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Sudan University of Science and Technology

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An Optimized Energy-Aware Stable Election Protocol for Heterogeneous Internet of Underwater Things (IoUT) Networks

بروتوكول إنتخاب مستقر مُحسَّن قائم على كفاءة الطاقة لشبكات إنترنت الأشياء تحت الماء غير المتجانسة

A Thesis Submitted in Fulfilment of the Requirements for the Degree of Doctor of Philosophy in Electronic Engineering - Communication

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Dedication

I dedicate this thesis to my parents whose unconditional love, silent sacrifices and constant prayers have enabled me to complete this journey. They taught me to approach knowledge with respect and to persevere even with difficulty. I offer this work with profound gratitude for your upbringing and for building my character on such a solid foundation and I hope it reflects your unwavering faith in my abilities.

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To my **dear wife**. Publications often include co-authors, who may be anyone who contributed to the work. If this were possible in my doctoral dissertation, my wife's name would certainly have appeared on it in recognition of her patience, unwavering support, and encouragement.

# Abstract

Internet of Underwater of Things (IoUT) networks offer real-time monitoring and data collection capabilities in marine environments for many application. However, the unique challenges of underwater acoustic communication and energy constraints requires a development of intelligent, adaptive and energy-efficient protocols. The thesis addresses these energy challenges particularly in IoUT heterogeneous networks by proposes an energy-aware clustering protocol to optimizing the cluster heads (CH) management and inter-cluster route decision based on Stable election protocol (SEP) computations. Two approaches are proposed, the first is hybrid Artificial Bee Colony (ABC) and Q-learning (QL) based energy-aware Stable Election Protocol (ABCQL-EASE) and its improved version as an energy-aware and Quality of Service (QoS) driven by Underwater Vehicles (UVs) relaying integrated Stable Election Protocol (EQURI-SE).

The ABCQL-EASE presents intelligence approach that combines the ABC algorithms with the adaptive decision-making by QL and multi-criteria decision-making (MCDM) approach. This integration enables the dynamic CHs management based on underwater nodes (UNs) status. The protocol continuously learns from network observations, balancing exploration and exploitation to avoid premature convergence and extend network lifetime. Building upon this foundation, EQURI-SE further enhances energy efficiency by incorporating UVs as mobile relays between CHs. To improve the selection of UVs, a comprehensive framework proposed which integrates Neural Network (NN) and Genetic Algorithm (GA) with MCDM to evaluate UV candidates based on energy, depth, distance and signal quality. A dynamic cooldown mechanism ensures fair usage of UV relaying and prevents overuse of any single UV, thereby extending relay availability and system lifetime.

Results show that, ABCQL-EASE reduces the energy consumption and dead UNs approximate between 30% and 61% compared to the baseline and benchmark studies. The EQURI-SE achieves a significant reduction in energy consumption compared to conventional protocols, substantially contributing to extending network lifetime while maintaining high throughput and achieving superior network efficiency. Compared to ABCQL-EASE, the EQURI-SE reduces energy consumption by up to 48%. Both ABCQL-EASE and EQURI-SE provides higher network efficiency compared to baseline given between 92% and 95%.

المستخلص

توفر شبكات إنترنت الأشياء تحت الماء قدرات المراقبة وجمع البيانات في الزمن الحقيقي ضمن البيئات البحرية للعديد من التطبيقات. ومع ذلك فإن التحديات الفريدة للاتصال الصوتي تحت الماء وقيود الطاقة تستلزم تطوير بروتوكولات ذكية تكيفية موفرة للطاقة. تتناول هذه الرسالة التحديات المرتبطة بالطاقة خصوصًا في الشبكات غير المتجانسة لإنترنت الأشياء تحت الماء وتقدم بروتوكول تجميع واع بالطاقة تعتمد على تبولوجيا توزيع الحساسات البحرية فى مجموعات من خلال تحسين إدارة رؤساء المجموعات واتخاذ قرارات التوجيه بينها فى بروتوكول الإنتخاب المستقر. تم إقتراح منهجين, الأول هو بروتوكول الإنتخاب المستقر الواعي بالطاقة والمبني على الدمج بين خوارزمية مستعمرة النحل الاصطناعي والتعلم المعزز (ABCQL–EASE)، أما الثاني فهو النسخة المطوَّرة منه المعتمدة على كفاءة الطاقة وجودة الخدمة باستخدام مركبات تحت الماء كعُقد ترحيل مابين رؤساء المجموعات والمسمى بـ (EQURI–SE).

يقدم بروتوكول ABCQL–EASE منهجًا هجينًا يجمع بين قدرة البحث الشاملة لخوارزمية مستعمرة النحل الاصطناعي وفاعلية اتخاذ القرار التكيفي للتعلم المعزز بالإضافة إلى منهجية اتخاذ القرار متعدّد المعايير. يتيح هذا التكامل عملية إدارة ديناميكية لرؤساء المجموعات بناءً على حالة الحساسات تحت الماء. كما يتعلم البروتوكول باستمرار من ملاحظات الشبكة موازنًا بين الإستكشاف والاستغلال لتجنّب الإكتفاء المحلي المبكر وتمديد عمر الشبكة. وبالإعتماد على هذا الأساس، يعزّز بروتوكول EQURI–SE كفاءة الطاقة بشكل أكبر من خلال دمج المركبات تحت الماء كمرحلات متحركة بين رؤساء المجموعات. ولتحسين إختيار هذه المركبات، تم تطوير إطار شامل يدمج الشبكات العصبية والخوارزمية الجينية مع منهجية إتخاذ القرار متعدّد المعايير لتقييم المرشحين من المركبات إعتمادًا على الطاقة، العمق، المسافة، وجودة الإشارة. كما يضمن نظام التهدئة الديناميكي توزيعًا عادلاً لإستخدام مركبات الترحيل، مما يمنع الإفراط في استخدام أي مركبة معينة ويسهم في إطالة مدة توفرها وعمر النظام ككل.

أظهرت النتائج أن بروتوكول ABCQL–EASE يقلل استهلاك الطاقة وعدد العقد الميتة بنسبة تقارب 30% و61% على التوالي مقارنةً بالدراسات الأساسية والمرجعية. كما يحقق EQURI–SE خفضًا كبيرًا في استهلاك الطاقة مقارنة بالبروتوكولات التقليدية مما يُسهِم بدرجة كبيرة في إطالة عمر الشبكة مع الحفاظ على معدل نقل مرتفع وكفاءة أعلى للشبكة. وبالمقارنة مع ABCQL–EASE، يقلل EQURI–SE استهلاك الطاقة بنسبة تصل إلى 48% وقد حقق كلا البروتوكولين كفاءة شبكية أعلى من البروتكولات الأساسية بين 92% الى 95%.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ABC	Artificial Bee Colony
ABCQL-EASE	Energy-aware Stable Election Optimized by Integrated QL Approaches
ACO	Ant Colony Optimization
AI	Artificial Intelligence
CMs	Cluster Members
CSMA-MAC	Carrier Sense Multiple Access - Media Access Control
DEECP	Distributed Energy-Efficient Clustering Protocol
DL	Deep Learning
EVA	Efficient Void-Aware
EQURI-SE	Energy-Efficient QoS-Aware UVs Relaying Integrated Protocol
GA	Genetic Algorithm
GPS	Global Positioning System
IoT	Internet of Things
IoUT	Internet of Underwater Things
LCAD	Location-Based Clustering Algorithm for Data Gathering
LEACH	Low-Energy Adaptive Clustering Hierarchy
MCCP	Multi-Event Congestion Control Protocol
MCDM	Multi-Criteria Decision Making
ML	Machine Learning
MVS	Multipath Virtual Sink
NN	Neural Network
PSO	Particle Swarm Optimization
QoS	Quality of Service
QL	Q-Learning
RF	Radio Frequency
RGs	Research Gaps
RL	Reinforcement Learning
RNs	Relay Nodes
RTS/CTS	Request to Send / Clear to Send

SEP	Stable Election Protocol
SI	Swarm Intelligence
TDMA	Time Division Multiple Access
TWSNs	Terrestrial Wireless Sensor Networks
UNs	Underwater Nodes
UVs	Unmanned Underwater Vehicles
UWSN	Underwater Wireless Sensor Network

CHAPTER ONE

Introduction

1.1 Background

Internet of things and its applications are become the most important technologies to provide a connection of everything to the internet. For underwater applications, the novel concept of intelligent interconnected underwater objects is related to the internet of underwater things (IoUT) approach. Underwater wireless sensor network (UWSN) can be connected to internet and promising to provide many practical applications such as underwater environmental monitoring, surveying, military purpose and others (Mohsan et al., 2022). However, UWSN connected to internet suffering from different impairments such as commination delay and underwater environment impacts related to energy efficiency and reliability performance aspects.

In IoUT network, underwater nodes (UNs), vehicles or monitor stations collects data for underwater objects and interact with internet through the network layer. Which it contains a coverage network that enable to internet connection with network administration in addition to cloud computing platforms (Nkenyereye et al., 2024). Information received by the network layer directly provided to the users by an intelligent application solution.

In general, for IoUT, the combination between the UWSN and IoT challenges must be overcome to have a highly IoUT operation performance. The most important challenge is energy efficiency due to UNs mobility because of wave's fluctuations, and propagation speed (Aoun et al., 2024). The UNs in IoUT are required more power to be communicate along large transmission distances, an intelligent algorithm for energy adaptation management. Mobility will change the underwater network topology and increase the energy consumption during reroute the communication link. An intelligent clustering protocol with efficient topology organization and management can ensure to save the IoUT network stability and adding to keep energy efficiency much better (Qiu, T et al., 2016).

1.2 Study Concept and Rationale

In IoUT network, UNs usually do not have enough energy. The most important problems that facing the IoUT is how to increase the network lifetime (Shelar et al., 2020). The UNs as transmitters are requiring more energy, so it's important to reduce the number of transmissions is useful in reducing the energy consumption especially in long distance communication and multi-hop path scenarios. From the literatures, the most efficient mechanism that can be used to reduce such energy consumption is by using clustering strategy (Wanget al., 2014). The fundamental is that, grouping the UNs in a cluster, and each cluster served by an elected cluster head (CH) to reduce an average energy consumption of each UNs and the energy consumption of the whole network (Islam and Lee., 2019). In IoUT, CHs forward the data to sink instead of each UNs to the sinks.

