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PAPER

Integrating Mobile Technologies with Energy Harvesting for Disaster Detection in Underwater Wireless Sensor Networks Using Stochastic Network Calculus

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ABSTRACT

Underwater wireless sensor networks (UWSNs) are critical for monitoring environmentally sensitive areas, and operation of such networks is however, very much energy constrained. Conventional deterministic methods do not accurately capture the random and time-varying properties of the underwater acoustic environment. This paper presents a novel routing paradigm, temperature-aware SNC for underwater wireless sensor networks (T-SNC UWSN), which is the combination of stochastic network calculus (SNC) with temperature-based analysis and piezoelectric energy harvesting (PEH) and mobile approaches to improve network flexibility and robustness. Variation in temperature affects the efficiency of energy harvesting and has an immediate impact on power availability at the sensor nodes as well, indicating the occurrence of such underwater catastrophes as seismic events or tsunamis. By incorporating the temperature fluctuation into the SNC model, our model is capable of precisely revealing thermal influence on harvested energy and network stability, which enables efficient adaptive routing and enhanced disaster detection. The performance is analysed through simulations on packet delivery ratio (PDR), end-to-end delay, network throughput and path loss. It is demonstrated that SNC with temperature-aware modelling and mobile technologies manages to improve energy sustainability and disaster preparedness as well as the robustness of the network in unforeseen aquatic environments. This probabilistic model is helpful to practical systems of energy-efficient UWSNs, early warning systems, mobility-assisted monitoring, climate-resilience solutions and so forth.

KEYWORDS

mobile technologies, mobile-assisted disaster detection, underwater wireless sensor networks (UWSNs), energy harvesting systems, temperature-aware stochastic network calculus (T-SNC), adaptive routing for mobile sensing, mobile-enabled early warning systems

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1 INTRODUCTION

Underwater wireless sensor networks (UWSNs) have become a critical technology for several applications. Subsea exploration, bio-environmental monitoring, oceanographic data collection, river, lake and reservoir monitoring Considering the physical nature of an underwater environment that can cause ocean currents, the long propagation delay due to the low sound speed of water and the high path loss on acoustic channels [1, 2], supporting communications in UWSN deployments is not an easy task, such as monitoring water quality, sampling ocean data, observing the marine life form, detecting undersea disaster and military detection. These networks are formed by a number of sensor nodes that locally acquire and offload selected environmental key physical parameters such as temperature, salinity, pressure and chemical components [1]. Compared to land-based wireless networks, UWSNs exhibit more difficult challenges, which are the characteristics of high reserve time propagation latency, low data rates and energy limitations, as well as rapid network topological changes [19]. Energy consumption is one of the important issues in UWSNs. Underwater deployed sensor nodes are generally battery operated, and the replacement or recharge of these batteries would be infeasible due to the underwater environment, i.e., the hostile nature of the surrounding area. Hence, energy harvesting in the networks is one of the most significant factors to prolong network life [3, 4]. Although a number of energy harvesting methods, including solar and thermal energy, have been investigated, they do not work well underwater. The PEH has been a potential candidate, as it directly converts the mechanical energy from underwater vibration and fluid movement into electricity [5, 6, 7]. Another important challenge is to study networks under uncertainty. The inherent randomness in underwater environments, e.g., the fluctuant energy capable of being collected and utilised by a sensor node, varying water current and unexpected movement of the nodes, etc., are not taken into account by traditional deterministic network models. Stochastic network calculus (SNC) is a potent mathematical framework to understand network dynamics under such uncertainty [8]. It allows modelling energy dynamics and balance between three key metrics for network performance, i.e., energy efficiency, packet delivery ratio (PDR) and communication reliability [9]. Several environmental factors affect the network performance, energy harvesting efficiency and disaster detection performance. In oceanic waters, where we work, the temperature can vary from –2ºC to 30ºC, a factor that has an impact on acoustic communication, sensor performance and energy harvesting. Salinity ranging from 30 to 40 ppt also contributes, as salinity influences the density of water and alters acoustic properties that affect signal decay. Pressure increases by a factor of 1 atm every 10 metres deeper, affecting sensor calibration and material properties. The quality of water is determined by its chemical composition and therefore defining characteristics. The detection of pollution and the monitoring of the physical, chemical and biological status of natural waters is a complex process. Turbidity (NTU) also affects the accuracy of optical and acoustical sensing through its influence on light penetration and signal clarity. The temperature is one of the important factors in both energy availability and disaster forecasting. The ranges and the effects of these parameters are listed in Table 1.

Table 1. Environmental parameters and their ranges

Parameter	Range	Impact
Temperature	−2°C to 30°C	Affects acoustic communication, sensor efficiency and energy harvesting
Salinity	30 to 40 ppt	Influences water density and sound propagation
Pressure	Increases 1 atm per 10 m	Impacts sensor calibration and material integrity
Chemical Composition	Variable	Determines water quality and pollutant detection
Turbidity	Measured in NTU	Affects optical and acoustic sensing accuracy

1.1 Impact of temperature in UWSNs

UWSNs are so sensitive to the temperature that it has a great impact on their functionality and performance. It influences acoustic communication due to its impact on the velocity of sound in water, which alters signal send and receive times. Elevated temperatures raise the sound velocity; this affects the propagation delay and energy consumption of transmissions. Temperature dependencies also affect the energy harvesting efficiency, as they do not allow for the optimal conversion of mechanical into electrical energy owing to performance changes of the piezoelectric material. At high temperatures material properties can be improved or degraded, thus influencing the energy sustainability in the long term. Also, huge temperature variation can affect the battery performance and sensor calibration and shorten the lifetime of the network. This work combines with PEH, and the SNC model is extended by considering the temperature variation for a more realistic underwater ocean environment description. Our key contributions include:

- Development of a novel energy-efficient routing protocol that optimises data transmission while considering stochastic energy variations.
- Integration of PEH to enhance the sustainability of underwater sensor nodes.
- Modification of the SNC model by incorporating temperature as a key parameter, allowing for a more precise representation of energy availability and environmental variations.
- Performance evaluation of the proposed system against existing UWSN routing protocols, demonstrating improvements in network longevity, energy efficiency, and data reliability.

