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Underwater energy harvesting model for agricultural applications using stochastic network calculus

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ABSTRACT

Underwater wireless sensor network (UWSN) is a specialized type of wireless sensor network (WSN) designed for underwater communication among sensor nodes deployed in oceans for monitoring purposes such as observing marine life, detecting pollutants, and keeping track of oceanographic conditions. Managing limited energy in harsh underwater environments presents unique challenges compared to terrestrial networks. This research addresses this challenge by developing a reliable energy harvesting model. It analyzes the effects of delay and energy storage constraints on the energy harvesting rate (EHR), a measure of the energy replenished over time to maintain sensor node operations. It quantifies the amount of energy that can be harvested and stored within a given period, which is crucial for sustaining the network's functionality. The study includes analyzing and simulating the model analytically using discrete event simulators to evaluate delay performance bounds. Simulation results indicate that larger packet sizes require a higher minimum EHR, while stricter delay requirements decrease it for a fixed arrival rate.

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1. INTRODUCTION

The immense growth in population all over the world leads to an increase in land depletion. This has a significant impact on the production capability of land-based cultivation. As per [1] UN's estimation 2% of the ocean can feed the globe. To carry out underwater cultivation monitoring of cultivation regions is vital. Employee humans in such monitoring is a tedious task. So, sensor-based monitoring suits these needs. Here comes underwater wireless sensor networks (UWSN) that facilitate the communication between sensor nodes that are in the face and the water surface. For, effective underwater cultivation monitoring of various water parameters such as i) pH, ii) temperature, iii) salinity, iv) dissolved oxygen, and v) quality along with acoustic data from sub-sea infrastructure [2]. Additionally, it explores the cultivation of plants underwater and the conditions necessary for their growth. Since these monitoring is carried out for a long period, the sensor node's energy plays a key role in deciding the network lifetime. However, this research concentrates on monitoring five key parameters: pH level, salinity, water circulation/flow, temperature, and nutrient levels. These parameters are crucial for maintaining optimal plant growth conditions. Monitoring parameters in underwater agriculture is crucial for ensuring optimal growth conditions, managing resources efficiently, and maintaining the health and productivity of the cultivated organisms. If these values deviate from the required range, sensor nodes relaying data to the buoy will face significant energy depletion. This research explores underwater energy harvesting techniques, considering traffic arrival rates and delay constraints, to enhance sensor nodes longevity and efficiency [3]. By harnessing underwater energy, the goal is to maintain optimal sensor function and data transmission integrity, even with fluctuating environmental variables. Some important parameters to monitor for underwater agriculture are presented in Table 1.

Table 1. Underwater parameter optimal ranges and importance

Parameter	Optimal range
Dissolved oxygen (DO)	5–8 mg/L (stress below 2 mg/L)
pH levels	6.5–8.5
Salinity	Varies between brackish and freshwater
Temperature	20–30 °C
Quality	200–1000 μS/cm

In terrestrial wireless sensor networks (WSNs), underwater sensor node batteries cannot be frequently replaced, so energy must be harvested from the underwater environment [4]. Two prominent methods are photovoltaic-based, using sunlight, and piezoelectric-based, harnessing ocean currents, waves, and tides [5]. Since piezoelectric-based harvesting works regardless of light conditions and utilizes multiple energy sources, it has been adopted in this research. Piezoelectric materials have the unique ability to generate electrical energy in response to mechanical stress, such as the movement of ocean waves. This capability makes them well-suited for the dynamic and energy-rich underwater environment. Here is a Table 2 comparing piezoelectric and traditional energy harvesting (EH) methods to focus on their advantages for specific applications.

Table 2. Comparison between traditional vs piezoelectric wave EH methods

Aspect	Traditional	Piezoelectric
Source	Solar, wind	Wave motion
Applications	General	UWSN
Conversion	Electromagnetic	Mechanical stress
Efficiency and setup cost	High	Moderate
Scalability and maintenance	High	Low
Impact	Variable	Low
Conditions	Specific	Versatile
Lifespan	Long	Long

The communication and energy harvesting process (EHP) in underwater environments is complex and non-linear. To analyze it effectively [6], analytical modeling is necessary. Given the random nature of arrival and service processes underwater, mathematical theory capable of characterizing these processes is required [7]. This research adopts stochastic network calculus (SNC) to model the system, with a focus on deriving probabilistic bounds for the energy efficiency (EE) factor to ensure the underwater network system's efficiency. This research is addressing the SNC models to analyze energy harvesting in UWSNs. Existing models derived from deterministic network calculus models for underwater energy harvesting, which often do not account for the SNC nature of underwater environments. This research employs SNC to model and analyze the random process involved in underwater EH, aiming to enhance the longevity and performance of sensor node's in UWSN.