In IoUT networks, clustering is an energy efficient way to organizing the network in a systematic way for proper load distribution and maximize network lifetime. However, many factors may impact the performance of cluster based protocol especially in selection CHs, replacement, and inter-cluster communication (Kebkal et al., 2019). From different studies by Wanget al., (2014), Islam and Lee., (2019) and Farhan et al., (2021), these main factors related to UNs and CHs such as their residual energy, depth, and distances are most impact factors to the energy efficiency. Moreover the signal quality is also adding negative impact with the main factors which required an optimized clustering mechanism and energy efficient clustering protocol to optimize the IoUT network implementation in different aspects, the CH management, and inter-cluster route decisions.

1.3 Motivations

Energy efficient clustering approach and route management are essential for long-term deployment of IoUT networks since the limited and non-rechargeable energy of UNs fundamentally limits their works and lifetime. Mobility, UNs heterogeneity, depth-dependent acoustic route loss and time-varying channel quality are all not considered by current studies related to clustering-based methods which frequently rely on static election probabilities or single criteria metrics.

These constraints lead to poor Quality of Service (QoS), inconsistent energy consumption, excessive control overhead and inappropriate CH selection. Additionally, routing inefficiencies are made worse by the dense and dynamic topology of underwater environments current solutions lack to achieve adaptive mechanisms to dynamically improve CH management and inter-cluster routing decision in real time.

These challenges motivate the development of an intelligent energy aware clustering framework that continuously adapts to underwater constraints while maximizing energy efficiency and network stability. Specifically, this thesis is driven by the need to the following.

- Integrate underwater environmental factors such as depth, motion, signal quality and heterogeneous energy level into a unified and adaptive energy consumption model.
- Replace random static probability-based CH management with a multi-criteria and AI-driven optimization process that balances exploration and exploitation of CH management.
- Providing dynamic routing mechanism that minimizes long-haul acoustic transmissions and reduces propagation latency with ensuring network QoS.
- Deliver a protocol that simultaneously extends network lifetime, improves QoS and scales across heterogeneous IoUT deployments.

The expected outcome obtains a robust energy-aware stable election protocol that leverages hybrid AI optimization to dynamically manage CH selection and inter-cluster routing decision by delivering measurable improvements in network lifetime, throughput and adaptability under realistic underwater conditions.

1.4 Problem Statement

Despite significant advances in underwater acoustic networking, IoUT deployments continue to face critical energy bottlenecks due to inefficient cluster formation, suboptimal CH rotation, and reactive routing strategies (Wang et al., 2014). Conventional clustering protocols such as low-energy adaptive clustering hierarchy (LEACH), stable election protocol (SEP) and distributed energy-efficient protocol (DEECP) variants utilize fixed election probabilities or heuristic thresholds that ignore depth-induced path loss, UN motion, signal quality degradation and energy heterogeneity, also they are designed for terrestrial WSN (Islam and Lee., 2019) . Consequently, these approaches frequently elect deep or low-energy nodes as CHs leading to premature node failure, increased retransmissions, unbalanced energy consumption and reduced QoS. Moreover, current protocols lack closed-loop adaptation mechanisms making them unsuitable for dynamic underwater environments where topology and underwater channel conditions evolve continuously (Islam and Lee., 2019)(Kebkal et al., 2019).

This thesis addresses these gaps by proposing an optimized energy-aware clustering protocol for heterogeneous IoUT networks. The proposed protocol introduces core innovations by introduces hybrid mechanism that combines meta-heuristic and multi-criteria fitness with reinforcement learning (RL) adapted exploration to consider the underwater environmental criteria during CHs management and inter-cluster routing decision (Kebkal et al., 2019).

1.5 Research Questions

Current clustering protocols such as the SEP were originally used in terrestrial WSN based IoT and not fully account for underwater-specific environment. Additionally, while swarm intelligence techniques such as the artificial bee colony algorithm (ABC) and reinforcement learning approaches such as Q-learning (QL) have shown promising optimization capabilities, which their coordinated integration within a unified IoUT clustering and routing framework remains insufficiently explored. To address these limitations this thesis investigates the following research questions (RQ).

- **RQ1:** How can standard clustering protocols like SEP be modified to handle depth and heterogeneity aware modifications to improve energy efficiency and stability period in heterogeneous IoUT networks compared to conventional clustering protocols?
- **RQ2:** How can a hybrid optimization framework integrating ABC and QL to enhance CH management decisions under dynamic underwater conditions?
- **RQ3:** How can adaptive energy distribution and inter-cluster routing decision strategies reduce transmission overhead and extend network lifetime while maintaining QoS requirements in IoUT environments?
- **RQ4:** How can the best underwater vehicles (UVs) be selected as relays to minimize long-range acoustic transmission energy consumption and improve network scalability?
- **RQ5:** To what extent does the proposed hybrid energy-aware stable election protocol outperform existing IoUT clustering and routing approaches?

1.6 Research Objectives

The main aims of the thesis is to develop an intelligent and energy aware stable election protocol driven by QoS metrics for IoUT, which will considers all the following objectives.

- *Customize the IoUT Energy Challenges:* Considering the heterogeneity of IoUT operations and tasks, in addition to impact factors those are required to be handled due to developing intelligent clustering protocol to provide proficient usage of energy.
- *Investigates on Clustering based Swarm Intelligence Protocol:* Present innovative techniques for CH selection to handle the unique issues provided by the environments of the IoUT by examining the integration of SI algorithms, specifically with handle the complexity of IoUT networks to provide efficient energy consumption by dynamically adjusting the CH selection and replacement.
- *Modeling an Energy Efficiency and Optimization Scheme:* Establish a more equitable distribution of energy consumption among UNs, hence increasing the network's operational lifetime by utilizing the ABC algorithm improved by the RL approach. In addition to taking all the factors related to the underwater environment such as UNs depths, distances, motions, energies, and signal quality according to the type of the underwater environment to develop an energy efficient model.
- *Developing an Energy-Aware and QoS driven Clustering Protocol:* Provide an intelligent scheme to adjust the CH management process in response to changes in UNs status in addition to distribute energies among CHs during inter-cluster communications by integrating ABC, QL and multi-criteria decision making (MCDM) approaches . Moreover, optimize the inter-cluster communication by using UVs as relay between CHs.

1.7 Research Methodology

The thesis will focus on developing an energy-aware stable protocol for IoUT by optimize the energy efficient model based on clustering approach optimized by ABC and QL approaches. The research plan shown in Figure 1.1, describes the steps taken during the thesis stages. The study begins with an extensive literature review to clarify the problem space and highlight gaps in energy management techniques within heterogeneous IoUT networks.

The initial literature classification in the plot provides a basis for the study showcasing the importance of clustering technology, energy efficiency mechanisms and AI-based optimization strategies for designing efficient underwater network communication. Then investigates on various methods show the significant impact of managing energy consumption through effective distribution of transmission loads across UNs. The reviewing these clustering techniques will guide the selection of an optimized approach suitable for IoUT applications.

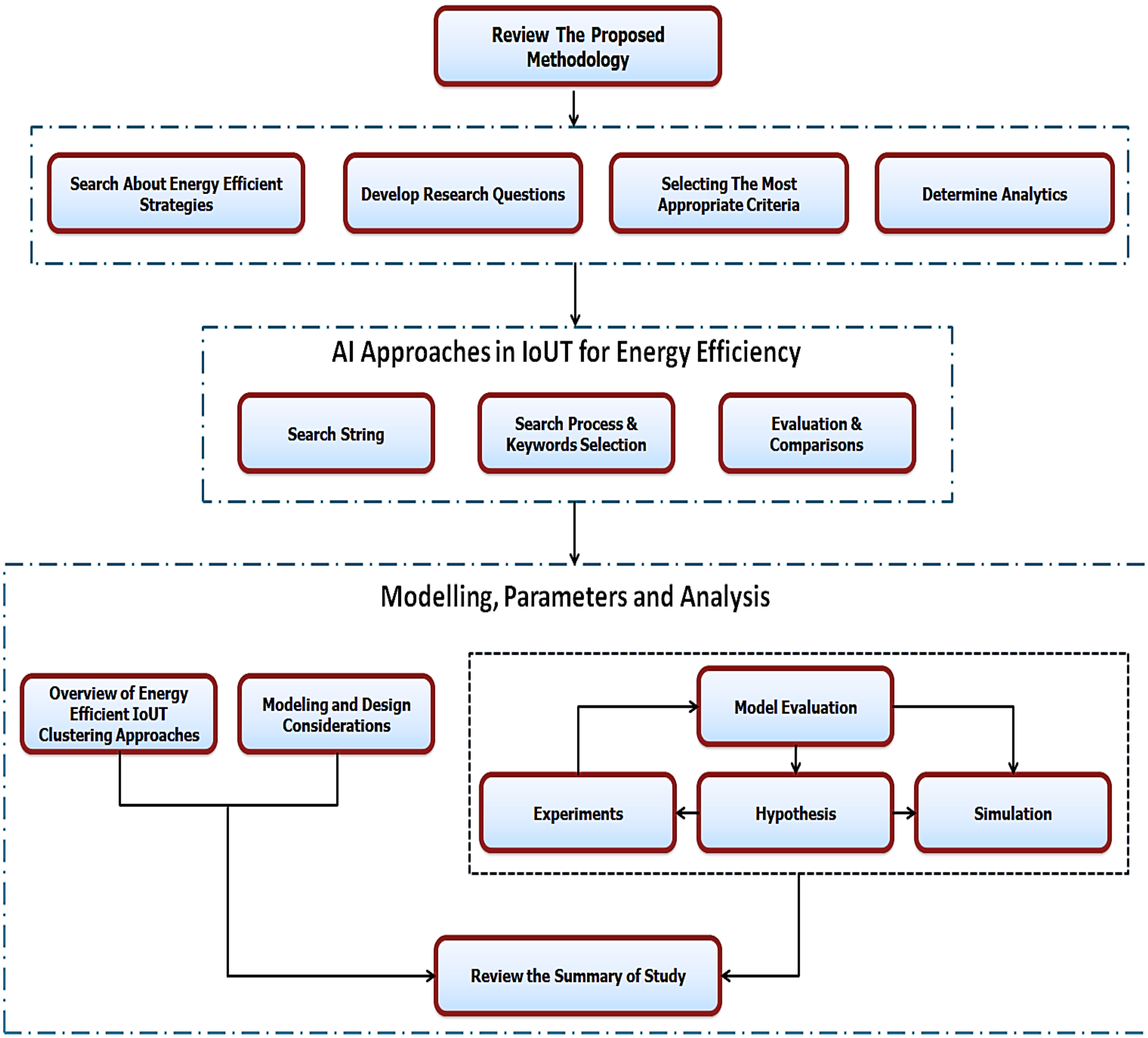


Figure 1.1. Research Plan

Through the thesis, an energy efficient model is evaluated to create a comprehensive energy management mechanism that combines clustering with adaptive clustering protocols. The methodology used MATLAB's statistical and graphical tools to support the data analysis phase, visualizing energy distribution, packet delivery, and improves inter-cluster routing scheme performance across various underwater conditions. These visualizations will follow the approach presented in the plot to align results with expected performance metrics. Accordingly, the methodology was developed based on four implementation phases and outlining the simulation environments used for testing as follows.