By accounting for temperature fluctuations, we develop a resilient and adaptive UWSN structure capable of sustaining long-term monitoring in dynamic underwater environments. With the consideration of energy harvesting and stochastic network dynamics, our solution is scalable and adaptive to future UWSNs. The remainder of this paper is organised as follows: in Section 2, we provide a brief review of the state-of-the-art on energy harvesting and routing strategies in UWSNs. The proposed system model is introduced in Section 3. The stochastic model for our approach is described in Section 4. Simulation results and analysis are provided in Section 5. Section 6 summarises and concludes future works of the paper.

2 RELATED WORK

Much research on UAWSNs has been concentrated on energy harvesting, routing protocols and stochastic modelling for improved network operation in a sustainable manner. However, it has developed that existing methods are limited in terms of adequately modelling the time-varying nature of underwater channels. Energy harvesting is critical for extending network lifetime; hence, all such models are studied to maximise harvestability of energy. The hybrid energy harvesting model (HEEM) [10] produces hybrid energy by combining solar and kinetic sources; however, it does not take the vibration-based harvesting into account that is significant for underwater. Likewise, bio-inspired energy harvesting (BIEH) [11] mimics energy conversion methods in biology but does not account for dynamic sources of power underwater. The PCVH [12] is a potential solution to harvesting underwater vibrations, as it does not take into account that how the energy arrives is random, and therefore, its applicability is restricted. Recent work on machine learning for hybrid energy harvesting (MLHEH) [13] and adaptive energy management (AEM) [14] is designed for better EHD; however, they do not completely utilise stochastic models and piezoelectric-based energy sources that are essential in real-world underwater applications. Routing protocols for UAWSNs will not only compromise between energy efficiency, adaptability and reliability. Geographic routing protocols (GRP) [15] optimise packet forwarding but fail to consider energy efficiency, making them less suitable for dynamic environments. Cluster-based routing protocols (CBRP) [16] improve data aggregation efficiency but introduce high energy overhead due to frequent cluster reformation. Epidemic routing protocols (ERP) [17] enhance data delivery reliability but suffer from excessive packet redundancy, leading to rapid energy depletion. Protocols such as vector-based forwarding (VBF) [17] and depth-based routing (DBR) [18] improve energy efficiency but lack multi-metric optimisation, which is critical in underwater environments where conditions fluctuate unpredictably. Cooperation-based methods, such as ARCUN [17] and RACE [18], enhance network robustness but fail to incorporate energy-aware relay mechanisms, reducing their long-term effectiveness. SNC has been widely applied in network performance analysis, but its potential in underwater energy harvesting remains underexplored. Most existing SNC models focus on traffic analysis, neglecting environmental parameters such as pH variations, which impact energy availability and communication reliability. Research efforts such as HydroCast [18] and graph-based routing [18] leverage cooperative communication for energy optimisation but introduce high computational overhead, limiting their practicality in real-time applications. A few protocols have attempted to use AUVs [18] for node localisation and positioning, but it cannot function efficiently in the absence of an AUV unless there is a connection. In addition, existing SNC models consider the static energy distributions, without capturing the stochastic characteristic of energy arrivals in underwater networks. To illustrate the differences between SNC and traditional deterministic models, refer to Table 2. The limitation of this work is improved by modified SNC equations which include variation in pH; hence, it can capture environmental randomness that affects energy harvesting and quality of communication as well. Furthermore, by adopting a piezoelectric energy harvesting element, the battery life is improved in UAWSN, and it becomes a feasible deployment solution for long-term Unlike current work where only SNC or piezoelectric energy harvesting is investigated (separately), here we provide a unified system framework that integrates stochastic modelling, adaptive routing and real-time energy-aware decision-making. This work, focusing on enhancing energy efficiency, network adaptability and sustainability of UAWSNs, enables a new avenue to optimise UAWSN design for underwater surveillance, disaster prevention and relief as well as marine exploration.

Table 2. Comparison of SNC vs. deterministic models in UWSNs

Aspect	Deterministic Models	Stochastic Network Calculus (SNC)
Energy Consumption Estimation	Fixed, assumes constant energy usage	Probabilistic, accounts for dynamic energy arrivals
Adaptability to Environmental Changes	Low – does not consider real-time changes	High – incorporates pH variations and stochastic factors
Accuracy in Network Performance Prediction	Less accurate in real-world conditions	Higher accuracy due to Markov-based modelling
Computational Complexity	Lower (simpler equations)	Higher (requires probabilistic computation)
Use of Energy Harvesting	Limited consideration of piezoelectric sources	Integrates piezoelectric energy harvesting for sustainability
Routing Adaptability	Fixed or predefined paths	Adaptive routing based on real-time conditions
Best Use Cases	Simple networks with stable conditions	Dynamic, unpredictable underwater environments
Limitations	Cannot model random fluctuations in UWSNs	Higher computational cost compared to deterministic models