The rest of this research article is organized as: section 2 discusses related works. Section 3 introduces the fundamental methods of energy harvesting SNC model. Section 4 shows the analytical model of energy harvesting in UWSN. Section 5 details the result and discussion for energy harvesting in UWSNs describes the simulation setup, parameters, and results validation. Section 6 concludes with a summary of the key findings and future research directions.

2. RELATED WORKS

The various techniques and objectives related to energy harvesting and network stability in diverse contexts [8]. focused on network stability and finite battery effects by using packet transmission based on energy levels and queue status for accessing networks with energy harvesting. The studies [9], [10] developed bionic stretchable nano-generators inspired by electric eels for wearable electronics. Faria *et al.* [11] examined wave energy harvesting devices to power underwater sensors. Guan *et al.* [12] studied bubble buoyancy-driven turbine generators for energy generation from bubbles in water, aimed at powering underwater equipment. Li *et al.* [13] created an acoustic fish tracking transmitter powered by fish movement. The studies [14], [15] investigated underwater sensor localization using received signal strength for sensor network management. Cha *et al.* [16] researched novel materials for energy conversion from underwater movement to power underwater devices. Saeed *et al.* [17] proposed a hybrid network combining acoustic-optical communication with localization for underwater sensor networks. The study [18] aimed to optimize underwater network operations by utilizing tidal energy. Erdem *et al.* [19] extended the lifetime of underwater acoustic sensor networks through compressive sensing, energy harvesting, and transmission power (TP) control, and explored using piezoelectric bimorphs for low-energy device power on the sea floor. Previous studies have delved into various energy harvesting techniques, such as mechanical, thermal, and solar energy harvesting, with piezoelectric harvesting being particularly noted for its efficiency in converting wave-induced mechanical vibrations into electrical energy. SNC, a mathematical framework for optimizing networks with stochastic properties, has been applied in telecommunications and power systems, and this paper extends its application to underwater energy harvesting [20]. Here is a Table 3 comparing Stochastic and deterministic models for analyzing energy harvesting rates. Effective underwater agricultural monitoring systems rely on sustainable power sources to ensure the continuous operation of sensors and communication devices, with EH improving their reliability and reducing the need for battery replacements and maintenance costs.

Table 3. Comparison of deterministic and SNC models

Feature	Deterministic	Stochastic
Randomness	No	Yes
Suitability	Less accurate for variable conditions	Better for unpredictable environments
Energy rate	Simplified, potential inaccuracy	Realistic, suitable for underwater
Data requirement	Fixed data sets	Requires extensive data
Model flexibility	Rigid	Adaptive
Prediction horizon	Short-term	Long-term

3. METHOD OF STOCHASTIC MODEL FOR ENERGY HARVESTING

We assume that the energy demand (ED) and energy harvesting process (EHP) are independent. Since interference occurs in the EHP, it is considered to be SNC [21], [22]. To maintain the transmission and to store the harvested energy, a battery with a delimited capacity is used. Upon full charge, the battery discards the surplus energy [23]. Apart from this, it is assumed that the system has a piece of perfect information about the state of the channel. The power controller in the proposed system always assigns the appropriate power required for transmission of incoming traffic based on the delay requirements, on condition that the energy that is being harvested meets the need. Figure 1 illustrates the overall system architecture, highlighting the interactions between the components.

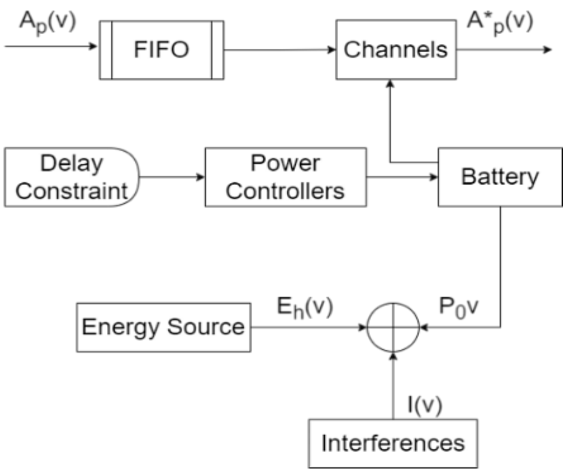

Figure 1. System model

The total traffic arrivals in the time interval $[u, v]$ is denoted by $A_p(u, v)$. We also assume that $A_p(0, v) = A_p(v)$ for simplification. Similarly, departure in the system is denoted by $A_p^*(v)$. Furthermore, we also assume that,

$$A_p(0) = A_p^*(0) = 0 \quad (1)$$

Similarly, delay of the last packet arriving at the is denoted by $W_p(v)$ and it can be represented as (2),

$$\mathrm{W_p(v)} = \inf\{\mathrm{v_0}: \mathrm{A_p(v)} \leq \mathrm{A_p^*(v + v_0)}\}, \quad (2)$$