- **Phase 1***: Advanced CH Selection Strategy:* derive a depth-aware CH selection scheme based on SEP computations by using the ABC algorithm to efficiently selecting the CH by consider the UNs depth, energy levels, and distance from SBS to achieve an efficient cluster organization.
- **Phase 2***: CH Management Optimization:* implementing a lightweight QL with ABC to optimize the process of CH selection, and replacement. The process of selection and replacement are based on optimized ABC by QL decision considering the reward functions tied to residual energy, depth, signal quality, distance and motion allow for adaptable route selection.
- **Phase 3***: Energy-Aware and QoS driven Clustering Protocol:* the model incorporates a dynamic inter-cluster route adaptation mechanism and distribute the energies between CHs for multi path routing. The energy distribution is based on QL to reduce the network energy consumption and optimized by MCDM approach.
- **Phase 4:** *UVs Relaying selection optimization*: Developed a strategy of using UVs as relay by selects the best UVs based on neural network (NN) and genetic algorithm (GA) to serve as relay for inter-cluster communication to reduce the CH overhead, and improves the energy utilization.

The methodology introduces two main optimization approaches, an energy-aware stable election protocol, and UVs relay section to enhance the inter-cluster communication. The methodology integrates ABC, QL to optimize the clustering management and inter-cluster routing decision. In addition, NN and GA are used to select the best UVs to serve as relay in inter-cluster communication. The MCDM is used in both optimization approaches to enhance the QoS and UVs ranking processes. The justification of the proposed optimization methodologies highlighting how each approach improves upon or diverges from existing solutions. Two optimization methodologies are used and their justification highlighted in the following subsections.

A. **Energy-Aware Stable Election Protocol**

This methodology use of meta-heuristic approach in CH selection process for stable clustering protocol which apply ABC algorithm to improve energy efficiency. The proposed ABC-based clustering method introduces depth-aware fitness function that considers signal attenuation effects, in addition to residual energy. QL approach has been explored in IoUT for routing decisions which able to optimize data forwarding paths. The proposed QL improves CH replacement based on real-time energy thresholds and link quality. Moreover, the inter-cluster routing decision between the CHs are controlled by QL by dynamic rewards derived from MCDM outputs, allowing QL to learn policies that balance energy conservation and QoS.

Several studies have use MCDM techniques into routing protocols. The proposed approach enhances the CH management by using MCDM dynamically, with time-varying weights based on network conditions like energy efficiency, packet delivery ratio, network lifetime, and network efficiency. Feeding MCDM rankings into processes of ABC for fitness scoring and QL for reward updating, creating a feedback loop between decision-making and optimization status. The integration of MCDM with meta-heuristics and QL creates a hybrid decision architecture. This integration ensures that decisions is optimal and also context-sensitive. The cooperation between heuristic search strategies and learning-based decision-making as hybrid approach will improves energy efficiency and network lifetime by combining the global search capabilities of meta-heuristics with the quick convergence of QL.

B. **UVs Relay Selection for Inter-Cluster Communication**

While the proposed energy-aware stable protocol provides significant energy improvement, predictive modeling for relay based clustering approach provides more efficiency. The proposed approach uses NN model introduces a predictive capability. It predicts the best UVs to serve as relay based on historical mobility patterns, environmental noise, and energy, enabling proactive relay scheme. It learns conditions that affect communication, such as communication performance and signal quality, along with distance, motions, and depth.

The proposed GA-based relay optimizing mobile relay selection by incorporating NN-predicted reliability scores into the GA fitness function, allowing GA to gives solutions based on expected performance, not on current state. The approach of using NN with GA enable efficient multi-hop relay between CHs, reducing energy consumption on direct long-range transmission. The combination of GA with NN enables evolutionary search over future scenarios providing a forward-looking optimization strategy. The proposed approach uses MCDM for UV relay ranking ensuring consistency in multi-criteria evaluation across network layers. This dual-stage MCDM application enables cross-layer optimization where both fixed UNs and mobile UVs are evaluated under a unified decision framework.

1.8 The Contributions

A. **Contribution 1**: Depth Based Stable Election Protocol

- ***Article:*** *Depth based stable election protocol for heterogeneous internet of underwater things (IoUT) energy efficiency*

Introduces a depth-based SEP protocol for the IoUT which addressing critical challenges related to energy efficiency and network lifetime. It shows that the energy heterogeneity of UNs and their depths significantly influence clustering scheme performance particularly in heterogeneous IoUT scenarios. By developing a depth-aware strategy for CH selection the proposed protocol enhances energy-efficient stable election by factoring in the varying energy levels of UNs, their depths and the distance to the SBS. Experimental results indicate that the depth-based SEP-IoUT protocol significantly outperforms conventional protocols, including the traditional SEP and the SEP-IoUT, achieving a 19.6% improvement in average stability period and a reduction in energy consumption by 39% and 15.7%, respectively. The success of the proposed protocol is due to its intelligent CH selection process which considers both depth and energy metrics leading to balanced energy usage and reduced interference. This contributes to a longer network lifetime making the protocol particularly well-suited for IoUT where energy management is crucial.

B. **Contribution 2**: Advanced CH Selection Strategy Based on ABC and QL Approaches

- ***Article:*** *Energy Efficient CH Selection Scheme Based on ABC and Q-Learning Approaches for IoUT Applications*

Develop an enhanced clustering scheme for the IoUT. Its address the challenges of energy efficiency and network lifetime particularly in heterogeneous IoUT applications by introducing a novel approach that combines the ABC algorithm with QL optimization. By considering multiple factors such as residual energy, depth, distance from the base station and signal quality the proposed scheme effectively selects CH to optimize energy consumption. The results of the study show that the improved ABC algorithm enhanced by QL outperforms traditional swarm intelligence algorithms for CH selection process. The performance evaluation highlights a significant increase in energy efficiency up to 56.39 % in low UNs dense networks and 23.53% in larger dense compared to the conventional ABC. Additionally the modified algorithm improves the selectivity of CH selection promoting network stability and reducing the number of dead UNs. This adaptability is primarily due to the QL component which enables the algorithm to learn and make informed decisions based on network conditions. At this study stage, the proposed scheme does not consider a fully protocols for inter-cluster communications it focus only on optimizing the process of CH selection scheme for IoUT network.

C. **Contribution 3**: Developed an Energy Aware Stable Protocol

- ***Article:*** *Theoretical Modelling for Optimized Energy Efficiency in IoUT Networks using Hybrid QL-based Meta-heuristic and MCDM Approaches*

Developed a novel optimization method that combines ABC, QL and MCDM to improve CH replacement, and routing process for inter-cluster communication mainly focus on energy efficiency and QOS optimization. The developed protocol enable dynamic and flexible reward system for QL by modifying the MCDM framework to include important parameters like depth, energy, distance, and signal quality. The QL provides contextually aware decisions that maximize network performance based on current environmental conditions based on this hybrid incentive mechanism. The MCDM enhanced QL reward function contribute to dynamically prioritizes criteria according to network demands, thereby addressing QL constraints such as reward conflicts and static weight allocation. This strategy increases routing stability, permits balanced energy use and lowers the frequent replacement of CH which all contribute to a longer network lifetime and more reliable data transmission. A more robust and effective IoUT network that can sustain high QoS standards under a variety of underwater situations achieved by the adaptive and thorough reward structure which also increases QL's convergence rate and decision correctness.

D. **Contribution 4**: Developed UVs Relying Selection Approach for Inter-cluster Communication.

- ***Article:*** *Theoretical Framework for Efficient UV-Relay Selection in IoUT Using Hybrid NN-GA Model with MCDM Approach"*

Proposed a method to optimize the inter-cluster communication by using UVs as relay which acts between CHs and the SBS. Unlike conventional protocols that rely on direct long-range acoustic transmission leading to high energy consumption and rapid UNs depletion, this approach uses UVs as mobile relays to offload inter-cluster communication, thereby minimizing transmission distances and preserving UN energy consumption. The selection of optimal UVs is performed using a hybrid decision-making framework that integrates a GA with NN and MCDM, evaluating candidates based on critical factors such as residual energy, depth, distance, and signal quality. This ensures that only the most suitable UVs are activated at any given time, balancing performance and fairness. Furthermore, a dynamic cooldown mechanism is introduced to prevent overuse of specific UVs, extending their operational lifetime and promoting equitable resource utilization.

E. **Minor Contribution**: Review on Energy Efficiency in IoUT

- ***Article:*** *A systematic review on energy efficiency in the internet of underwater things (IoUT): Recent approaches and research gaps*

Review a different recent energy efficiency methods for IoUT with an in-depth evaluation of the existing approaches discussed in the literature. As a part of this research a systematic review of energy efficiency strategies in IoUT is conducted. This review investigates on the primary methods used to reduce energy consumption in IoUT networks also the challenges of the unique underwater environment and the role of AI approaches to enhance energy efficiency. Additionally, the review identify the gaps in current methodologies and highlights areas for further research to develop more robust and adaptable solutions for IoUT network applications.

1.9 Thesis Organization

Each chapter in this dissertation presents the details of the study that was conducted in a sequential manner to clearly reflect the concept of the study, while presenting the methodology and the targeted logical analysis. The remainder of this thesis is organized as follows.

- **CHAPTER 2*:*** This chapter reviews the technical concepts about IoUT as a promising technology enables UNs to communicate with terrestrial IoT networks. It provides a comprehensive background on IoUT details of its architecture and system models related to both shallow and deep water environments also energy consumption considerations. The chapter provides a review to identify the research gaps in clustering-based methods and outlines future directions for investigation. Ultimately, it serves as a valuable resource for IoUT network designers providing insights into effective energy-efficient protocols and highlighting emerging trends and unaddressed issues in the field.