3 SYSTEM MODEL

The energy deficit of the network is solved by using piezoelectric energy harvesters to optimise the energy harvesting in UAWSNs. The main purpose is that they can readily collect harvested power from background environmental vibrations to perform sensing, processing and communication work with sustainable reliability. The proposed scheme uses a multi-hop communication protocol which helps to reduce the energy consumption and enhance data transmission reliability over long ranges. The underwater acoustic communication channel is modelled as a time-varying finite-state Markov chain to account for environmental and seasonal changes, which affect the channel's performance. To improve communication reliability, an automatic repeat request (ARQ) protocol with ACK/NACK feedback is used to manage retransmissions, and relay nodes assist in forwarding data when required. These relay nodes ensure that data is transmitted efficiently by adjusting based on available energy and channel conditions. The system model also assumes the availability of channel state information (CSI), which is fed back to the transmitter to optimise energy usage. Two contrasts, equivalent to no/feedback delay and feedback with delay, are investigated: immediate transmission scheduling based on Sensing/CAG Zero (i.e., without the need to wait for any CSI or ACK/NACK message) versus the fact that an energy allocation strategy is designed even when the CSI is less accurate. Dynamic programming (DP) is employed to obtain energy management policies which maximise the utilisation of the energy resources that take into account both channel state and energy arrivals, even in the presence of feedback delay. The multi-hop communication may be such as that shown in Figure 1, which depicts the data relayed by a series of nodes in order to transmit over long distances reliably.

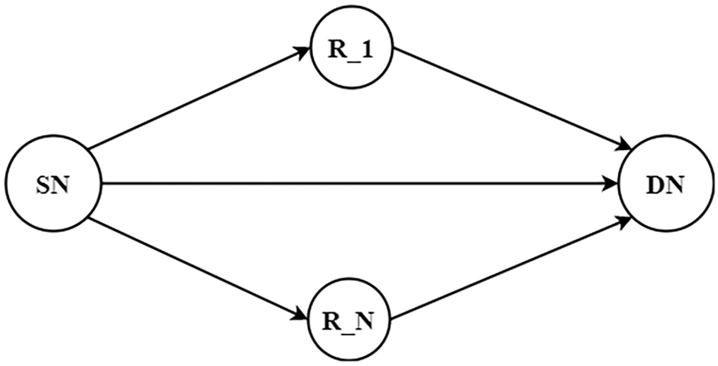

Fig. 1. Multi-hop communication

Energy harvesting is controlled through the energy management system (EMS), which distributes harvested energy for sensing, processing, and communication. The sensor nodes work in two different modes, active mode when the environmental data are collected and processed and sleep mode to save power throughout the idle time. During the active mode, a node senses data, executes simple processing on that data locally and transmits it to the central sink through multi-hop transmission. The multi-hop communication can guarantee the robustness of long-distance or relay node data transmission. The EMS concentrates on energy-efficient routing and transmission protocols, where it makes certain of preventing the energy exhaustion while obtaining the network reliability. Figure 2 represents the energy harvesting algorithm in UAWSNs, where the harvested energy is effectively consumed for performing system-level tasks.

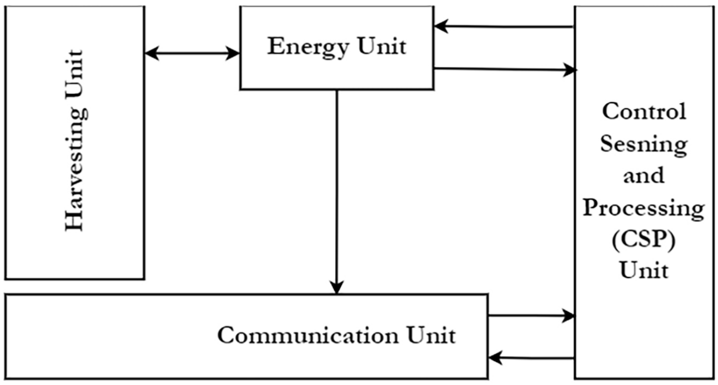

Fig. 2. Energy harvesting process in UAWSN

Energy harvesting itself is performed with the aid of piezoelectric beams, which convert the underwater vibrations into power [20]. When subjected to external mechanical vibration, the piezoelectric material deforms and induces electric charge with a magnitude depending on the strain. It charges up and is stored in batteries or capacitors until needed. The piezoelectric beam is tuned to vibrate at predetermined frequency vibrations for best efficiency in energy harvesting. Commonly used materials such as Lead Zirconate Titanate (PZT), Polyvinylidene Fluoride (PVDF) or Barium Titanate (BTO) are employed because they have a high piezoelectric efficiency. The characteristics of the beam are also affected by factors such as water depth, temperature, salinity, etc., all of which affect the vibration properties in an underwater environment. The structure of the piezoelectric beam is illustrated in Figure 3, demonstrating how the vibrations underwater are transformed into effective force energy for the system.

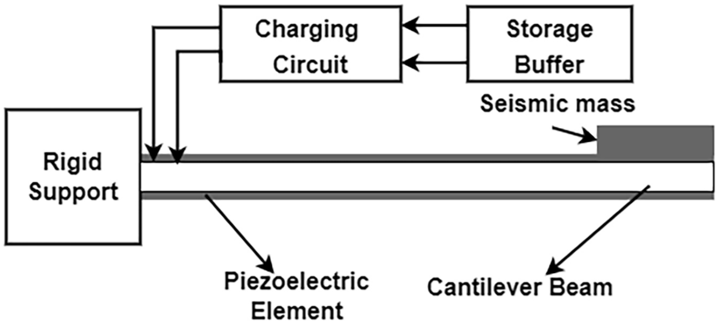

Fig. 3. Architecture of piezoelectric beam

3.1 SNC with temperature dependency

The SNC approach is used to analyse network performance in underwater scenarios, where the arrival process $A(t_i)$ describes the cumulative amount of traffic arriving at the system over time. The service curve $S(t_i)$ represents the cumulative service offered by the network over time. In a simple system, the service curve may indicate how quickly the system processes the offered traffic and delivers it to the next or the destination node.