The delay constraint, denoted by (ϵ_d, v_0), is defined as (3).

$$Prob\ \{W_P(v) > v_0\} \leq \epsilon_d \quad (3)$$

To ensure that traffic delays do not excessively exceed a specific threshold, v_0, we have established a probabilistic violation bound, ϵ_d. This bounds functions as a regulatory constraint, limiting the probability of delays surpassing v_0 to a maximum of ϵ_d. The SNC consists of two basic concepts: stochastic arrival curve (SAC) and stochastic service curve (SSC), which describe input traffic arrivals and service processes, respectively. A network flow $A_p(v)$ has a SAC $\alpha(v)$ for all $v \geq u \geq 0$ and $a \geq 0$ with the bounding function $f(v)$ is represented by the notation $A_p \sim< f, \alpha >$ then there holds [24].

$$S_c\left\{\sup_{0 \leq u \leq v} \{C(u, v) - \alpha(u, v)\} > x\right\} \leq f(x) \quad (4)$$

A network transmission channels has an SSC $\beta(v)$ for all $v \geq 0$ and $a \geq 0$ with the bounding function $g(a)$ is represented by the notation $S_p \sim< g, \beta_0 >$ then there holds:

$$Prob\left\{A_p \otimes \beta(t) - A_p^*(v) > x\right\} \leq g(x) \quad (5)$$

The following relationship holds true when considering the minimum-plus convolution operation (*).

$$A_p \otimes \beta(v) \triangleq \inf_{0 \leq u \leq v} \left\{A_p(u) + \beta(u, v)\right\} \quad (6)$$

The $(\sigma(\theta), \varrho(\theta))$ traffic model is utilised in this paper to analyse traffic behaviour. This model characterises the stochastic arrival process A with a curve $A_p(v) \sim< e - \theta_X, \varrho(\theta)v + \sigma(\theta) >$, where $(\sigma(\theta), \varrho(\theta))$ represents a chosen parameter. It has been demonstrated that various types of traffic patterns, such as exponential ON-OFF, Markov modulated, and Poisson processes, can be effectively represented using this model.

$$\begin{aligned} &\frac{1}{\theta} \ln\ E_a\left[e^{\theta A_P(0,v)}\right] \leq \sigma(\theta) + \varrho(\theta) \\ &\quad C_h = C_b \log_2\left(1 + \frac{P}{N_0 C_b}\right) \end{aligned} \quad (7)$$

This (7) describes the channel capacity C_h in a communication system. Here, C_b represents the bandwidth of the channel, P is the power of the transmitted signal, and N_0 denotes the noise power spectral density. The logarithmic term captures the impact of the signal-to-noise ratio (SNR) on the channel capacity, indicating that as the power of the transmitted signal increases relative to the noise, the channel capacity increases logarithmically. This relationship highlights the balance between bandwidth, power, and noise in determining the effective capacity of a communication channel. In this research, we show that traffic characteristics and the delay limitation (d, v_0) influence the transmission energy E. Furthermore, we employ the generally accepted necessary condition for stability of the system in the scope of SNC [25], [26].

In the context of underwater applications, we can adapt the energy harvesting model to account for the unique challenges of underwater environments. We consider a two-state Markov chain interference process denoted as $I(v)$, characterised by ON and OFF states [27], which affect energy harvesting. Energy is depleted in the ON state, while it is conserved in the OFF state. Transition times between ON and OFF states follow exponential distributions with means of $1/\mu$ and $1/\lambda$ respectively, resulting in an average state transition cycle (STC) denoted by $S_T = (\mu + \lambda)/1$. The mathematical representation of our assumption that the interference process exhibits stationary and independent increments, meaning that $I_p(v, u)$ remains unaffected by $I_p(u + x, v + x)$ for non-negative variables $\mathrm{u, v, x}$, and y is represented as (8).