- **CHAPTER 3:** This chapter proposes the methodology of energy-aware optimization approaches based on meta-heuristics and QL optimization for IoUT networks. It first presenting the development of energy-aware stable election protocol and the integrated ABC and QL model to optimize the clustering strategy. The chapter reviews step by step methodology of proposed solutions to optimize the inter-cluster communications with dynamic CH replacement mechanism, and energy distribution among CHs based on QoS driven approach by using MCDM. Moreover, the UVs selection optimized method using hybrid NN-GA approach to serve as relay between CHs in inter-cluster communication was discussed in this chapter, highlights its methodological process and conceptual of developed approach.

- **CHAPTER 4:** This chapter provides the simulation and evaluation of the developed approach and provides a discussion for the experimental results and evaluation of different developed solutions and their stability, ability in reducing the energy consumption, and increase IoUT network lifetime. Additionally, reviews the protocol's effectiveness, showcasing improvements in energy efficiency enhancement and network reliability in underwater environments. The results show that the energy aware protocol achieves the highest network efficiency by 92% compared with baselines approaches, gains exceptional performance in balancing data delivery and energy saving. And the use of UVs as relay will reduces energy consumption by up to 48%.

- **CHAPTER 5:** This chapter provided summaries of the thesis, the conclusion, limitations of study and some recommendations for potential further studies.

CHAPTER TWO

Literature Review

2.1 Background

In IoUT networks, many UNs used to collect data from the underwater environment and access the Internet through the network layer, enabling data to be passed to monitoring stations (Monika et al., 2022). The network layer enables to exchange the received information between UNs to the application layer to be proceeded by intelligent applications (Mari., 2012). The IoUT faces many deployment challenges and problematic issues such as, low data rates, and low reliability, especially if the network communications are based on acoustic waves. Nevertheless, the acoustic communications are suitable for the different underwater environment compared with optics and RF communications. Acoustic waves have the advantage of providing stable switching operations in both deep and shallow waters, however may be affected by propagation delays with high energy consumption in long communication scenarios, in addition to many underwriter environment impacts (Xu et al., 2019). The IoUT has unique features that should be addressed well in design and deployment which are reviewed in the following points.

- Enabling communications between the UNs and other devices on the land, while the operations will take place in different ecological environments.
- Enabling transmission over any kind of underwater medium, in oceans, seas, or lakes, in shallow or deep water, with different pressure, salinity, and temperature values.
- Providing long-distance communications, by using acoustic signals, as was considered a practical choice for IoUT applications.

In general, the most important issues that can affect IoUT performance are energy efficiency due to the heavy traffic loads during communications because of limited UNs energy capacity. These issues are related to different IoUT network layers, especially in networking, and physical layers. Figure 2.1, shows the general problematic management issues corresponding to each IoUT communications management layers (Xu et al., 2019).

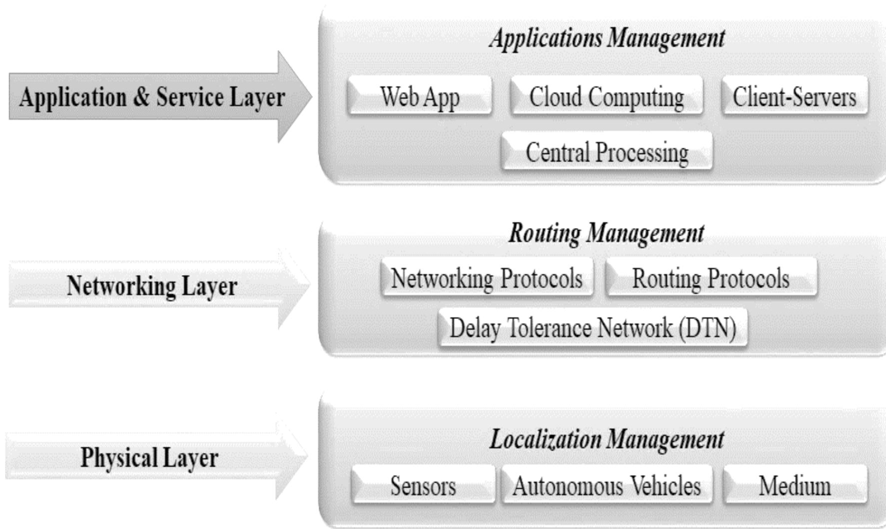


Figure 2.1. General IoUT Management Layers Affected by Energy Efficiency Issues

In IoUT, UNs required more energy to enable communications for long distances. The distribution of these UNs in the underwater environments either shallow neither deep waters will be impacted due to dynamic motions, in addition to multipath effect. Accordingly, IoUT networks need an appropriate energy management strategy (Awan et al., 2019). Moreover, the structure of the communication topology of the IoUT network, and the routing protocols are two aspects may significantly affect the performance of the IoUT network. Both aspects must be well designed to intelligently manage the UNs energy for location-based applications (Liou et al., 2018).

2.1.1 IoUT Network Energy Challenges and Solutions

In IoUT, one of most challenges is energy consumption, because the UNs run for a limited period due to battery exhaustion (Farhan, L et al., 2021). Several studies have been conducted to reduce the energy use of smart objects to extend the life of the network. The stability of the network and its lifetime are considered among the most important criteria required in IoUT networks due to their impact by any changes in the energies of the UNs and their rapid weakness or death (Liu and Wu, 2019). The low energies in UN will defect their tasks and damage the network operations. Studies on energy efficiency in IoUT networks are required by designing mechanisms and algorithms that work as energy efficiency protocols to maintain the stability of the network for an as long time as possible through energy and communications management (Lu et al., 2020).

There are an estimated number of previous studies that were concerned with reducing energy consumption in UNs networks, as they presented a number of methods that can effectively reduce energy consumption and extend the life of the network (Miller, T et al., 2025). Such methods relate to routing selection, data scheduling, efficient data collection, etc. These methods can be broadly classified into several categories as summarized in Figure 2.2 which provides a rating of energy consumption solutions and technologies.

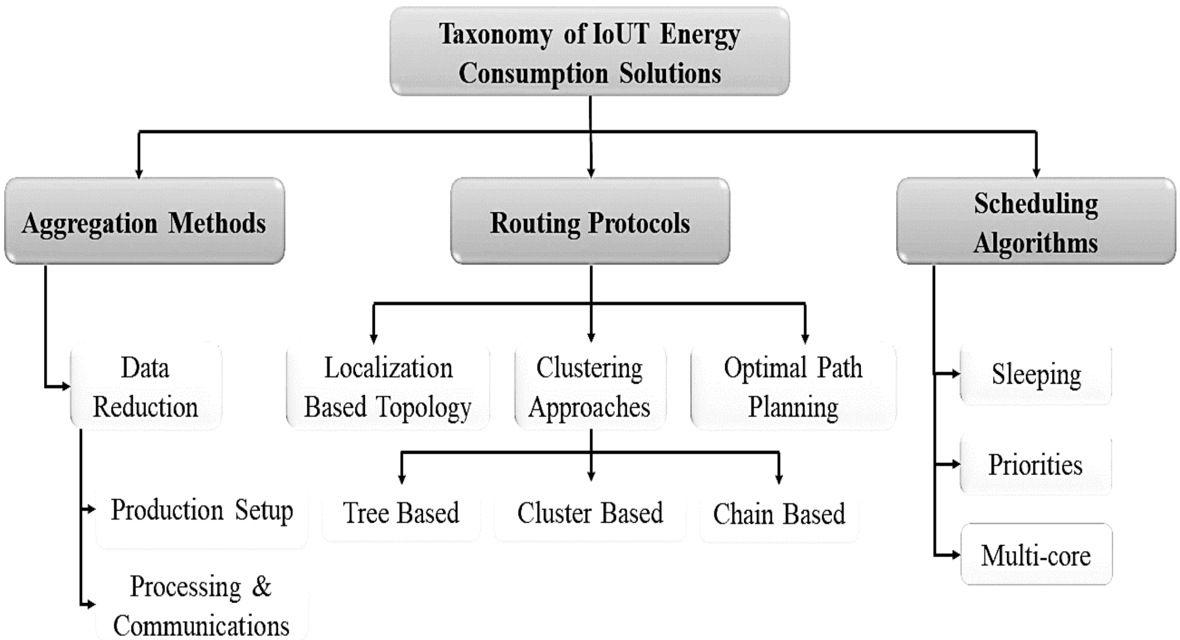


Figure 2.2. IoUT Energy Consumption Solutions Taxonomy

In IoUT network, clustering approach is one of the most suitable scheme for design a routing protocol according to literature, especially for multi-hop routing communication. This because, in multi-hop communication, all UNs inter-communicate using wireless channels without any control and shared infrastructure (Papadokostaki et al., 2017). Finding a suitable route from the source UNs to the SBS is related to the network layer. Clustering UNs into smaller groups have an essential role in conserving network energy and increasing network lifetimes. A high number of UNs are grouped into small clusters served by CH, and other UNs are cluster members (CMs). UNs need to transmit their sensed data to their CHs using low energies, short distance transmitting. Then, the CHs aggregate and send the collected data to the SBS using high energies long distance transmitting. Thus, CHs energy might run out earlier than others.

Distributing CHs uniformly throughout the network is an influencing factor for clustering effectiveness. Arranging CHs too close or too far from each other might lead once more to too small or big clusters. In both cases, the result is inefficient energy protocols. In addition to the CHs' distribution, the proper number and scale of clusters are essential for clustering effectiveness. Otherwise, the network cannot benefit from clustering advantages (Hollinger et al., 2012). A large number of clusters lead to a large number of CHs, which have to communicate with the SBS using the long distance transmission, thus, a greater number of UNs will rabidly lose their energies. Furthermore, a small number of clusters leads to clusters with big diameters, and in each cluster, a significant amount of energy is consumed to send data from CMs to CHs. Consequently, a trade-off should be made between these two opposite circumstances.

2.1.2 Clustering Approaches

Many various techniques have been proposed to minimize energy consumption in the UWSN which were conducted to increase the network lifetime (Khan et al., 2022). These techniques are related to the strategy of how to make the UNs network save the residual energy and be kept in sleep mode as much as possible in addition to finding the optimal communication route. The UNs are such applications that are responsible for many functions like data sensing and aggregation, and data processing, in addition to the common function of sending the receiving data (Y. Zhou et al., 2021). Due to these missions, the IoUT should have efficient resource utilization, together with energy to increase the life time and efficiency.

