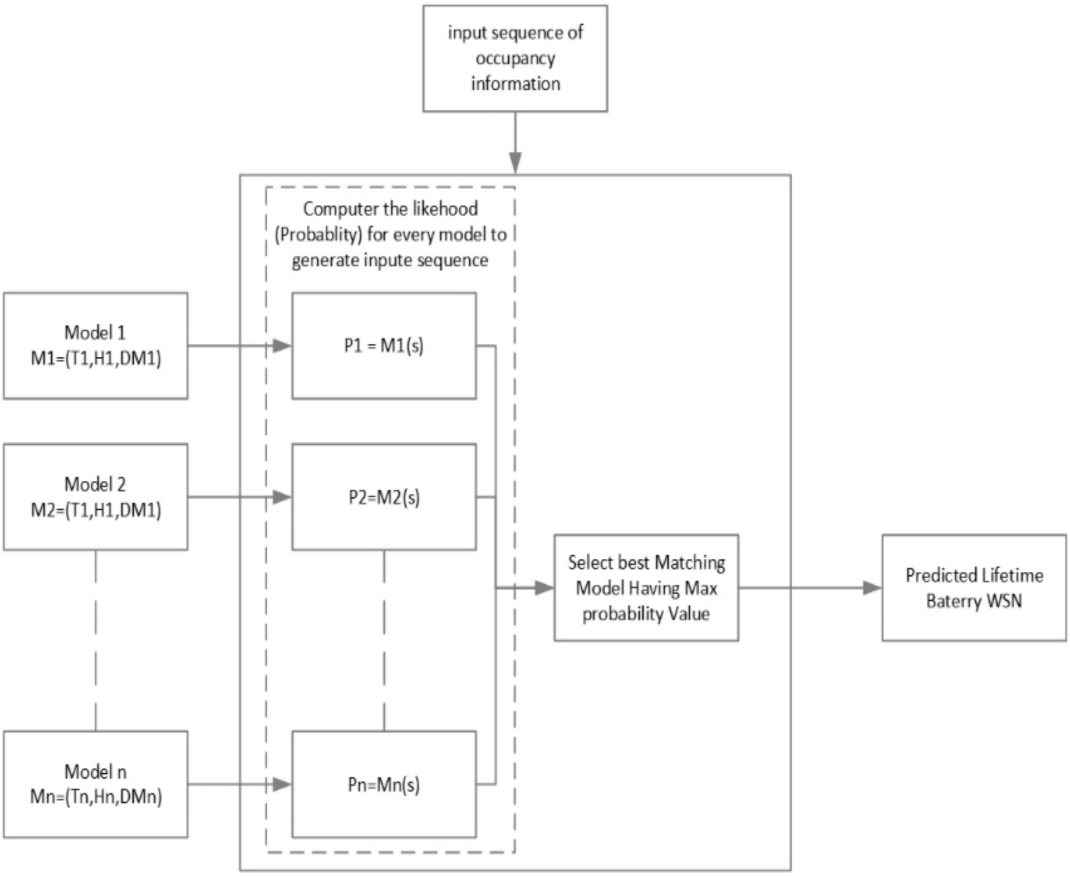

Figure 1. Markov Model Prediction

The Markov model illustrated in Figure 1 indicates that each model is formulated with various potential outcomes. Each model is established under the influence of three critical parameters precisely: temperature (T), humidity (H), and data movement (τ). The triad of parameters employed in this investigation will serve as the determinants that influence the longevity performance of the battery. The temperature and humidity metrics within the battery can be ascertained by acquiring data from the sensor integrated into the deployed WSN. Conversely, the data movement can be computed by assuming all nodes remain static while competing for access to each channel. By allowing the backoff counter time slot t for a particular node to be denoted as cn(t), the Backoff stage is denoted by sn(t). Consequently, the probability of temperature, humidity, and data movement can be depicted in Figure 2.