$$S_c\{I_p(v,u) > y\} \equiv S_c\{I_p(u+x, v+x) > y\} \tag{8}$$

Similarly, the EHP processes $E_h(v)$ is represented as (9).

$$E_h(v) = P_0 v - I_p(v) \tag{9}$$

The energy demand process is modelled by $E_d(v)$. To ensure system stability, we make the assumption that for any $\theta > 0$ and $v > 0$, the following conditions are met:

$$E_a\left[e^{\theta E_h(0,v)}\right] \geq E_h\left[e^{\theta D(0,v)}\right] \tag{10}$$

Given that both $E_h(v)$ and $E_d(v)$ are random variables, it is possible that $E_d(v)$ could be greater than or equal to $E_h(v)$ at certain times. Consequently, we introduce the notation $C_E(v)$ to represent the cumulative lower level of energy up to time v, and

$$\begin{aligned} C_E(v) &= max\{0, C_E(1-v) + E_d(1-v)\cdot(t) - E_h(v)\cdot(1-v)\} \\ &= \sup_{0\leq u\leq v}\{E_d(u,v) - E_h(u,v)\} \end{aligned} \tag{11}$$

Assume that at time 0 battery has full capacity. When a lower level of energy in a communication network exceeds the available capacity of the battery, there will be energy insufficiency. Assume that we have a battery with capacity b_c then the probabilistic bound for energy inefficiency can be modelled as (12).

$$S_c\{A_p(v) > b_c\} \leq \varepsilon_{b_c}, \tag{12}$$

In (12), that characterize the energy storage constraint in the proposed model ε_b represents the violation bound. Furthermore, the efficiency of the gathered energy in the underwater sensor nodes is measured using the definitions. The EE of an UWSN, expressed as $\frac{E_b}{N_0}$ (in decibels), is calculated by dividing the energy per bit by the spectral density of the noise (N_0), *i.e.*

$$\frac{E_b}{N_0} \cdot\!= 10\, log_{10}\left(\frac{P_0}{rN_0}\right), \tag{13}$$

where 'r' represents the mean arrival process. As a result of the assumptions and descriptions given above, we can formulate the energy optimisation enhancement as: where the minimum or maximum rate of energy harvesting and rate of throughput can be derived reciprocally under the energy storage constraint denoted as $(\epsilon b, b)$ and delay constraint denoted as $(\epsilon d, v0)$. An energy optimization enhancement can be expressed in the manner:

$$\begin{aligned} &\mathrm{Min} P_0(r, I_0, I_1) \;\text{ or }\; \mathrm{max} r(P_0, I_0, I_1) \\ &C_h \geq \rho(\theta),\, S_c\{W_p(t) > v_0\} \leq \epsilon_d,\, \mathrm{E}_a\left[e^{\theta E(0,v)}\right] \geq \mathrm{E}_a\left[e^{\theta D(0,v)}\right],\, S_c B_{nd}(v) > b \leq \epsilon_b \end{aligned} \tag{14}$$

where $I_0 = \epsilon_d,\, v_0,\, I_1 = \epsilon_b, b$. In this research, our primary objective is to establish a correlation between the rate of data packet arrival and the rate of energy harvesting. This research has direct relevance to underwater environments, where understanding how traffic patterns relate to energy generation is crucial. This study can offer insights into optimising energy resources for underwater agriculture monitoring.

4. ANALYTICAL MODEL FOR ENERGY HARVESTING IN UWSN

In order to conduct the performance analysis of the proposed model we have considered the stochastic arrival traffic that is Poisson in nature with the packets of constant size. The analysis of two folds: The first fold deals with the relationship between transmission rate (TR) and traffic arrival rate (TAR) and its impact on two different constraints: energy storage and delay. Similarly, the second fold deals with the relationship between energy harvesting rate (EHR) and TP with respect to energy storage constraints. The analytical representation of the SAC with the bounding function.

$$\begin{aligned} &\alpha(v) = \frac{1}{\theta} ln\; E\left[e^{\theta A(0,v)}\right] = \frac{rv}{L\theta}\left(e^{\theta L} - 1\right) \\ &f(x) = e^{-\theta x} \end{aligned} \tag{15}$$

In the (15), average arrival rate and packet size are represented with the notations r and L respectively. The optimization parameter θ that is non-negative in nature is also considered. In addition to the assumptions made in section 2. The fixed transmission rate with the delay constraints and traffic characteristics that are provided. The following conditions that represent the channel's service curve hold,

$$\beta(v) = Cv, g(x) = 0 \tag{16}$$

To ensure the stability of the system we have (17).