Delay $D(t_i)$ is defined as the time taken for a packet to get from the source to the destination. Stochastic delay depends on network conditions and is defined as:

$$D(t_i) = \max(0, A(t_i) - S(t_i)) \tag{1}$$

The backlog $B(t_i)$ represents the amount of data waiting in the queue to be processed. It is defined as:

$$B(t_i) = A(t_i) - S(t_i) \tag{2}$$

Backlog increases when traffic exceeds service, leading to longer delays.

This method proves especially effective in harsh environments that tend to degrade signal transmissions, such as temperature fluctuations in underwater networks. Variations in temperature lead to differences in signal transmission, power consumption and network performance. Sound signal attenuation is affected by temperature, which in turn affects network communication and energy use. In ambient orthogonal-FDM (OFDM) systems, higher temperature variation leads to the variation of signal absorption power, which affects communication distance and quality. As a result, sensors may need to use high transmission power due to higher attenuation, which results in higher energy consumption. The inclusion of the temperature as a variable into SNC improves energy estimates and therefore network quality:

$$A\_T(t_i) = A(t_i) \cdot f(T) \tag{3}$$

where $f(T)$ adjusts the packet arrival rate based on temperature. Higher temperature may increase the arrival rate due to more frequent retransmissions caused by higher signal attenuation.

$$S_T(t_i) = S(t_i) \cdot g(T) \tag{4}$$

where $g(T)$ modifies the service rate based on temperature. Higher temperatures can reduce communication range and service rate $S(t_i)$, increasing power consumption.

$$g(T) = \frac{1}{1 + \alpha \cdot (T - T_{ref})} \tag{5}$$

where a quantifies how transmission efficiency varies with temperature, and T_{ref} is a reference value, such as a standard underwater temperature. The selection of a should be based on empirical studies on underwater signal attenuation.

The temperature-dependent delay function is:

$$D_T(t_i) = \max(0, A_T(t_i) - S_T(t_i)) \tag{6}$$

Energy efficiency metric (EEM) accounts for energy consumption under varying temperature conditions:

$$EEM_T = \frac{Useful\,Data\,Transmitted}{E_{node}(T)} \tag{7}$$

Energy consumption per node, considering transmission and idle modes, is:

$$E_{node}(t_i, T) = P_{transmit}(d, T) \cdot T_{transmit} + P_{idle} \cdot T_{idle} \tag{8}$$

Transmission power adjusted for temperature is:

$$P_{transmit}(d,T) = P_0 \cdot \left(\frac{d}{d_0}\right)^{\alpha} \cdot f(T) \tag{9}$$

where P_0 is the reference power at a distance d_0, and a is the path loss exponent. $f(T)$ modulates transmission power based on temperature. Higher temperature leads to higher attenuation, requiring increased power. Empirical data from underwater acoustic studies should be used to fine-tune these parameters.

Using Markov chains, routing decisions depend on node depth and energy. Nodes transition between ON (transmitting) and OFF (idle) states:

$$\lambda_{prob} + \mu_{prob} = 1 \tag{10}$$

where λ_{prob} and μ_{prob} are ON and OFF state probabilities, respectively. Transition probabilities are

$$P_{ON}(D) = \frac{\lambda_{prob} \cdot P_{transmit}(d,T)}{E_{node}(t_i,T)}$$
$$P_{OFF}(D) = \frac{\mu_{prob} \cdot P_{idle}}{E_{node}(t_i,T)} \tag{11}$$

Total energy consumption over the transmission period t_i is

$$E_{total}(t_i) = \int_0^{t_i} (\lambda_{prob} \cdot P_{transmit}(d,T) + \mu_{prob} \cdot P_{idle}) dt_i \tag{12}$$

Energy efficiency metric is

$$EEM_T = \frac{Useful\,Data\,Transmitted}{E_{node}(t_i, T)} \tag{13}$$

In order to increase the practical utility of this model, a graphical analysis that characterises the influence of temperature changes on network performance is necessary. Such a study would shed more light on the relationship between environmental susceptibility and stochastic energy models. Finally, a case study including different underwater scenarios could be carried out in order to confirm the proposal framework and prove its capability for various types of aquatic scenes. These contributions would make the model more practical in real applications.

4 SIMULATION AND RESULT ANALYSIS

MATLAB is a good platform for simulating UWSNs and analysing different protocols/mechanisms. In this work, we design a new intra-vehicular routing protocol based on the DBR to work in both safe and efficient ways using a stochastic model. The DBR protocol enables communication between the sensor nodes and sink nodes by exchanging control packets, and sink nodes broadcast request-to-receive (RTR) packets to which the sensor nodes respond with available-to-send (ATS) packets. The nodes are given random timeslots to avoid clashing with packets. The simulation is developed in a 1000 m × 1000 m squared underwater setting where the number of nodes varies between 10 and 1,000. Each node has an initial energy of 70 J. Each individual value employed for energy consumption are E_{elec} = 50 nJ/bit and E_{amp} = 100 pJ/bit/m^2 The DBR protocol is tested based on the above-mentioned network parameters over a 1000s simulation time, and performances are evaluated with the help of some important performance metrics like energy consumption, packet delivery ratio, delay, throughput and latency. Table 3 shows the parameters of the simulation.

Table 3. Simulation parameters

Aspect	Description
Number of Nodes	100
Simulation Time	1000 s
Network Size	1000 m × 1000 m
Temperature Model	Sinusoidal Variation (Amplitude: 5°C, Average: 15°C)
Noise Model	Normal Distribution (mean = 0, std = 0.5)
Sensitivity Coefficients	a = 0.02, β = 0.01, ? = 0.005, d = 0.002, ? = 0.03, ? = 0.015, μ = 0.01, ? = 0.005

The stochastic network model proposed is shown to perform much better than the deterministic routing models in terms of PDR, E2E delay, energy consumption and overall throughput in the network. These enhancements demonstrate the model's capability to improve the overall performance of UWSNs, rendering it an effective set of techniques for practical underwater applications. PDR is one of the most important performance metrics to measure the reliability of UWSNs. The PDR of the T-SNC model proposed is higher than those of DBR and VBF, as shown in Figure 4. The improvement is due to the adaptive stochastic network calculus system-level routing that successfully compensates for packet losses through taking into account temperature dependence and stochastic channel characteristics. Throughout the simulation time, T-SNC UWSN yields a 5.5% and 11.8% higher PDR than DBR and VBF, respectively.