For long-distance communication in IoUT, multi-hop transmission is preferred, however, the process of establishing routing to deliver the data communication probable to face different problems, such as delay, void region, and long propagation losses, and these issues lead to more energy consumption (Ghullam et al., 2022). Besides these, the traffic load and data collision will also affect the overall IoUT network energy efficiency. For these problems, the clustering approach will help to reduce energy consumption by grouping the UNs in clusters, then each group has a CH to manage the communications (Shelar et al., 2022)(Z. Zhao et al., 2019). The clustering approach enables to management of the data traffic to keep the UWSN operating for a long time (Subramani et al., 2022). Figure 2.3, shows the clustering approach which describes the operation of the UWSN according to the CHs, the gateways, and the cluster member's elements.

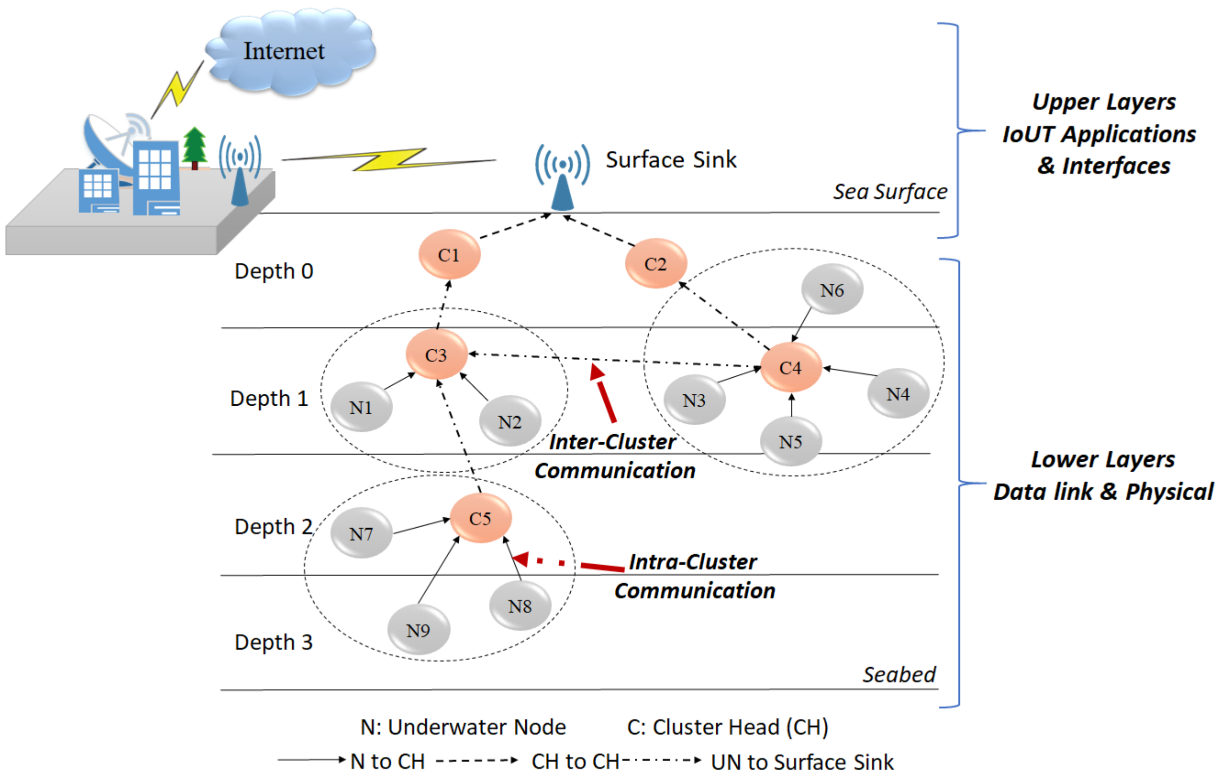


Figure 2.3. IoUT Clustering Approach Structure

The multi-hop clustering protocols are considered the best choice for an energy-efficient solution for UWSN. However, the traditional clustering approach cannot be given an efficient and optimal solution because of different other issues like underwater fluctuations, high water pressure, propagation delay, and low bandwidth (Aljanabi et al., 2022). For these challenges, different studies were focused on how to solve these problems and ensure optimal energy efficiency by using a different intelligent-based clustering approach. Most studies are investigated selecting optimal CHs and route decisions (Kunduet al., 2025).

2.2 Clustering based Routing Protocol

The clustering approach has to be optimized by considering different aspects when selecting the number of clusters, and CHs. These aspects are the dynamic nature of underwater objects, and other situations related to UNs such as position, energy and traffic load, distance from CHs, and the strategy of transmission during inter-cluster or intra-cluster routes (Robinson et al., 2021). The following recent studies investigated the mentioned aspects related to routing protocols based different developed approaches such as clustering, localization topology, path planning, and queuing-based approaches.

For IoT heterogeneous networks, several clustering-based schemes have been suggested, including distributed energy-efficient clustering (DEECP) and stable election protocols (SEP) (El-Fouly et al., 2022) The majority of these protocols, however, were created for terrestrial WSN networks. In terms of the underwater environment and acoustic communication, there are critical required modifications to these protocols to be used for IoUT, in both, communication channels and energy modelling.

In IoUT, there are variations in the UN resources and network topology, with the main emphasis being on the heterogeneity of UN energy levels according to the stability of the CH selection and communication between them. As a result, clustering protocols designed specifically for this situation like SEP have been developed (Shah et al., 2023). The need for fundamental modifications to this protocol, is to meet the requirements of the underwater environment to effectively use UN energy heterogeneity to increase network throughput and extend network lifetime.

For heterogeneous IoUT, many important aspects must be taken into consideration while planning and developing energy-efficient protocols for IoUT networks. The UNs remaining at different energy levels are one of these crucial elements (Elmustafa et al., 2023). These UNs rely on small batteries to operate in a resource-constrained environment. An efficient routing protocol must balance the network energy consumption by consider the energy levels of each UN and make routing decisions accordingly. The protocol can increase the network total operational lifetime by giving preference to routes that involve nodes with the highest residual energy.

Another crucial factor is the functional depth of UNs. Signal propagation is impacted by the underwater environment with varied depths and water quality (Zhu and Wei, 2018). These factors must be taken into consideration by routing protocols when defining routes for data transport. Routing algorithms should seek to reduce energy consumption by taking into account depth-specific methods such as using shallow UNs as relays or altering transmission energy levels dependent on depth. On the other hand, in the process of CHs selection the energy levels with depth of the potentially chosen UNs have a direct impact on the efficiency of energy use (Zhang et al., 2023). The optimal selection of CH includes factors such as the UNs distance to the SBS, energy levels, depth, and communication capabilities (Zhang et al., 2023)(Nadeem et al., 2024).

The intelligent CH selection process can ensure that energy-efficient UNs assume the role of CHs, reducing the energy consumption associated with data aggregation and task redirection.

In IoUT, many factors must be considered such as UN energy levels and, the dynamic underwater environment. The CH selection method as used in literature based on residual energy and distance only may not be appropriate in such circumstances. Adaptive CH selection is essential to ensure the best-selected CHs based on changing network conditions. Accordingly, enhanced SEP by taking the mentioned considerations will effectively account for energy heterogeneity and underwater environment conditions (Mhemed et al., 2022). It can assure stable CH election with fairer energy consumption pattern across the UNs, extending the network's operational lifetime, by adapting the process of CHs based on UNs parameters to effectively allocating energy-intensive tasks during the inter-CHs routing process (Su et al., 2019).

2.2.1 Intelligent Approaches

Various energy efficiency studies are conducted for IoUT to explore the underwater environment for different purposes. This type of network faces one of the most important challenges, which is limited energy due to high energy consumption, in addition to the impact of end-to-end delay, and low packet delivery rate. The use of AI algorithms has a great ultimate solution to maximize UWSNs networks' lifetime. AI approaches enable intelligent architecture for maritime networks and improves sensing operations in addition to gathered data processing and underwater communications (X. Hou et al., 2021).. It also provides reliable high transmission of real-time underwater information for IoUT critical missions. The gathered data classifications can be improved by AI approaches to categorize the sensor data for both security and energy efficiency issues.

2.2.1.1 Meat-Heuristic Approaches

For energy efficiency, different Meat-Heuristic techniques as a swarm intelligence (SI) approaches provide different solutions for energy issues related to IoUT. For resource allocation and management, SI optimization approaches provide best solutions to obtain the targeted results in addition to improving the decisions (Pathak, 2020). The SI algorithm enable to optimize route planning and clustering approach in IoUT. As shown in Figure 2.4. SI enable route improvement by adapting to the complex underwater environment for global route planning, and considering the optimization criteria for the optimized route by local route planning schemes. Global route planning enables global optimization reference routes based on underwater environment, in addition to constraints related to network topology, and physical performance (Nonoyama et al., 2022). For real-time operations, local route planning enables UNs/UVs to re-planning the local route according to different factors such as residual energies, depth, and the distance to the SBS.