$$C_h \geq \frac{r}{L\theta} \cdot \left(e^{\theta L} - 1\right) \tag{17}$$

The probabilistic bound for the delay parameter can be modeled as follows with the assumption that there is a sufficient energy and delay requirement v_0:

$$\text{Prob}\{W_p(v) > v_0\} \leq \text{Prob}\left\{\sup_{0\leq u\leq v} [T_i + C_h \otimes \beta(u + v_0) - C_h^*(v + v_0)] > 0\right\} \leq f \otimes g(C_h v_0)$$
$$= e^{-\theta C_h v_0}$$
$$\text{where } T_i = C_h(u, v) - \alpha(u, v) \tag{18}$$

Furthermore, to study energy inefficiency in the proposed model correlation between probabilistic bounds of energy inefficiency and delay parameters is represented by the (19).

$$\text{Prob}\left\{W_p(v) > v_0\right\} = \text{Prob}\left\{W_p(v) > v_0 \mid B_{nd}(v) \leq b\right\} + \text{Prob}\left\{B_{nd}(v) > b\right\} \tag{19}$$

As a result, there holds

$$\epsilon_d = e^{-\theta C v_0}(1 - \epsilon_b) + \epsilon_{b,}$$
$$e^{-\theta C_h v_0} = \frac{\epsilon_d - \epsilon_b}{1 - \epsilon_b}$$

Similarly, transmission rate holds as with $\epsilon = \frac{\varepsilon_d - \varepsilon_b}{1 - \varepsilon_b}$

$$C_h = \frac{\ln(1/\epsilon)}{\theta v_0} \tag{20}$$

Substituting (17) and (20), the correlation derived between transmission rate and traffic arrival rate is attained as (21),

$$C_h \geq \frac{L\ln(1/\epsilon)}{v_0 \ln\left(\frac{\ln(1/\epsilon)}{r v_0/L} + 1\right)} \tag{21}$$

where the equality holds if and only if

$$\theta = \frac{\ln\left(\frac{\ln(1/e)}{r v_0/L} + 1\right)}{L} \tag{22}$$

Here, equation (21) represents minimum transmission rate that is required in order to meet the energy storage and delay demands of underwater agriculture for traffic that arrives into the network. Contrarily, the maximum sustainable throughput can be estimated based on (21) for the given transmission rate. In underwater communication rate of harvesting energy E_H have a correlation with TP denotes P. Provided the characteristics of traffic, energy demand in the network can be represented as $\mathrm{D}_e(v)$. Now, based on this energy deficit in the system is probabilistically bounded and the same is derived as:

$$\text{Prob}\left\{B(v) > x\right\} \leq \text{Prob}\left\{e^{\xi(P - E_H(1))} > e^{\xi x}\right\} \leq e^{-\xi x} E_H\left[e^{\xi(P - E_H(1))}\right] \leq e^{-\xi x} \tag{23}$$

In (23), ξ is a free parameter that is non-negative in nature. Assuming that the sensor node's battery has a capacity of y, then energy inefficiency probability is characterised by (23) and the same is bounded by $\mathrm{e}^{-\xi y}$. Assume the network system has a storage constrain denoted by (ϵ_b, b),

$$\xi = \frac{\ln(1/\epsilon_b)}{b} \tag{24}$$

The correlation between EHR and TP is stated in (10):

$$P =\leq \frac{1}{\xi v} \ln E_H\left[e^{\xi E_H(v)}\right] = \frac{1}{\xi v} \ln E_H\left[e^{\xi\left(P_0 v - I(v)\right)}\right] \leq \frac{1}{2\xi}\left(P_0\xi - \lambda - \mu + \sqrt{(P_0\xi + \lambda - \mu)^2 + 4\lambda\mu}\right) \triangleq \gamma(P_0, \xi) \tag{25}$$

In (25), ξ is attained from (24). To characterize the relationship between TR and EHR for a given energy storage capacity (7), (24) and (25) respectively.

$$C_h \leq C_b \log_2\left(1 + \frac{\gamma(P_0, \ln(1/\epsilon_b)/b)}{N_0 C_b}\right) \tag{26}$$

In (26), $\gamma(P_0, \ln(1/\epsilon_b)/b)$ is determined based on the (25). For the given energy storage constraint and delay, to sustain the incoming network traffic with average arrival rate r, the minimum harvesting rate P_0min is attained from the solution of inequality derived in (26).