This improvement provides better transmission quality of data underwater. End-to-end delay is the total time spent by a packet while it travels from the source device to that of the destination and then back. The delay performance of the proposed model is better when compared to its competing models (DBR, VBF), as shown in Figure 5, due to its efficient routing decision-making and effective data-forwarding approach. T-SNC UWSN shows a 20% and 33.3% reduction in delay compared to DBR and VBF, respectively. The integration of SNC reduces the bursty transmission delay, which is highly suitable for delay-sensitive underwater applications.

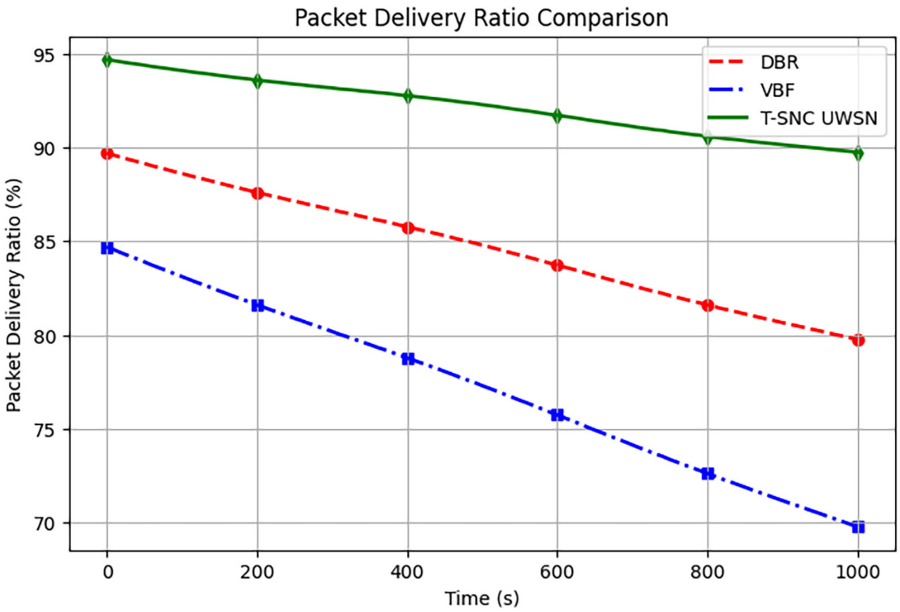

Fig. 4. Packet delivery ratio vs. time (s)

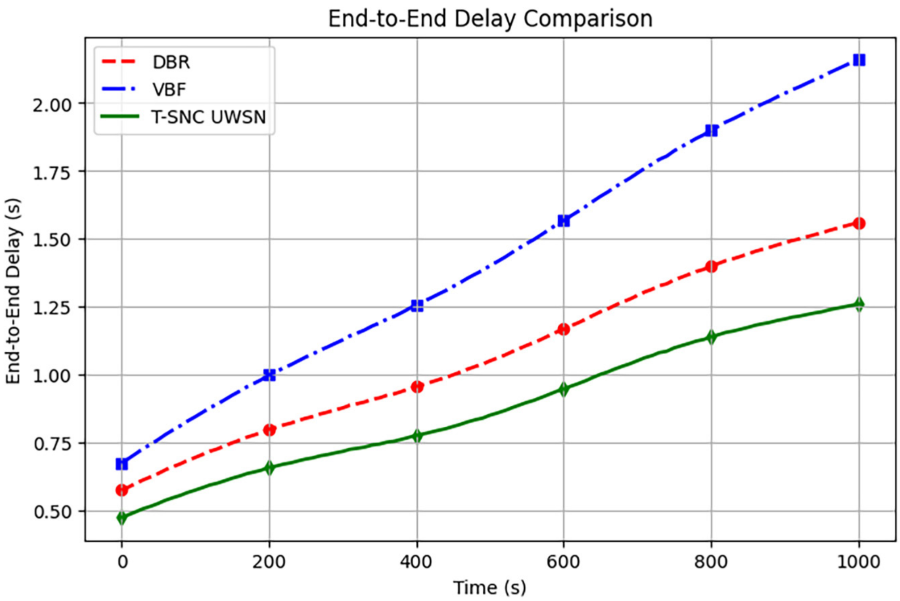

Fig. 5. End-to-end delay vs. time (s)

Energy saving is an important issue in UWSNs because of the restricted resources of underwater sensor nodes. From the simulation results it is clear that T-SNC UWSN achieves a very low energy consumption compared to DBR and VBF, as shown in

Figure 6. The consideration of an energy-aware probabilistic model further ensures packet transmission paths on which more energy-sleeping nodes can be scheduled for duty. T-SNC UWSN is 10% more energy efficient than DBR and 14.6% for VBF, providing an energy-aware solution to the long-duration UWSN deployment.