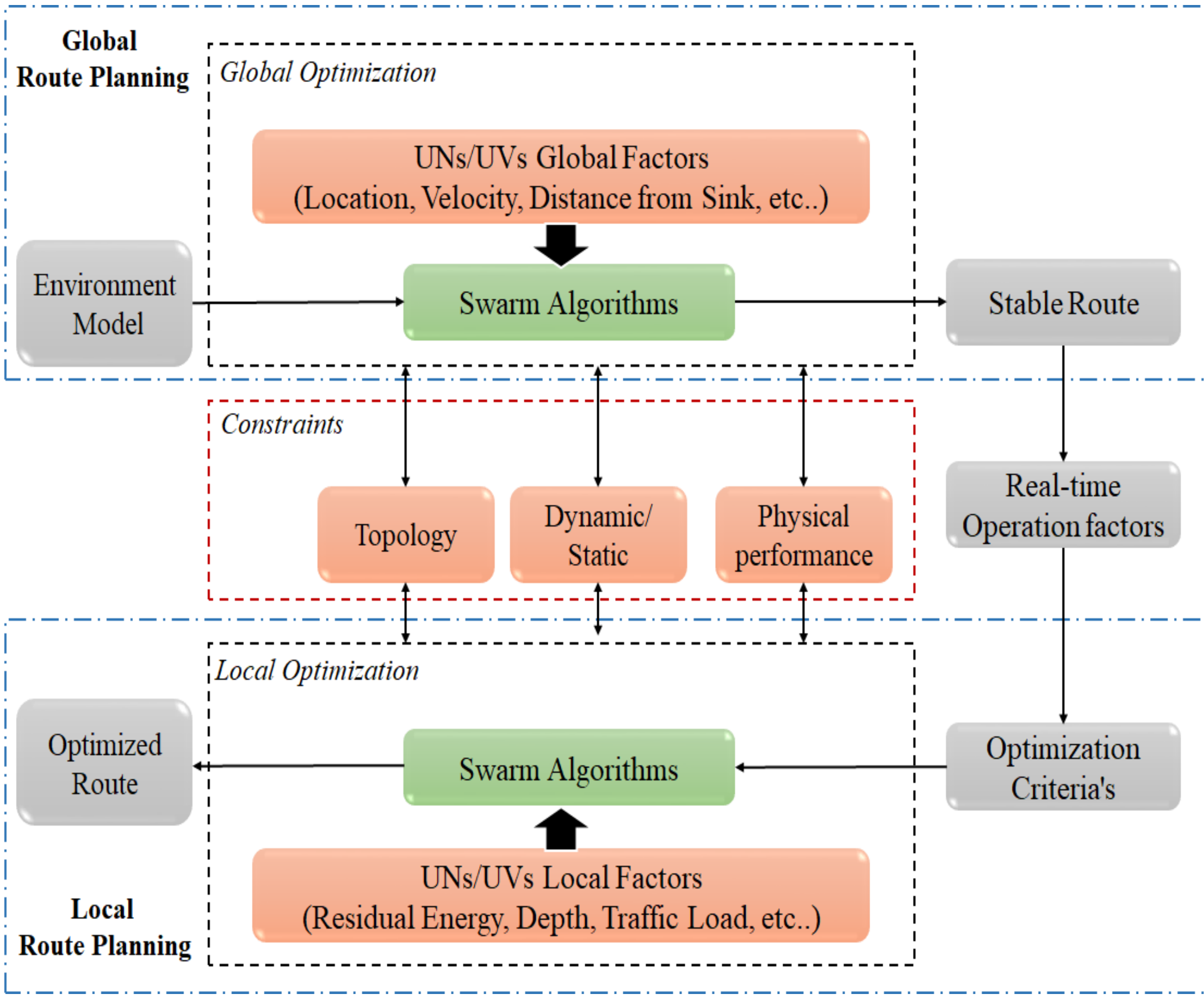


Figure 2.4. General Model for IoUT-UNs/UVs Route Planning Based Swarm Intelligence Approach

In heterogeneous IoUT network, while energy-efficient-based clustering approaches have been presented, their appropriateness for large-scale IoUT networks remains shortcomings when relied upon. However, SI algorithms provide solutions for resolving energy consumption concerns within these expanding networks (Nonoyama et al., 2022). The integration of SI algorithms such as GA, ACO, ABC, and PSO is a promising best solution for these difficulties. These algorithms provide adaptive decision-making processes, optimizing methane selection dynamically and adapting to changes in energy availability in real-time.

A. Genetic Algorithm

Genetic Algorithm (GA) enables to select CHs by representing the CH solutions as chromosomes and evaluating their fitness based on variables like energy consumption and distance. It begins with an initial population of chromosomes and uses the Euclidean formula to determine UN distances. Each chromosome serves as a potential CH selection solution, with genes serving as CH indices. For IoUT, CH solutions as chromosome which are viewed as probabilistic groupings that change as a result of fitness function, mutation, and crossover operations (Sajwan et al., 2023). The best cluster is chosen based on the chromosome with the highest fitness, which takes into account elements like balancing a CHs residual energy, mean intra-cluster distance, and the distance of the CHs from the SBS. As a result, the crossover probability, or crossover, is a crucial element in the crossover operator and is defined as such for random crossover by the following equation.

$$\text{Crossover= round (k} \times (G_{max} - G_{min}) \qquad (2.1)$$

where k is rand between (0, 1), G_{max} is the maximum number of genes and G_{min} is the minimum number of genes in the chromosome.

To reduce energy consumption in the IoUT the selection operator which comes after the crossover and mutation operators chooses the chromosomes with the highest fitness or the nearly optimal solution among the new population and the chromosomes formed as the next generation for the clustering problem (Nonoyama et al., 2022)(Sajwan et al., 2023). To balance the energy consumption of each cluster in this situation the CHs assigned to each cluster with the highest residual energy with shortest mean intra-cluster distance and the closest distance to the SBS. GA however may run into issues with convergence, parameter tweaking, communication model accuracy, boundary handling, scalability and real-world validation. To implement successful CH selection in real-world IoUT deployments, several issues must be resolved.

B. Particle Swarm Optimization

Practice swarm optimization (PSO) optimizes CH selection by using collective intelligence, where each particle's location indicates a potential CH structure. The possible CHs are encoded by the position of each particle (Jalal and Aliesawi., 2023). The evaluation is based on the objective function-based calculation of each particle's fitness. Each particle maintains a record of its fitness score and best position configuration. The particle with the best personal best is regarded as the global best among the entire swarm. This is the optimal CH arrangement that the swarm could find. Each particle's velocity and position are updated based on its present velocity, local best, and global best (Sajwan et al., 2023)(Jalal and Aliesawi., 2023). . The velocity update equation for the particle k's dimension i can be written as follows.

$$V_{ki}^{t+1} = \omega \times V_{ki}^{t+1} + c_1 \times r_1 (P_{ki}^{t} - X_{ki}^{t}) + c_2 \times r_2 (G_{k}^{t} - X_{ki}^{t}) \quad (2.2)$$

where, V_{ki}^{t+1} is the updated velocity of particle k in dimension i at time (t+1). Ω is the inertia weight. c_1 and c_2 are cognitive and social learning factors, respectively. r_1 and r_2 are random values between 0 and 1. P_{ki}^{t} is the personal best position of particle k in dimension i at time t, G_{k}^{t} is the global best position of particle k at time t. And $X_{ki}^{t}$is the current position of particle k in dimension i at time t.

The PSO algorithm enable to identify an ideal or nearly ideal configuration of CHs while considering variables like energy efficiency, communication range, and other pertinent requirements (Sajwan et al., 2023)(Jalal and Aliesawi., 2023). However, it faces challenges related to convergence, parameter tuning and handling boundary conditions. Addressing these shortcomings is crucial to ensure effective CH selection in IoUT networks.

C. Ant Colony Optimization

Ant colony optimization (ACO) optimizes CH selection by replicating pheromone trails, taking influence from ant foraging behavior. In ACO model, CH candidates who travel shorter distances and use less energy leave stronger pheromone trails, are selected as a solution candidate. CHs are chosen based on the pheromone value assigned to each UNs (Xiao and Huang., 2020). CH is chosen from UNs by using a probability threshold. Based on the ant's weight and position, a probability threshold is generated for each node to be chosen as the cluster head. The following equation can be used to determine the probability.

$$P(i) = \frac{w_t \times \alpha + [ph(i)] \times \beta}{\sum_{N=0}^{n} w_t \times \alpha + [ph(i)] \times \beta} \quad (2.3)$$

where, w_t represents the weight associated with each node (N). ph(i) is the pheromone concentration associated with each node for an iteration. α Controls the importance of pheromone information in the decision-making process and β controls the importance of heuristic information in the decision-making process respectively.

The ACO can be used for CH selection shows many acceptable results and performance factors. Notably, the algorithm prioritizes energy efficiency optimization, and enable to balances energy efficiency and network coverage (Xiao and Huang., 2020). However, when IoUT networks get increasingly sophisticated, the ACO starts to run into scaling problems. The selection of a CH is made more difficult by the requirement for precise modeling of underwater communication conditions.

D. Artificial Bee Colony

Artificial bee colony (ABC) imitate bee foraging behavior to optimize CH selection. In ABC, the CH selection process uses the fitness evaluation to evaluate how well a specific CH configuration performs concerning predetermined criteria. Depending on the particular aims and purposes of the IoUT network, the fitness function's precise parameters may change (Zehra et al.,2021). For instance, a fitness function might be established to balance these parameters while minimizing energy use and maximizing network coverage. The fitness function of ABC can be represented as f(i) is specified as follows.

$$f(i)= k\{Re(i)+ N_D\} + \{1-k\} \times \{\frac{1}{Eu(i,b)}\} \tag{2.4}$$

where, k, is the scaling factor. Re (i) of residual energies of nodes. N_D The UN degree is the number of connecting UNs to a particular UN within its transmission range. Eu is the Euclidian distance from UN_i to the sea surface station. The Re (i) is based on the underwater conditions' impact on energy consumption.

In IoUT networks, the ABC algorithm provide an efficient method for CH selection. It enable to optimize CH setups, based on energy efficiency and underwater consequences (Zehra et al.,2021). ABC is suitable for solve the issues of CHs selection in IoUT applications because of its flexibility to adapt to the underwater environment and possibilities for modification. However, the effectiveness of the selected fitness function and the success of parameter adjustment for a given network requirement ultimately determine its performance.

E. Clustering Based Swarm Intelligence Approach

In IoUT the design of a clustering protocol that can reduce energy consumption latency is a great challenge in the underwater environment (Rodoshi R et al., 2021). The meta-heuristics as swarm intelligence (SI) algorithms enable UNs and UVs to interact with the environment. The UNs/UVs can set a previous status to evaluate the energy level based on their operations. The SI algorithms integrated into this model enable to intelligent manage the operations of the UNs/UVs by taking into consideration the energy consumption corresponding to the depth and motions, in addition to underwater environments impacts (Rodoshi R et al., 2021)(Elmustafa et al., 2021).

The SI algorithms enable to simulated ensemble biological intelligently with complex problem-solving characteristics, self-adaptive capabilities, with an ability to optimize the energy management for IoUT. Some studies have relied on the use of a different SI algorithms such as, PSO, ACO, ABC, and GA (Petritoli et al., 2020). Most of these algorithms work to find the optimal solution based on exploratory information of the underwater environment surrounding underwater vehicles/nodes and make decisions related to dynamic based energy optimization.

The SI algorithms provides different solution to reduce energy consumption by maximizing the values of the information collected by underwater nodes/vehicles, as well as from the ambient environment, and working to reduce the cost of its activity time according to energy consumption, in addition to operational risks in specific underwater environment conditions (Kazi et al., 2022). To validate the SI algorithms optimization based clustering energy efficiency approach in IoUT, several parameters should be considered such as connection rate, route length, number of CHs hops, routing load, sensing radius of UNs/UVs, localization and depth, coverage rate and throughput.

2.2.1.2 QL Optimization Approach

For the energy efficiency-based clustering approach, QL enables to provision of an intelligent solution for a clustering approach which can efficiently select the CHs with optimal status. In addition, QL enables to balancing of energy consumption among different UNs by setting the reward points to learn the dynamic underwater environment conditions (Nonoyama et al., 2022)(Yao et al., 2022). Moreover, it able to modify the routing of information's between UNs and manages the combinations through CHs and relay nodes according to the scenario used. For clustering optimization, QL with SI approaches enables better utilization and solves the energy issues in IoUT networks.