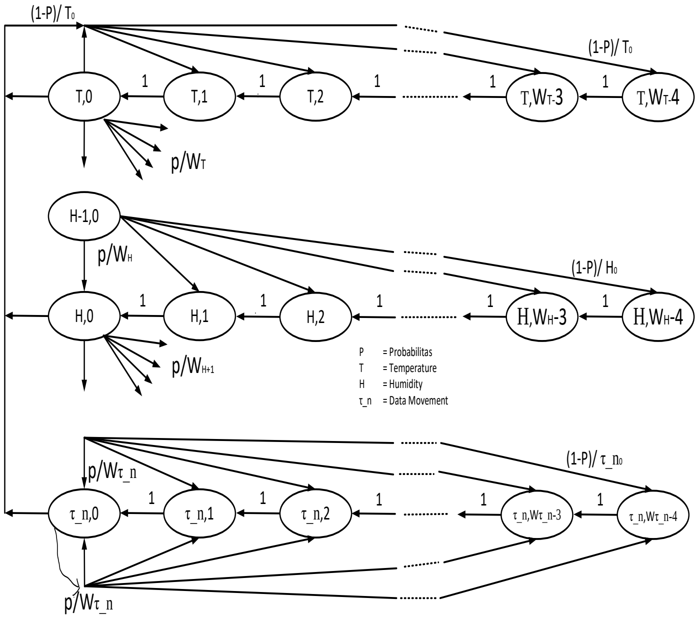

Figure 2. A two-dimensional Markov chain model of a node's backoff stage and backoff counter.

The forecasting of temperature, humidity, and movement data, illustrated in Figure 2, may serve as supplementary inputs or attributes for the models outlined in Figure 1. Such information is instrumental in enhancing the precision of battery life estimations, as environmental conditions and patterns of network utilization can significantly influence sensor energy expenditure. Figures 1 and 2 function synergistically within the WSN behavior modeling and forecasting framework. Figure 2 offers a stochastic framework for environmental and network parameters, whereas Figure 1 employs this data (either directly or indirectly) to project battery lifespan. By combining these two methodologies, one can better understand WSN dynamics and formulate more precise predictions regarding its battery longevity.

Figure 2 delineates three distinct Markov chains, each characterized by Temperature, Humidity, and Data Movement variables. Each chain encompasses a designated initial state, a transition mechanism between states, and a terminal absorption state.

Temperatures (T):

- Initial Status, Transition from T, $k\ to\ T, k+1$:

$$P(T, k \ \rightarrow T, k+1 = 1 \ for\ 0 \ \leq k \ \leq \ W_T - 2 \qquad (3)$$

- Transition between statuses, Transition from $T, W_T - 1\ to\ T, W_T - 1$:

$$P(T, W_T - 1) \rightarrow T, W_T - 1) = \frac{P}{W_T}$$

- Absorption Status, Transition from $T, 0\ to\ T, W_T - 1$:

$$P(T, 0 \ \rightarrow T, W_T - 1) = \frac{1-p}{T_0}$$

Humidity (H):

- Initial Status, Transition from H, $k\ to\ H, k+1$: (4)

$$P(H, k \ \rightarrow H, k+1 = 1 \ for\ 0 \ \leq k \ \leq \ W_H - 2$$

- Transition between statuses, Transition from $T, W_T - 1\ to\ T, W_T - 1$:

$$P(H, W_H - 1) \rightarrow H, W_H - 1) = \frac{P}{W_H}$$

- Absorption Status, from $T, 0\ to\ T, W_T - 1$:

$$P(H, 0 \ \rightarrow H, W_H - 1) = \frac{1-p}{H_0}$$

Data Movement (τ_n):

- Initial Status, Transition from τ_n, $k\ to\ \tau_n, k+1$: (5)

$$P(\tau_n, k \ \rightarrow \tau_n, k+1 = 1 \ for\ 0 \ \leq k \ \leq \ W_{\tau_n} - 2$$

- Transition between statuses, Transition from $\tau_n, W_{\tau_n} - 1\ to\ \tau_n, W_{\tau_n} - 1$:

$$P\big(\tau_n, W_{\tau_n} - 1\big) \rightarrow T, W_{\tau_n} - 1) = \frac{P}{W_{\tau_n}}$$