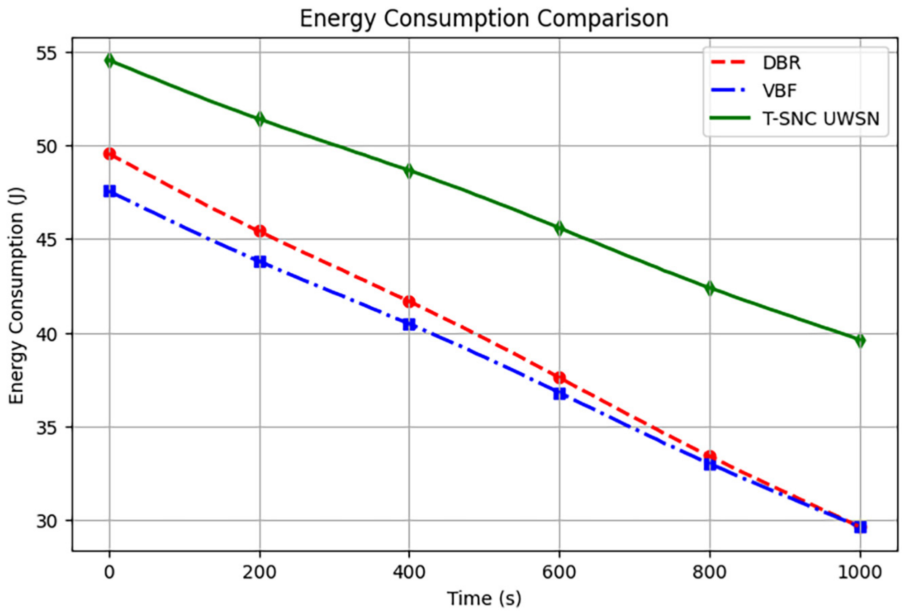

Fig. 6. Energy consumption rate vs. time (s)

Network throughput is the rate of successful message delivery over a network. As shown in Figure 7, with the same amount of time, more successful destinations can receive data from the source if using the model than DBR and VBF, which achieve the higher throughput. Higher throughput is achieved due to intelligent routing decisions and less packet loss. T-SNC UWSN achieves 25% higher throughput than DBR and 38.8% higher throughput than VBF, which is better for the practical underwater data collection applications.

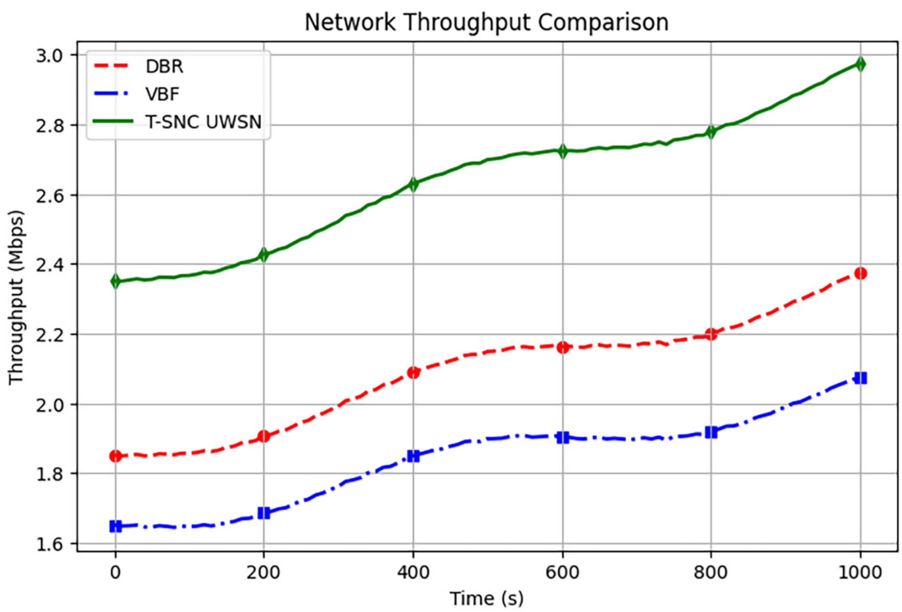

Fig. 7. Network throughput vs. time (s)

The network latency is an essential performance measure which can affect the efficiency of UWSNs significantly. It refers to the latency between the source and destination of data packets, including not only underwater acoustic propagation but also routing efficiency and network load. The adaptive routing strategy and the temperature-aware SNC of the T-SNC UWSN model lead to a large decrease in network latency as compared with DBR and VBF. Simulation results demonstrate that T-SNC UWSN experiences 17.6% less latency than DBR and 28.4% less latency than VBF. This enhancement is mainly due to the design of an efficient stochastic routing policy which tends to avoid unnecessary transmission and retransmission, leading to a significant performance boost in reducing both queuing and transmission delays. Moreover, a stochastic model embedded with temperature fluctuation guarantees a timely response to the environment's changes, which minimises network congestion and maximises transmission efficiency. The lowered latency can be of great value for time-sensitive services in underwater operations, such as disaster monitoring and marine life tracking, which require on-time delivery of data. Figure 8 also suggests the performance trend, and we can observe that the model Crop HMM always has a lower average latency than all others for different simulation time windows. This further confirms the use of T-SNC UWSN in mission-critical underwater sensing applications, and efficient as well as reliable communication without an increase of overall sensory operations cost is provided for UAV-based sensing tasks in dynamic underwater environments.