Energy efficient based QL schemes enable to provide better IoUT lifetime by developing an efficient energy aware routing scheme. The QL enable to utilize the IoUT network by reduce load overhead in dynamic network topology. The strategy can be achieved by using QL to efficiently monitors the environment and extract information about topology, UN residual energies and the overhead of load exchanged between UNs, to optimize the next selected hop route (Pathak., 2020) (Zahoor et al.,2021).

For CH selection, the general approach of using the QL approaches able to optimize the clustered based routing protocols for IoUT networks. In such approaches, the UNs are divided into clusters led by CHs which can communicate with relay UNs or directly to base stations. QL approach will help to optimize the route in long-range combinations (Kesari et al., 2022). The process of QL shown in Figure 2.5, enables indicates the next communication according to the reward function that indicates the distance between the CH and SBS (Zhao et al., 2022). The selection of CHs-based QL is based on historical learning, in addition to different factors, such as the residual energy(E_i), depth (D_i), and traffic load of the CH candidate, in addition to the distance (d_i) from CH to SBS.

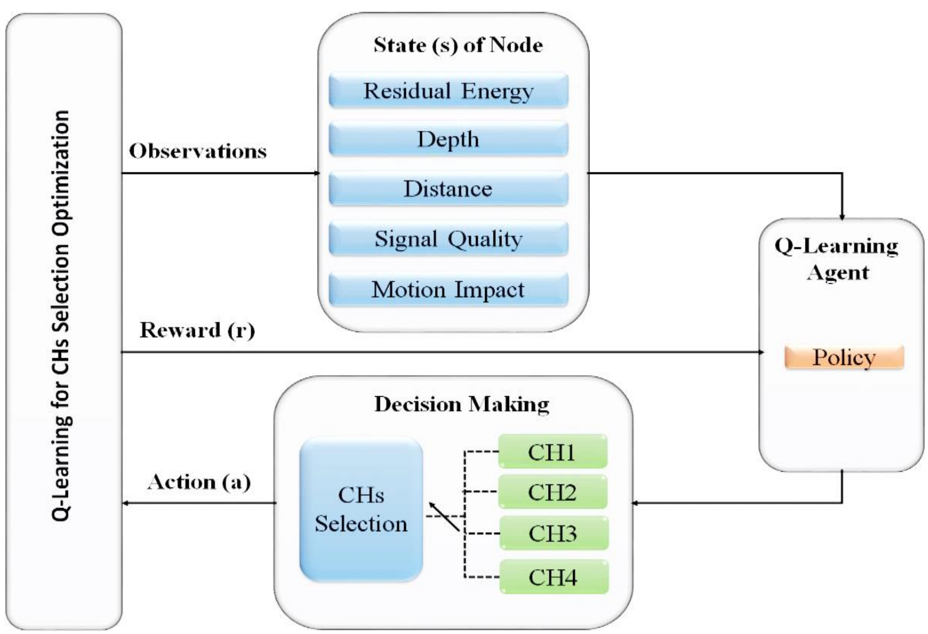


Figure 2.5. QL Approach for CHs Selection Strategy

The QL method as shown in Figure 2.5 improve the CH selection process for ABC optimization by dynamically building incentive functions. With the help of QL, it is possible to learn information from environmental input repeatedly until the best course of action is identified (Faheem et al., 2019). Depending on the decisions taken, the best CH will be chosen. The agent moves from state s_i, to state sj by performing action ai from strategy. The assessment of an agent's behavior is called reward. The reward is known as the Q^{π} (s_i, a_i) is the sum of the direct reward plus discounted future rewards, as stated below (Faheem et al., 2019)(Anjan et al., 2025).

$$Q^{\pi}\ (s_i, a_i)= r_i + \gamma \sum_{sj \epsilon X} P_{sisj}^{ai} \times Q^{\pi}\ (s_j, a\ \ ) \tag{2.5}$$

where, r_i denotes the current reward. The future reward's discount factor is $\gamma \in (0, 1)$. P_{sisj}^{ai} is the likelihood of an agent in state si leaving state sj. After implementing an optimal policy, the ideal value for a state can be determined. Additionally, it is possible to identify at least one optimal method using the Bellman equation (Anjan et al., 2025). The policy's definition of the ideal value is as follows.

$$V^{*}(\text{s}) = max_a(Q^{*}\ (\text{s, a})) \tag{2.6}$$

$$Q^{*}\ (\text{si, ai})) = r_i + \gamma \sum_{sj \epsilon X} P_{sisj}^{ai} \times V^{*}(\text{sj}) \tag{2.7}$$

The predicted reward earned by carrying out action aj following the best course of action at state si is Q* (si, ai). As a result, the ideal course of action a_i^* is as follows:

$$a_i^*= \begin{Bmatrix} argmax\ Q\ (s_i, a_i) & ;\ random\ number\ <\ \epsilon \\ random\ action & ;\ otherwise \end{Bmatrix} \tag{2.8}$$

Where, $rgmax\ Q\ (s_i, a_i)$ represents the calculations of the Q-value for each potential action in the current state, enabling the selection of an action with the highest Q-value. The state of random action is chosen when it is less than the exploration rate and always selected between 0 and 1. The agent decides to explore by performing a random action if this random integer is less than the range within [0, ϵ]. Otherwise, if the outcome is greater than or equal to, the agent takes advantage of its present knowledge by picking the course of action with the highest Q-value (Anjan et al., 2025).

The QL solution enable to optimize the meta-heuristic approaches process while considering and dynamically checking the CHs conditions. To capture the states of UNs and actions of choosing CHs, the Q-table stores the Q-values for state-action pairings (Anjan et al., 2025)(Chang and Duan, 2019). The following equations update the QL during each iteration of meta-heuristic approaches.

$$Q_{target} = \text{reward} + \gamma \times Q_{max} \tag{2.9}$$

$$\text{Next Q} = Q_{j,k}(\text{next State (j)}) + \alpha \times (Q_{target} - Q_{j,k}(\text{next State (j)}) \tag{2.10}$$

The current Q-value for the chosen state-action pair is represented by $Q_{j,k}$(next State (j)). The $Q_{j,k}$(next State (j)) can be described by the Q based on current UNs, neighbor UNs, and next state. The learning rate regulates how much the new information affects the Q-value. The discount factor weighs potential rewards in priority (Chang and Duan, 2019). The immediate benefit from the chosen action is the reward. Q_{max} is the highest Q-value among potential responses in the upcoming state. Then, the maximum amount of the current Q can provide the best-chosen action. By iteratively updating the Q-values based on observed rewards and making decisions to maximize expected rewards, equations (2.6) and (2.7) identify an optimal strategy for selecting the best CHs.

2.2.2 Multi-Criteria Decision-Making Approaches

Multi-criteria decision-making (MCDM) approaches are effective in solving the potential complexities of decision-making processes related to multiple conflicting objectives and criteria. They provide a systematic and structured decision-making framework for breaking down complex problems into manageable components enable to evaluating alternatives according to well-defined criteria and making decision (Avramova et al., 2025). For IoUT clustering protocols Analytical Hierarchy Process (AHP) plays an important role in ensuring QoS by enabling hierarchical analysis of key performance metrics such as network throughput, signal quality, and energy efficiency (S. Chinnasamy et al., 2022). Through binary comparisons, AHP systematically assigns relative weights to these metrics based on their impact on network reliability and sustainability establishing a consistent and less biased weighting system.

The AHP approach ensures that QOS parameters such as low latency, reliable packet delivery, and balanced energy consumption which are prioritized during the CH selection to provides more robust and adaptive network behavior under dynamic underwater conditions (Avramova et al., 2025)(Jiang et al., 2023). Figure 2.6 shows the MCDM approach with a QL optimization for adaptive decision-making in IoUT network (Avramova et al., 2025)(Lekhraj et al., 2022).

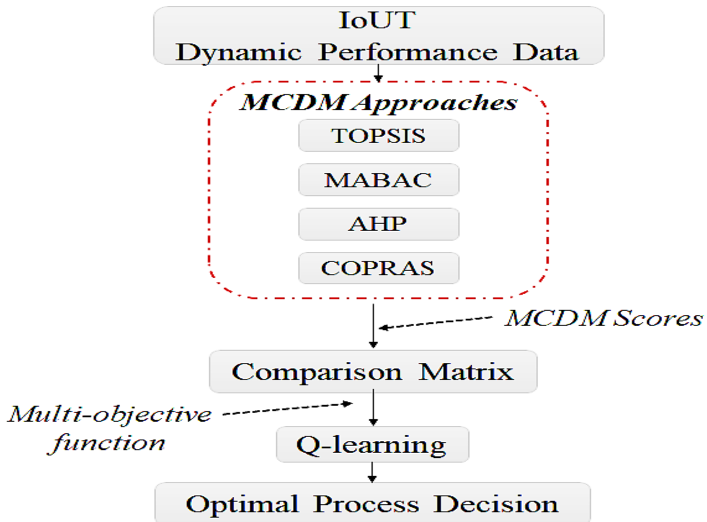


Figure 2.6. Hybrid MCDM-lightweight QL approach

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) can be used to rank the candidate UVs as relay by selecting the most suitable forwarders for inter-cluster communication (Guo et al., 2023). By modeling each UN as an alternative evaluated across normalized criteria TOPSIS identifies the positive-ideal solution and negative-ideal solution then ranks candidates based on their relative closeness to the ideal. This allows the proposed approach to effectively balance trade-offs between competing factors like preferring a slightly deeper UNs with high residual energy over a shallow but nearly depleted one (Jin et al., 2024). As a result the top-ranked UVs are selected as relays to ensuring optimal forwarding paths that maximize network lifetime, minimize transmission delays, and maintain high link stability.

2.3 Related Works

In IoUT, optimizing network lifetime and energy efficiency is a major concern. Unbalanced energy usage in IoUT networks is a result of UNs' diffused location across different depths (Mari, 2008). The literature indicates that clustering-based routing has already demonstrated efficacy in enhancing energy efficiency; however, optimal selection and replacement of CHs are essential due to the dynamic nature of undersea communications. Recently, many related studies have been conducted to provide clustering-based routing algorithms for IoUT networks to improve energy efficiency. Table 1 summarizes the related works' contributions and their limitation.