- Absorption Status, Transition from $\tau_n, 0\ to\ \tau_n, W_{\tau_n} - 1$:

$$P\big(\tau_n, 0\ \rightarrow \tau_n, W_{\tau_n} - 1\big) = \frac{1-p}{\tau_{n_0}}$$

For each parameter (Temperature, Humidity, and Data Movement), the expected value or mean state duration can be derived from the transition probabilities and states. The predicted value for data movement (τn) is given by

$$\tau_n(p) = \frac{1}{1 + W_i + \frac{p}{1-p} W_i \sum_{i=0}^{m-1} (2p)^i} \tag{6}$$

W_i = The weights or parameters corresponding to each state.
P = The probability of transitioning from one state to another.

The relationship between the energy in Eq. (2) and (6) is in managing and optimizing energy use in various operational statuses. An efficient and adaptive energy use model can make predictions that are more dynamic and responsive to environmental changes. In addition, the model developed shows that the model to be created is a model of interaction between the physical environment and digital technology in sustainable system design. The following is an exponential model of energy consumption influenced by temperature, humidity, and data movement.

$$E_{component}(T, H, \tau) = E_{component}\ x\ e^{\alpha T + \beta H + \gamma \tau} \tag{7}$$

$E_{component}$ = essential energy consumption of components without environmental impact.
(T, H, τ) = index values of the status in the respective chains for temperature, humidity, and movement data.
α, β, γ = parameters that determine how sensitive a component is to temperature, humidity, and data movement changes.

Each parameter functions as follows:
A = This parameter determines how strongly temperature affects energy consumption. Positive values indicate that increasing temperature increases energy consumption, while negative values indicate the opposite effect.
β = Like α, but for humidity. This parameter adjusts how humidity affects energy consumption.
γ = Determines the impact of data movement on energy. This can reflect the increase in energy consumption required to process and transmit data at higher data movement rates.

By utilizing the exponential function, it becomes feasible to ascertain energy consumption adjusted by fluctuating environmental parameters, thus offering pertinent data for managing energy in systems responsive to environmental changes. Utilizing Eq. (7), it is possible to compute the energy consumption for each model by incorporating variables such as temperature, humidity, and motion data, as illustrated in Figure 1. From the derived energy consumption metrics, it is feasible to establish the likelihood model and select the optimal model for estimating the lifespan of the WSN battery, following the subsequent procedural stages:

1. Stage 1. Determine the Energy Consumption by Eq. (7).
2. Stage 2. Evaluate the likelihood: Based on the energy determined within each model, it is feasible to derive the likelihood utilizing the exponential inversion formula:

$$P_i = e^{-(\alpha T + \beta H + \gamma \tau)}$$

3. Stage 3. (Select the most appropriate model): The model exhibiting the highest value P_iIt is deemed the most fitting for predicting optimal battery longevity.

The lifetime of each battery is calculated using Eq. (8)

$$Lifetime = \frac{Capacity\ x\ Voltage}{E_{modified}\ x\ C\text{-}rate} \tag{8}$$

The research endeavor will compute predictions concerning battery longevity utilizing the Markov model framework. The battery type employed in this analysis corresponds to that used, as delineated in Table 2. The study above meticulously elaborated on methodologies for battery characterization and parameter extraction pertinent to small load applications. This investigation examined four distinct battery chemistries to ascertain the most suitable battery for WSN applications. Pre-conditioning assessments were conducted to mitigate battery passivation effects and to stabilize the battery's capacity, resulting in the recovery of nearly 4% of the battery's original capacity. Moreover, the relaxation assessment facilitates the computation of the optimal duration for battery energy recovery across all battery types examined in the study. Lithium-ion batteries exhibit a superior flat voltage and a larger surface area across all discharge rates. Additionally, the thermal effects associated with elevated discharge rates in lithium-based batteries were minimal, thereby rendering these batteries the most advantageous option for WSN applications.