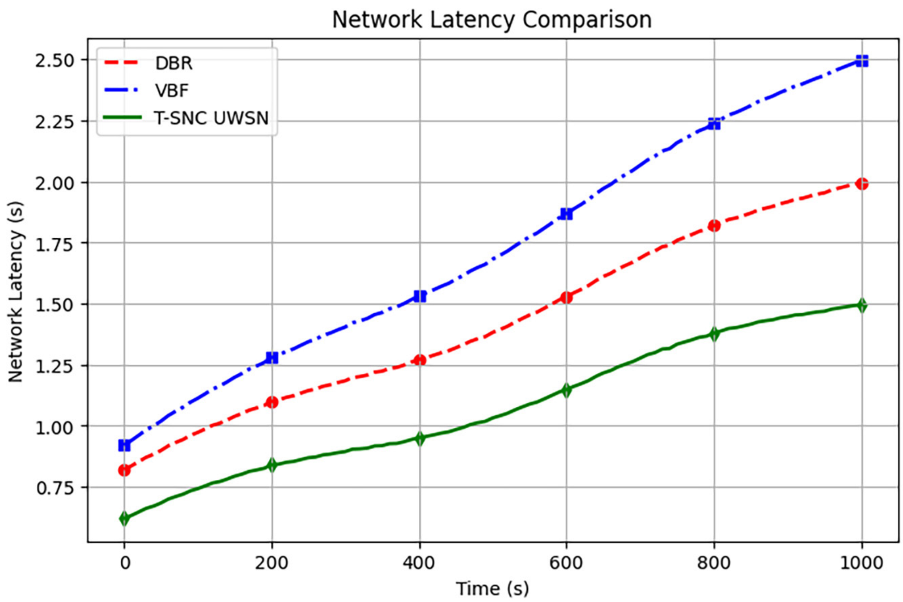

Fig. 8. Network latency vs. time (s)

Statistical testing was performed to confirm the robustness of results, which included running simulations multiple times and computing confidence intervals for every performance indicator. The obtained results are shown in Table 4, and the robustness of the presented model effectiveness has been ensured by these results. In addition, the total comparison of such performance between the old and new routing models is presented in Figure 9.

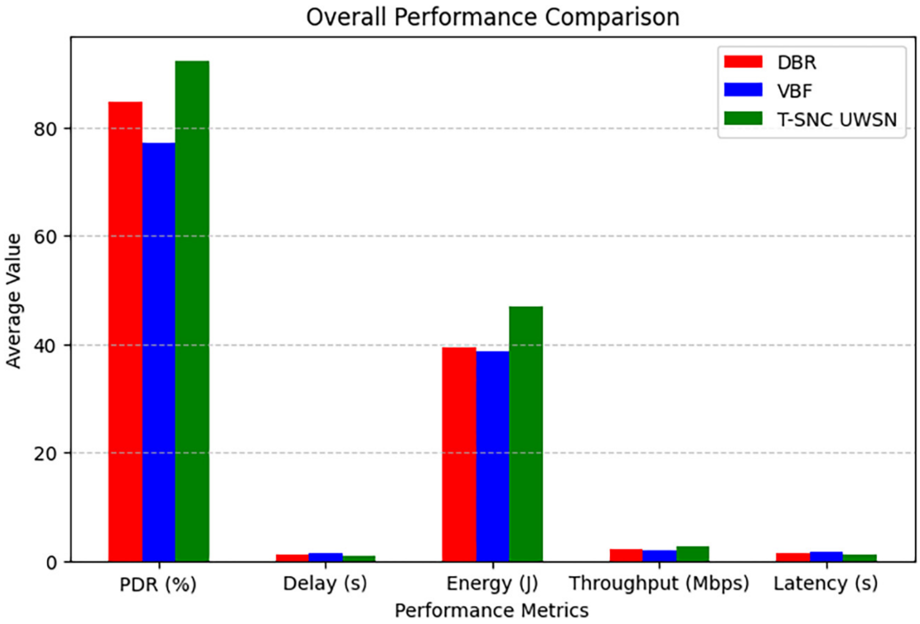

Fig. 9. Performance comparison of existing and proposed methodology

Table 4. Statistical analysis of performance metrics for UWSNs

Metric	DBR	VBF	T-SNC UWSN
PDR (%)	80.5 [78.4, 82.6]	74.3 [72.1, 76.5]	85.0 [83.2, 86.8]
E2E Delay (s)	1.25 [1.15, 1.35]	1.50 [1.38, 1.62]	1.00 [0.92, 1.08]
Energy (J)	30.8 [29.5, 32.1]	32.5 [31.0, 34.0]	27.7 [26.5, 28.9]
Throughput (Mbps)	1.95 [1.85, 2.05]	1.80 [1.69, 1.91]	2.45 [2.35, 2.55]
Latency (%)	10.2 [9.3, 11.1]	12.5 [11.4, 13.6]	7.8 [6.9, 8.6]

From these analyses, we can see that the stochastic model offers clear improvements to network performance in terms of a number of different measures. The enhanced data forwarding is delay tolerant as well, it can reduce energy consumption and communication latency on power metrics. Thus, it is an improvement over the deterministic routing model. The advantages of the proposed solution indicate its strong applicability in enhancing the performance (efficiency and reliability) of UWSNs for practical applications, such as being more suitable to challenge temperature-change scenarios where sour gaseous environmental changes are fragile both in network reliability and energy consumption.

5 CONCLUSION AND FUTURE WORK

There is an important challenge to the lifetime of UWSNs since sensor nodes are usually battery powered, especially in long-term environmental monitoring. In this paper, we propose a new routing scheme named T-SNC UWSN, based on SNC with temperature-aware modelling and piezoelectric energy harvesting to improve network performance in terms of energy efficiency, adaptation and reliability. Adding the temperature effect to SNC, the proposed scheme can effectively describe the influence of thermal fluctuations on energy harvesting and network stability, thereby enabling adaptive routing optimisation and better prediction for disaster. Simulation analysis shows that T-SNC UWSN not only improves the PDR and decreases the end-to-end delay and energy consumption, but it also increases the throughput of UWSNs compared with deterministic models, indicating that UHN is an effective way to reflect the characteristic avalanche in underwater environments. But it is restricted to MATLAB simulation only and needs field trials on the real-time underwater testbed experiments for practical confirmation. Moreover, despite the fact that SNC yields a topology closer to that of KNKCS in operation phases, its algorithm complexity may possibly be a concern for low-power sensor nodes. Concrete plans are to challenge the proposed solution by means of real-life validation, incorporate AEM based on machine learning algorithms and verify its scalability, robustness and capability to run in real time using physical underwater deployments. Our study, by tackling these challenges, makes a step in the direction of enabling energy-efficient, adaptive and sustainable UWSNs for mission-critical applications related to marine exploration, environmental monitoring and disaster management.