$$P_{0\ \min} = \frac{\left(2^{\frac{C_h \min}{C_\mathrm{b}}} - 1\right) N_0 C_b \left(\left(2^{\frac{C_h \min}{C_b}} - 1\right) N_0 C_b \xi + \lambda + \mu\right)}{\left(2^{\frac{C_h \min}{C_h}} - 1\right) N_0 C_b \xi + \lambda} \tag{27}$$

Subsequently, if we know the delay constrain, energy harvesting rate and energy storage constraint, $r_m ax$ representing the maximum throughput that is sustained can be conversely deduced and there holds,

$$r_{\max} = \frac{K}{e^{K/C_\mathrm{h}\max} - 1}, \tag{28}$$

In the (28), $K = \frac{L \ln(1/e)}{v_0}$ and $\epsilon = \frac{\varepsilon_d - \varepsilon_b}{1 - \varepsilon_b}$. Similarly, $\mathrm{C}_{\max}$ is dependent on P_0.

5. RESULTS AND DISCUSSION

To create a simulation procedure for energy harvesting using SNC in Riverbed Modeler, you will model an UWSN consisting of 100 nodes distributed within a 1000m network area. Each node will have an initial energy of 50 J, and the network will operate with varying storage capacities of 100, 200, and 300 J. The energy harvesting rate will be set at X, Y, and Z, with an event interval of 1000 s. The simulation will incorporate background noise and channel bandwidth. State transitions will occur every 1s, allowing for dynamic changes in energy availability and consumption. The goal is to analyze the performance of energy harvesting strategies, focusing on the balance between energy intake and expenditure under stochastic conditions. The procedure will involve configuring the network parameters in Riverbed, implementing SNC to model energy flows, and running simulations to observe the effects of varying energy storage capacities and harvesting rates on overall network stability and efficiency. Channel conditions were simulated using different capacities and Markov chain techniques. Table 4 details the simulation parameters. This analysis validates the theoretical predictions by comparing them with simulated outcomes, ensuring the model's robustness and accuracy across various scenarios.

Table 4. Simulation parameters

Parameters	Values
Number of nodes	100
Network area	1000 m
Event interval	1000 s
Initial energy	50 J
Storage capacity	100, 200, 300 J
EHR	0.1, 0.2, 0.3 J/s
Background noise N_0	10^{-7} W/Hz
Channel bandwidth W	11 W/Hz
State transition cycle T	1 s

5.1. Effect of packet size on EHR and EE

In the study investigating the impact of packet size variations and arrival rates on the minimum energy collection rate required for efficient EHR transmission, several key findings were observed. Altering the packet sizes and arrival rates revealed significant implications for energy consumption. Figures visually encapsulates these findings, showcasing how changes in packet size directly influence the energy collection rates needed to maintain efficient EHR transmission. This graphical representation not only highlights the relationship between packet characteristics and energy requirements but also underscores the critical need for optimized packet design and transmission strategies to enhance EE in healthcare applications. To analyze the impact of packet size on minimum energy collection rate, two different packet sizes of 100 (kbits) and 500 (kbits) are considered and the simulation has been conducted.

In Figure 2, it is evident that a positive relationship exists between the average arrival rate and the minimum rate of energy harvesting. Moreover, with larger packet sizes, the system consumes more energy to transmit traffic. This is due to the fact that a larger packet size results in more stochastic arrival rates, which in turn requires a higher transmission rate and subsequently a higher data harvesting rate to maintain the energy storage constraint and the delay constraints.

However, if we consider P_0 as the independent variable and r as the dependent variable, we can also observe the maximum sustained throughput rate. Subsequently, the efficiency of the harvested energy denoted by $\frac{E_b}{N_0}$ has been studied. As per the definition in (13) the efficiency of energy is higher if $\frac{E_b}{\mathrm{N}_0}$ lesser. As a result, packet size has a negative correlation with EE. Moreover, EE has a convex functional relationship with arrival rate r. This implies that a higher arrival rate is needed to maximise EE as illustrated in Figure 3.