Table 2: Various battery chemistries are used in characterization [28].

Tag	Manufacture	Model	Battery Chemistry	Capacity (mAh)	Nominal Voltage	C-rate
Batt-1	Powerizer	MH-AAA1000APZ	nickel-metal hydride (Ni-MH)	1000	1.2 V	1 C
Batt-2	Data Power Technology	DTP603450	polymer lithium-ion (LiPo)	1000	3.7 V	1 C
Batt-3	Panasonic	UF553443ZU	lithium-ion (Li-ion)	1000	3.6 V	1 C
Batt-4	Energizer	LR-6	Alkaline (zinc, magnesium dioxide)	Variable, load-dependent	1.5 V	2 C

According to the data presented in Table 2, the operational lifespan of a battery can be determined by employing a mathematical model that incorporates energy consumption metrics, which are modulated by variables such as temperature, humidity, and motion parameters. These factors subsequently relate to the battery's capacity and other pertinent attributes.

3. Results and Discussions

3.1 Influence of Temperature on Energy Consumption and Lifetime.

An increase in temperature tends to increase the energy consumption of the sensor, especially in active components such as the microcontroller and communication module. High temperatures can cause increased internal electrical resistance, reduced efficiency, and the need for additional cooling. In this test, the temperature was set to vary from 20°C to 40°C, while other conditions were kept constant, with Humidity (H) at 80% and Data Movement (τ) at two units. The simulation results show that as the temperature increases, the energy consumption of the sensor node increases slightly exponentially, and the battery lifetime experiences a moderate decrease, as shown in Table 3.

Table 3: Influence of Temperature on Lifetime

Temperature (°C)	**Bat-1 (Ni-MH)**	**Bat-2 (LiPo)**	**Bat-3 (Li-ion)**	**Bat-4 (Alkaline)**
20	3.58 hours	11.03 hours	10.74 hours	2.24 hours
25	3.24 hours	9.97 hours	9.70 hours	2.03 hours
30	2.93 hours	9.03 hours	8.79 hours	1.84 hours
35	2.65 hours	8.18 hours	7.97 hours	1.67 hours
40	2.40 hours	7.42 hours	7.24 hours	1.53 hours

Energy Consumption increases slightly exponentially with rising temperature. Battery Lifetime for Batt-1 (Ni-MH) experiences a decrease of ±33% from 20°C to 40°C, Batt-2 (LiPo) experiences a decrease of ±33%, Batt-3 (Li-ion) experiences a decrease of ±33%, and Batt-4 (Alkaline) experiences a decrease of ±32%. All battery types show a consistent and significant decrease in lifetime. Battery-2 (LiPo) and Battery-3 (Li-ion) consistently have longer lifetimes than Battery-1 and Battery-4. Battery-4 (Alkaline) has the lowest lifetime across the entire temperature range. High temperatures (above 30°C) have a dominant impact on accelerating energy depletion in sensor nodes. Every 5°C increase in temperature results in a lifetime reduction of approximately 10–12% for all battery types. Temperature control is a primary priority in WSN system design to extend operational life, especially for deployments in hot climates (tropical, desert, uncooled indoor spaces). It is recommended to use Battery-2 (LiPo) or Battery-3 (Li-ion), and it is advised to implement thermal insulation for sensor nodes. Adaptive operational strategies can be considered, such as reducing data transmission frequency at high temperatures to conserve energy.

Table 4: Influence of Humidity on Lifetime

Battery Type	**Voltage (V)**	**C-rate**	**Initial Lifetime (RH 40%)**	**Final Lifetime (RH 100%)**	**Decrease (%)**
Ni-MH (Batt-1)	1.2	1	1062 hours	344 hours	~67.6%
LiPo (Batt-2)	3.7	1	3279 hours	1063 hours	~67.6%
Li-ion (Batt-3)	3.6	1	3192 hours	1035 hours	~67.6%
Alkaline (Batt-4)	1.5	2	1237 hours	401 hours	~67.6%

Table 4 illustrates the influence of humidity on the lifetime of four battery types—Ni-MH, LiPo, Li-ion, and Alkaline—by comparing their performance at 40% and 100% relative humidity (RH). All batteries experienced a significant and consistent decline in operational lifetime of approximately 67.6% when exposed to higher humidity levels. For instance, the LiPo battery's lifetime dropped from 3279 hours at 40% RH to 1063 hours at 100% RH, and similarly, the Li-ion battery decreased from 3192 to 1035 hours. Despite differences in voltage and C-rate, the degradation pattern remained uniform, indicating that high humidity environments adversely affect battery longevity, regardless of battery chemistry.