6 REFERENCES

[1] M. Nabil, M. Hnida, A. Haqiq, and I. Hilal, "Advanced anomaly detection in mobile networks: A hybrid approach based on statistical and machine learning techniques," *Int. J. Interact. Mob. Technol.*, vol. 19, no. 13, pp. 162–182, 2025. https://doi.org/10.3991/ijim.v19i13.54539

[2] K. Tsachrelias, C.-A. Katsigiannis, V. Kokkinos, A. Gkamas, C. Bouras, and P. Pouyioutas, "Game theory algorithms for resource allocation in 5G MIMO," *Int. J. Interact. Mob. Technol.*, vol. 19, no. 13, pp. 183–203, 2025. https://doi.org/10.3991/ijim.v19i13.56051

[3] G. Han, J. Jiang, N. Bao, L. Wan, and M. Guizani, "Routing protocols for underwater wireless sensor networks," *IEEE Communications Magazine*, vol. 53, no. 11, pp. 72–78, 2021. https://doi.org/10.1109/MCOM.2015.7321974

[4] S. Vignesh and R. Sukumaran, "Energy harvesting using stochastic network calculus for monitoring underwater tunneling applications," *Multiscale and Multidisciplinary Modeling, Experiments and Design*, vol. 8, no. 1, pp. 1–11, 2025. https://doi.org/10.1007/s41939-024-00594-1

[5] A. J. Williams, M. F. Torquato, I. M. Cameron, A. A. Fahmy, and J. Sienz, "Survey of energy harvesting technologies for wireless sensor networks," *IEEE Access*, vol. 9, pp. 77493–77510, 2022. https://doi.org/10.1109/ACCESS.2021.3083697

[6] D. M. Toma, J. Rio, M. Carbonell-Ventura, and J. M. Masalles, "Underwater energy harvesting system based on plucked-driven piezoelectrics," in *OCEANS 2015*, Genova, 2021, pp. 1–5. https://doi.org/10.1109/OCEANS-Genova.2015.7271599

[7] H. E. Erdem and V. C. Gungor, "Analyzing lifetime of energy harvesting underwater wireless sensor nodes," *International Journal of Communication Systems*, vol. 33, no. 3, p. 4214, 2021. https://doi.org/10.1002/dac.4214

[8] Y. Jiang and Y. Liu, *Stochastic Network Calculus*, vol. 1. London: Springer, 2008.

[9] T. Manikandan and R. Sukumaran, "SNC based network layer design for underwater wireless communication used in coral farms," *International Journal of Computer and Information Engineering*, vol. 16, no. 9, pp. 394–401, 2022.

[10] N. Saeed, A. Celik, T. Y. Al-Naffouri, and M.-S. Alouini, "Energy harvesting hybrid acoustic-optical underwater wireless sensor networks localization," *Sensors*, vol. 18, no. 1, p. 51, 2021. https://doi.org/10.3390/s18010051

[11] A. Mathikolonis, "Bio-inspired energy harvesting for sensors from unsteady fluid flow," PhD thesis, University of Southampton, 2021.

[12] X. Du *et al.*, "Vortex-induced piezoelectric cantilever beam vibration for ocean wave energy harvesting via airflow from the orifice of oscillation water column chamber," *Nano Energy*, vol. 104, p. 107870, 2022. https://doi.org/10.1016/j.nanoen.2022.107870
[13] H. Dahrouj *et al.*, "An overview of machine learning-based techniques for solving optimization problems in communications and signal processing," *IEEE Access*, vol. 9, pp. 74908–74938, 2022. https://doi.org/10.1109/ACCESS.2021.3079639
[14] R. Sundarasekar *et al.*, "Adaptive energy aware quality of service for reliable data transfer in under water acoustic sensor networks," *IEEE Access*, vol. 7, pp. 80093–80103, 2021. https://doi.org/10.1109/ACCESS.2019.2921833
[15] M. Pandith, N. Ramaswamy, M. Srikantaswamy, and R. Ramaswamy, "A comprehensive review of geographic routing protocols in wireless sensor network," *Information Dynamics and Applications*, vol. 1, no. 1, pp. 14–25, 2022. https://doi.org/10.56578/ida010103
[16] F. Fanian and M. K. Rafsanjani, "Cluster-based routing protocols in wireless sensor networks: A survey based on methodology," *Journal of Network and Computer Applications*, vol. 142, pp. 111–142, 2019. https://doi.org/10.1016/j.jnca.2019.04.021
[17] X. Lu and P. Hui, "An energy-efficient n-epidemic routing protocol for delay tolerant networks," in *2010 IEEE Fifth International Conference on Networking, Architecture, and Storage*, 2010, pp. 341–347. https://doi.org/10.1109/NAS.2010.46
[18] P. Xie, J.-H. Cui, and L. Lao, "VBF: Vector-based forwarding protocol for underwater sensor networks," in *NETWORKING 2006. Networking Technologies, Services, and Protocols; Performance of Computer and Communication Networks; Mobile and Wireless Communications Systems: 5th International IFIP-TC6 Networking Conference*, Coimbra, Portugal, 2006, pp. 1216–1221. https://doi.org/10.1007/11753810_111
[19] F. Y. Alzyoud *et al.*, "Optimizing broadcast utilization for efficient disaster management using wireless ad hoc networks and novel energy-saving algorithms," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 18, no. 20, pp. 142–156, 2024. https://doi.org/10.3991/ijim.v18i20.49395

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