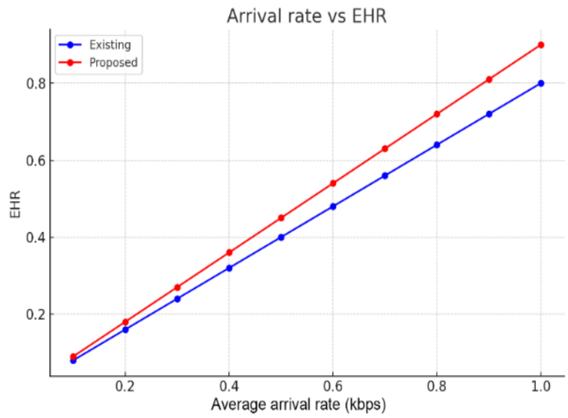

Figure 2. Arrival rate vs EHR for different packet sizes

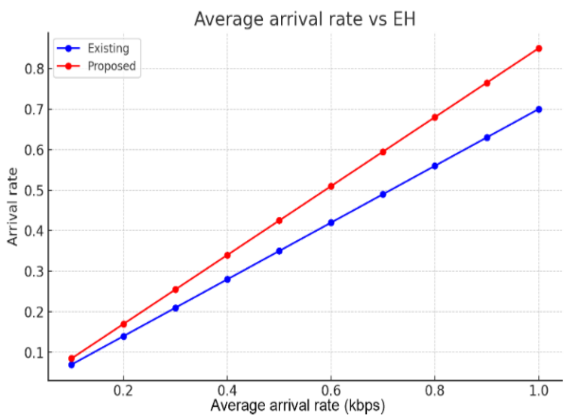

Figure 3. Average arrival rate vs EH for different packet sizes

5.2. Effect of delay constraint on EHR and EE

In this subsection, the study focuses on evaluating the influence of delay constraints on EHR and EE using a fixed packet size of 500 kbits. The simulation is carried out with two distinct arrival rates: 5 and 10 Kbps. This setup allows for a comparative analysis of energy rates of data arrival affect the performance metrics under consideration. By varying the arrival rates while maintaining a consistent packet size, the study aims to assess how delays impact both the transmission of EHR data and the EE of the system, providing insights into optimal operational parameters for such other underwater applications.

To ensure differentiated delay constraints demanded by the underwater monitoring application that is in place, the energy harvesting model that has been proposed needs to offer a certain minimum transmission rate and minimum energy harvesting rate. The relationship between these two parameters with the required delay constraint has been analyzed in Figure 2 and Figure 3. From the illustration presented in Figure 4 it is evident that EHR and transmission rate have a negative relationship with the delay constraint. As a result of looser delay constraints, transmission rates will be lower, and energy harvesting rates will be lower as well. The curves resulting from analytical and simulation studies in both the figures demonstrate a smooth decreasing trend as the delay requirement increases. Furthermore, under an infinite delay requirement, the TR would be close to the arrival rate as per the definition presented in rectangular hollow section (RHS) of (21).

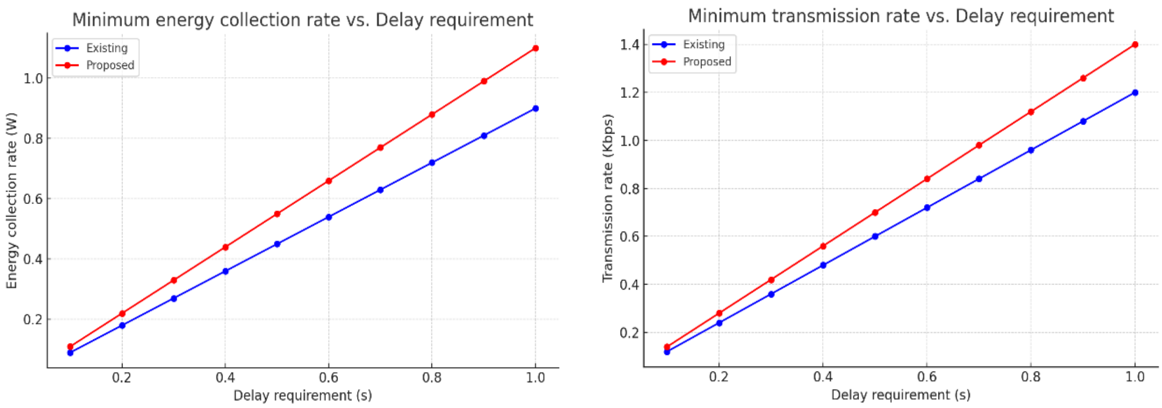

Figure 4. Minimum energy collection rate (W) and transmission rate (Kbps) vs delay requirement (s)

5.3. Effect of state transition table on energy insufficiency probability

In this section, the relationship between probabilistic bounds on energy insufficiency and energy storage capacity is examined through simulations using three distinct parameter values: 1, 10, and 100 s for the STC. The simulation process focuses on analyzing how these different STC values impact the interference process. By varying these parameters, the study aims to understand how energy storage capacity influences the probabilistic bounds on energy insufficiency. This approach allows for a nuanced exploration of how varying levels of STC affect the reliability and performance of energy storage systems under different operational conditions and demands. Figure 5 shows that as battery capacity increases, the probability of energy insufficiency decreases. Larger batteries can store more energy, supporting transmission even when harvested energy is low. However, as battery capacity increases to meet storage and delay constraints, the longer state transition cycle (STCs) due to interference. This occurs because the average time the harvested energy is depleted by interference during a cycle time T is $1/\mu$. With longer cycles, lower energy levels are more likely, necessitating larger batteries for storing and transmitting the remaining energy. Figure 5 provides a guideline for determining the necessary battery capacity to keep the system functional under varying interference and energy insufficiency levels.