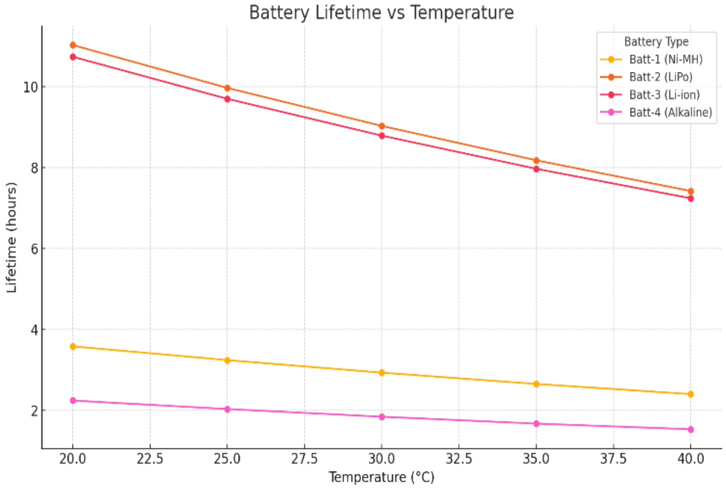

Figure 3. Influence of Temperature on Lifetime

Figure 3 shows how the operational lifetime of four different battery types—Ni-MH, LiPo, Li-ion, and Alkaline—changes with increasing temperature from 20°C to 40°C. Across all battery types, lifetime consistently decreases as temperature rises. LiPo and Li-ion batteries (represented by red and dark red lines) exhibit the highest lifetimes, starting above 10 hours at 20°C and declining to around 7.5 hours at 40°C. Ni-MH (orange line) follows with a moderate performance, decreasing from about 3.5 to 2.5 hours. Alkaline batteries (pink line) show the shortest lifetimes, dropping from approximately 2.5 to below 2 hours. This trend highlights that higher temperatures negatively affect battery performance, with Li-based batteries performing significantly better in thermal endurance compared to Ni-MH and Alkaline types.

3.2 Influence of Air Humidity on Energy Consumption and Lifetime.

The humidity parameter (H) influences exponential energy consumption through the sensitivity coefficient β. This β value indicates how sensitive energy consumption is to changes in humidity. If $\beta > 0$, then an increase in air humidity causes an increase in energy consumption. If $\beta < 0$, higher humidity reduces energy consumption, a rare case except in cooling or condensation systems. In general, WSN systems, $\beta > 0$, because moisture can increase conductivity or cause extra work to protect electronic components. Physically, humid conditions increase the risk of micro-short circuits or decrease sensor performance. WSN nodes often require additional power consumption for signal stabilization, circuit protection, or sensor recalibration in high relative humidity (RH) conditions. In extreme environments (such as greenhouses, tropical areas, or underground), humidity spikes cause the data transmission frequency and increase τ, increasing the energy load.

Based on Eq. (7), an increase in the humidity value (H) will increase the exponential value of eβH. This raises E-modified, and consequently significantly reduces battery lifetime. The following is a comparative analysis of the influence of battery chemistry type on endurance (lifetime) in high-humidity environments, based on simulations from 40% to 100% relative humidity (RH).

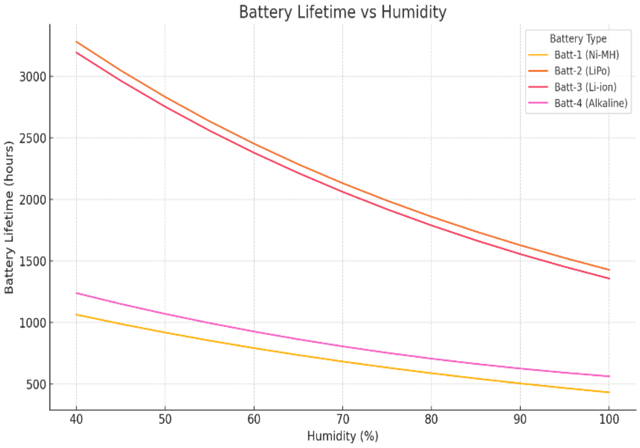

Figure 4. Influence of Humidity on Lifetime

The simulation conducted to investigate the influence of air humidity (relative humidity, RH) reveals that the energy consumption of a Wireless Sensor Network (WSN) node increases exponentially with increasing humidity. The energy model follows an exponential function of the environmental parameter, specifically humidity, which is controlled by the sensitivity coefficient β. Using a value of $\beta = 0.02$, it was found that an increase in humidity from 40% to 100% could more than double energy consumption. This directly affects the reduction of battery lifetime by more than 60%.

A comparative analysis of four battery types with different chemistries—Nickel-metal Hydride (Ni-MH), Lithium Polymer (LiPo), Lithium-ion (Li-ion), and Alkaline—indicates that the battery chemistry significantly determines the performance and endurance of the node in humid environments. All battery types experienced a decrease in lifetime in a nearly identical pattern (around 67.6%) with high humidity, due to the same exponential effect in the energy model. However, the absolute lifetime values are strongly influenced by each battery's voltage and discharge characteristics.

3.3 Influence of Data Movement on Energy Consumption and Lifetime.

Data movement (τ) plays a crucial role in the energy consumption of WSN systems. An increase in communication frequency causes the energy load to increase exponentially, directly reducing the node's battery lifetime. Therefore, it is essential to implement energy-efficient protocols such as duty cycling and sleep mode, reduce unnecessary communication, and design predictive systems based on Markov chains to minimize data transmission when environmental conditions are stable. Simulation results show that an increase in communication activity or data movement (τ) at the sensor node in a WSN directly affects energy consumption, significantly affecting battery lifetime. The exponential energy model shows that each unit increase in τ causes a nonlinear increase in energy. Simulation results show that energy consumption increases from 0.53 mW (at $\tau = 1$) to more than 0.82 mW (at $\tau = 10$), an increase of more than 50%. This reflects that data communication is one of the most energy-consuming components in WSN systems. The battery endurance against data movement was compared between four battery types, each with different chemical and technical characteristics:

Table 5: Influence of Data Movement on Lifetime

Battery Type	**Voltage**	**C-rate**	**Lifetime (τ=1)**	**Lifetime (τ=5)**	**Decrease (%)**
LiPo (Batt-2)	3.7 V	1 C	7039 hours	5763 hours	~18.1%
Li-ion (Batt-3)	3.6 V	1 C	6849 hours	5607 hours	~18.1%
Ni-MH (Batt-1)	1.2 V	1 C	2283 hours	1869 hours	~18.1%
Alkaline (Batt-4)	1.5 V	2 C	1427 hours	1168 hours	~18.1%

Note: The decrease in lifetime across all battery types is relatively consistent because the τ-based energy model uniformly affects the entire system.

Table 5 presents the effect of data movement intensity (represented by parameter τ) on the lifetime of four battery types: LiPo, Li-ion, Ni-MH, and Alkaline. As the data movement level increases from $\tau = 1$ to $\tau = 5$, all batteries show a consistent lifetime reduction of approximately 18.1%. For example, the LiPo battery's operational time drops from 7039 hours to 5763 hours, while the Alkaline battery falls from 1427 to 1168 hours. This uniform reduction suggests that the energy consumption model based on τ uniformly affects all battery types, regardless of voltage or C-rate.