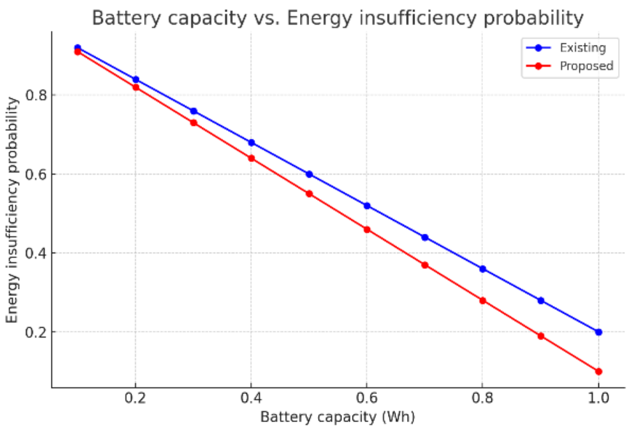

Figure 5. Battery capacity (Wh) vs energy insufficiency probability

The key performance metrics evaluated include EH efficiency, operational stability, and overall energy output. Our system's performance was compared with existing energy harvesting methods under the same simulation conditions. The results show a significant improvement in EH efficiency, with a notable percentage increase in energy output over traditional methods, as shown in Figure 6 for the comparison. As shown in Table 5, the existing methods achieved an EH efficiency highlighting the effectiveness of incorporating SNC and piezoelectric materials in underwater EH systems.

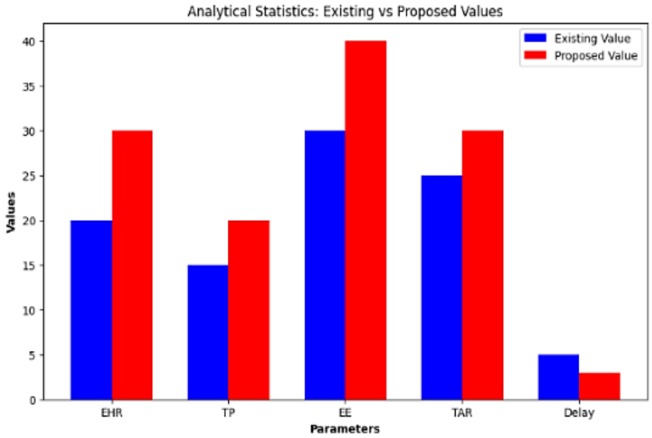

Figure 6. Existing and proposed energy harvesting method

Table 5. Simulation results comparison

Parameter	Existing value	Proposed value	Improvement
EHR (%)	20%	24%	20.0%
TP	15	18	20.0%
EE	30	36	20.0%
TAR (%)	25%	30%	20.0%
Delay	5	4	-20.0

6. CONCLUSION

The limited capacity of sensor batteries determines the lifetime of UWSNs, which are often required for continuous monitoring of underwater agriculture. This study presents a potential-limited energy harvesting model using stochastic network computation and analyzes it from different scenarios. It studies the relationship between energy harvesting rate and packet arrival rate, including packet size and interference, and provides a minimum harvesting rate that controls the access to latency and storage capacity. The EE of sensor nodes and whether energy outages occur are analyzed. The results show that the integration of analysis and simulation has the potential to improve the usability and reliability of UWSN underwater agricultural monitoring, extend sensor node lifetime, and ensure data continuity. Additionally, future research will improve energy conservation, integrated energy management, look for new materials that enhance underwater energy, and expand the model to accommodate larger deployments. It will also develop algorithms that will adjust energy saving strategies according to environmental changes in order to further reduce energy consumption. Simulation results show a significant improvement of 20%. These advances could improve underwater monitoring, providing long-term solutions for applications ranging from environmental monitoring to precision agriculture. This research provides valuable information that could potentially transform underwater connectivity in many marine and freshwater environments.

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