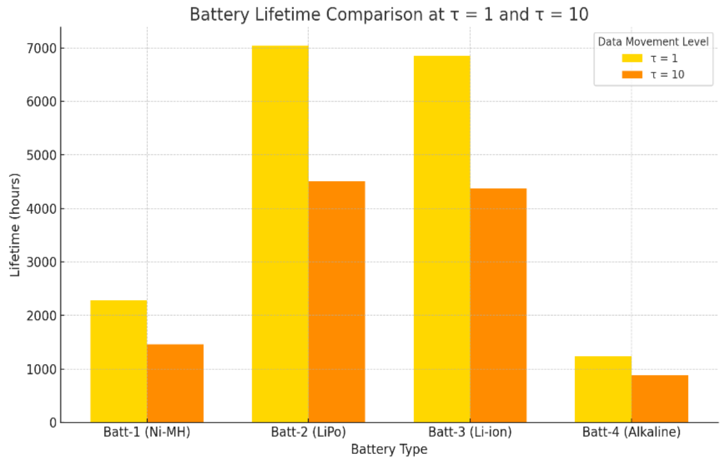

Figure 4. Influence of Data Movement and Lifetime

Figure 4 visually compares the battery lifetimes at two data movement levels: $\tau = 1$ (low) and $\tau = 10$ (high). The bar graph confirms the numerical data from Table 5, showing a noticeable decrease in lifetime across all battery types as τ increases. The LiPo and Li-ion batteries maintain the longest operational durations in both cases, followed by Ni-MH and then Alkaline. The consistent gap between the yellow ($\tau = 1$) and orange ($\tau = 10$) bars for each battery type emphasizes that higher data movement intensity significantly reduces battery longevity.

3.4 Influence of Temperature, Humidity, and Data Movement on Lifetime.

The battery lifetime in a WSN system is not determined by just one environmental or operational variable, but by the simultaneous interaction between three main components: temperature (T), humidity (H), and data movement (τ). These three factors act as complementary exponentials in increasing energy consumption, which drastically and non-linearly affect the reduction of battery lifespan. When all three variables increase simultaneously, the battery lifetime experiences a decrease of up to 85% from stable to extreme conditions. Data movement (τ) dominates in accelerating energy consumption compared to T and H individually. This phenomenon reveals that τ acts as a "multiplier" of the effects of temperature and humidity, making data communication not only a direct load but also an amplifying factor for environmental effects.

The four battery types show different responses to this multivariable stress. LiPo and Li-ion batteries, with their high voltage and internal efficiency, can maintain relatively high performance even in extreme conditions. Ni-MH and Alkaline Batteries, on the other hand, are highly susceptible to the combination of extreme variables. Their lifetime decreases drastically to <100 hours in the worst-case scenario. This fact provides a strong basis that energy endurance is not only a function of capacity and voltage but also thermal resistance and discharge rate efficiency, which are inherent in the chemical characteristics of the battery.

Table 6: Influence of the Three Parameters on Lifetime

Battery Type	**Stable** **(15°C, 45%, τ=2)**	**Moderate** **(25°C, 70%, τ=5)**	**Extreme** **(35°C, 95%, τ=9)**
Ni-MH	563 hours	218 hours	80 hours
LiPo	1736 hours	671 hours	247 hours
Li-ion	1689 hours	653 hours	240 hours
Alkaline	352 hours	136 hours	50 hours

Table 6 presents the influence of three environmental parameters—temperature, humidity, and data transmission rate—on the battery lifetime of four different battery types: Ni-MH, LiPo, Li-ion, and Alkaline. Under stable conditions (15°C, 45% humidity, and transmission rate τ=2), LiPo and Li-ion batteries show significantly higher lifetimes of 1736 and 1689 hours, respectively, compared to Ni-MH (563 hours) and Alkaline (352 hours). As environmental conditions worsen to moderate (25°C, 70%, τ=5) and extreme (35°C, 95%, τ=9), all battery types experience sharp declines in performance, especially Ni-MH and Alkaline, whose lifetimes drop to just 80 and 50 hours under extreme conditions. This highlights the superior durability of Li-ion and LiPo batteries under varying environmental stressors.

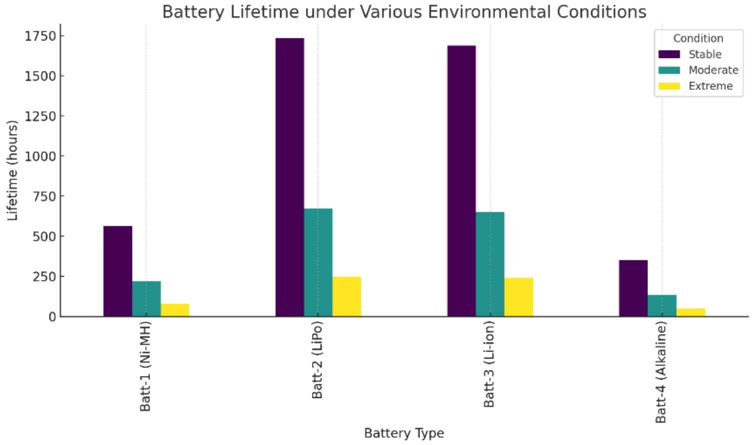

Figure 5. Influence of the Three Variables on Battery Lifetime

Figure 5 graphically illustrates the battery lifetime under stable, moderate, and extreme environmental conditions across the four battery types. The bar chart clearly shows that LiPo and Li-ion batteries consistently outperform Ni-MH and Alkaline batteries in all scenarios, maintaining higher operational hours even under extreme conditions. As conditions, become harsher, the lifetime of all batteries decreases, with Alkaline showing the steepest drop. This visual comparison reinforces the conclusion that battery selection should consider environmental stress resilience, with LiPo and Li-ion being the most suitable for high-performance, long-endurance applications in wireless sensor networks.

Unlike previous studies that partially analyzed the influence of temperature, humidity, or data load, this research introduces a simultaneous interaction model of three main variables within a unified exponential formula, reflecting the realistic dynamics of WSN systems in the field. Simulations were conducted under three classes of environmental conditions—Stable, Moderate, and Extreme—to connect physical data with WSN deployment strategies. This allows for the design of systems that are not only technically efficient but also contextual to the location and intended use. From the analysis results, the potential arises to develop adaptive predictive indicators based on τ values and humidity–temperature gradients that can automatically adjust data transmission frequency (e.g., through dynamic sleep scheduling or data aggregation switching)

4. Conclusion

This study presents a comprehensive predictive framework for estimating battery lifespan in WSNs, integrating environmental and behavioral variables, temperature, humidity, and data movement within a Markov Model and an exponential energy consumption formulation. Unlike prior approaches that treat energy parameters in isolation, this research demonstrates that the synergistic and exponential interaction among environmental variables significantly accelerates energy depletion and shortens battery lifetime. Simulation results confirm that temperature has the most dominant effect, followed by humidity, while data movement becomes critical under high-traffic conditions.

A notable contribution of this study is the comparative performance evaluation across four battery chemistries (Ni-MH, LiPo, Li-ion, and Alkaline), revealing that batteries with higher voltage and lower C-rate (LiPo and Li-ion) consistently outperform others across diverse environmental conditions. Furthermore, integrating energy modeling and Markov chains facilitates a robust prediction mechanism that captures temporal energy dynamics, enabling proactive energy management strategies. The novelty of this work lies in its multi-variable, environment-aware battery prediction model that bridges physical sensing behavior and digital forecasting. By characterizing how each battery responds to environmental stressors in terms of lifespan, this framework provides actionable insights for selecting optimal energy sources and designing adaptive operational strategies in real-world WSN deployments.

The model's adaptability will be enhanced for future work by incorporating reinforcement learning-based AI agents, capable of autonomously adjusting sensing frequency, transmission intervals, and energy modes in response to real-time environmental shifts. This evolution will transition the system from passive estimation toward active energy optimization, making it highly suitable for next-generation innovative sensing applications.

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