Sathish et al., (2025) use a multilevel clustering framework that creates hierarchical categories within the network according to UNs characteristics and residual energy content. The proposed approach adds an unequal clustering protocol known as an energy-efficient unequal multilevel clustering approach. This technique dynamically selects CHs based on their energy levels and proximity to the sink. Results show that it automatically directs data flows over energy-efficient routes, while adaptive data aggregation minimizes redundant transmissions to preserve system performance and save energy. A study by Homaei el al ., (2025) provides an RPL protocol with a tree network topology approach for topology control in UWSN, taking the considerations related to UNs mobility, link delay and limited bandwidth. The proposed approach uses the MCDM method to optimize the route decision-making. After evaluation, the proposed approach shows notable gains by increasing the packet delivery and network lifetime.

Arain et al., (2025) proposed an improved ORP-based QoS-aware approach to reduce excessive energy consumption in IoUT. A weighting cooperative CH selection is used, where candidate UNs are assessed according to link quality, depth, and residual energy. Simulation results show that the proposed method performs better than standard techniques and uses approximately 65% less energy. A study by Kaur et al., (2024) proposes a met heuristic-based clustering cognitive intelligent protocol to optimize CH selection by a hybrid Bees algorithm with artificial fish swarm behavior. It lowers communication overhead and improves clustering efficiency by dynamically taking into account the UNs residual energy. According to simulation results the proposed approach reduces energy consumption by 25.6%. An enhanced LEACH protocol is proposed by Tian et al., (2024) for cluster-based UWSN. The method uses a transmission scheduling algorithm to ensure conflict-free parallel data transmission. The simulation results show that the proposed protocol performs better than a variety of traditional approaches.

Rongxin et al., (2024) provide an effective cluster-based routing technique is presented that lets CHs use multi-hop forwarding to send the fusion data to the sink. The study uses a prediction model based on the Markov chain to overcome routing voids induced by UN failures during packet transmission. Also, the connection prediction method is used to take the received SNR and the UN's mobility into consideration. The best forwarding path for packet transmissions is determined by the opportunistic routing (OR) paradigm. The results show an efficient packet delivery ratio and energy consumption reduction.

A study by Çiğdem et al., (2024) proposed a unique RL-based method for CH selection. The study integrates the expected harvested energy into the decision-making process by combining a stochastic energy harvesting model with RL for CH selection. The evaluation of the proposed method shows significant reductions in energy consumption and notable improvements in network lifetime. Kaveripakam et al., (2023) propose an energy-balanced, reliable and effective clustering technique to improve data packet delivery in UWSNs. Results show that the proposed protocol outperforms current approaches in terms of residual energy, energy consumption, and network lifetime.

Vijay et al., (2023) proposes hybrid cat cheetah optimization algorithm for a UWSN clustering-based routing scheme. It enhances data transmission from UNs to sinks by optimizing the selection of CHs and multi-hop routing according to distance and residual energy. Results show that the proposed protocol performs better in terms of energy usage, packet delivery ratio and network lifetime. Bharany et al., (2023) proposes a simplified swarm optimization technique for energy-efficient clustering in UWSN to maximize the selection of CHs and cluster formation based on residual energy and overall energy consumption. The evaluation findings show that the proposed method performs better than the LEACH protocol. Usman et al., (2020) introduces the CH formation with an adaptive clustering habit protocol, based on calculations of various protocols, including LEACH, DBR, and SEP. The findings show that the suggested protocol enhances network performance in terms of packet transmission.

Table 2.1. Summaries of the Related Works, Contributions and Shortcoming Criteria

Citation	**Algorithm, Protocol**	**Contributions**	**Shortcomings (Limitations)**	**Optimization Requirements**	
				Dynamic Decisions	**QoS Driven Approach**
Sathish et al., (2025)	Unequal Multilevel Clustering approach	Improve energy efficiency and route quality	▪ Not considered the most important underwater impact factors ▪ Static routing decision	×	✓

Homaei el al ., (2025)	MCDM with RPL protocol	select optimal routes	▪ Depends only on the UN's position and the package's load ▪ Weak in large-scale networks	×	✓
Arain et al., (2025)	Improved ORP protocol	Improve energy efficiency	▪ Depends only on the UN's depth and residual energy ▪ High overhead with a large-scale network	×	✓
Kaur et al., (2024)	EAFSCCIP	CH selection optimisation	▪ Static CH selection ▪ Depends only on residual energy	×	×
Tian et al., (2024)	Improved LEACH	Reduce the signalling in the clustering and data transmission phases	▪ Not considering most underwater impact factors. ▪ scalability concerns high latency in large networks	×	×
Rongxin et al., (2024)	Markov chain and opportunistic routing approach	Improves multi-hop routing decision by overcoming the route voids during packet transmission	▪ Not considered the most important underwater impact factors ▪ scalability concerns	×	×
Çiğdem et al., (2024)	RL optimization	Optimises cluster formation and data routing to enhance energy efficiency	▪ computational complexity ▪ scalability concerns for large-scale networks	✓	×
Kaveripakam et al., (2023)	Energy Balanced, Reliable and Effective Clustering approach	Improve energy efficiency	▪ static CHs selection ▪ No, enhance service quality	×	×
Vijay et al., (2023)	HC2OA	Improve the CH selection, and optimise data transmission routing	▪ CH selection based only on residual energy and distance ▪ Static multi-hop route	✓	×
Bharany et al., (2023)	Simplified Glowworm Swarm Optimisation	Improve cluster formation and CHs selection	▪ Not considered the most important underwater impact factors ▪ limited scalability	×	×
Usman et al., (2020)	Away cluster head with adaptive clustering habit (ACH)2 approach	Optimise clusters based on balanced cluster size	▪ CH selection is based only on distance and residual energies	×	×
Proposed Study	ABC Optimisation with QL and NN-GA with MCDM Approaches	Optimise CH selection, replacement, and inter-cluster routing decision	▪ Adaptive decision-making based on all possible IoUT impacts. ▪ Adaptive CH management and inter-cluster routing ▪ QoS-driven, energy-aware approach	✓	✓

Clustering-based routing protocols for IoUT networks have advanced significantly but there are still a number of important issues to overcome. According to Table 2.1, current methods tend to ignore dynamic underwater factors such as traffic patterns, signal attenuation and UNs depth fluctuations which leads to inadequate energy efficiency and network instability (Shovon and Shin, 2022). The improved clustering-based approaches like those discussed in (Sathish et al., 2025)(Arain et al., 2025) and (Tian et al., 2024) as well as hybrid meta-heuristic techniques like those found in (Kaur et al., 2024) and (Vijay et al., 2023) are useful for lowering energy usage and improving data transmission efficiency. Furthermore, MCDM technique in (Homaei et al., 2025) and RL-based approaches in (Çiğdem et al., 2024) have been investigated to improve routing paths and integrate dynamic decision-making. However, despite these improvements, several critical limitations are observed across existing studies, which are highlighted as a research gap of the proposed study as follows.

- *Limited CHs management adaptability:* Most of the current methods are based on static or semi-static CH management strategies that are mainly based on distance and residual energy as in (Sathish et al., 2025)(Kaur et al., 2024)(Vijay et al.,2023). Even while these factors are significant they do not take into consideration the dynamic and varied characteristics of underwater impacts including depth-dependent communication limitations and UNs motions. Over time networks may suffer from high energy depletion with protocols in (Kaur et al., 2024) and (Usman et al., 2020) because of a lack of adaptive methods for CH replacement. As a result, more flexible CH management system that incorporates current network and environmental circumstances is required.

- *Lack of QoS-driven energy-aware optimization*: QoS parameters are included in some studies such in (Arain et al., 2025) (Homaei et al., 2025)(Sathish et al., 2025). However, they are frequently done so in a restricted or static way. In (Homaei et al., 2025) for example the MCDM-based RPL protocol takes QoS measures into account but it is unable to dynamically modify routing decisions in response to changes in network conditions. QoS is also integrated in the protocol in (Arain et al., 2025) however cluster stability and multi-hop routing efficiency are not taken into account.

- *Inefficient inter-cluster routing decision*: Studies that enhance clustering techniques such as those based on swarm optimization in (Bharany et al., 2023) and Markov chains in (Rongxin et al., 2024) focus on intra-cluster optimization while neglecting the significance of intelligent inter-cluster routing. As a result, suboptimal path selection and increased energy consumption during data forwarding to the sink will be raised.

- *Limited optimization techniques*: While meta-heuristics in (Kaur et al., 2024)(Vijay et al.,2023)(Bharany et al., 2023) and QL in (Çiğdem et al., 2024) showed potential in clustering and routing optimization but their integration is still incomplete. The cooperation between heuristic search strategies and learning-based decision-making is not being utilized in current studies which employ both techniques in isolation and with limited adaptability. With a hybrid approach energy efficiency and network longevity can be greatly increased by combining the global search capabilities of meta-heuristics with the quick convergence of QL.

2.3.1 Literature Review Synthesis Insights

Many techniques and methods have been utilized to enhance the energy efficiency for IoUT network, based on different schemes and algorithm as observed from the recent studies discussed. A variety of energy efficient protocols have been reviewed in this review, with their efficacy and advantages and disadvantages noted. The review provides an informed analysis of existing developed protocols and energy efficiency strategies which provides viewpoints offered by scholars by examining the most recent research. In addition, it fills gaps in the body of literature that have not been fully explored.

Current research in IoUT networks shows that a variety of energy-efficient methodologies and strategies can substantially reduce power consumption and extend network longevity. However, for maximum optimization, it is crucial to carefully select the right energy management strategies and parameters that are specifically adapted to underwater conditions. Many studies focus on effective CH selection, dynamic routing protocols, and energy harvesting techniques, which are pivotal in reducing power usage. The discussed related works taking the advantages of AI and meta-heuristic techniques in developing the protocols.

Even with improvements in energy efficiency for IoUT and IoUT proposed by different recent studies those discussed previously a number of issues still affect performance including the optimization of CH selection, replacement schemes, inter-cluster and intra-clustering communication in addition to energy efficient routing protocol. Important study areas for improving stability and efficiency are highlighted by the fact that high signal attenuation and limited energy resources impede IoUT energy optimization. AI algorithms and adaptive protocols including reinforcement learning-based or bio-inspired optimization approaches are frequently used in reviewed works to overcome these limitations. However, in order to guarantee the robustness and sustainability of IoUT networks more advanced energy-aware techniques are needed to ensure high QoS especially for IoUT networks particularly those that take into account a greater variety of variables affecting energy efficiency.

2.3.2 Open Research Gaps on IoUT Energy-Efficiency

In general, IoUT energy efficiency faces different challenges which are reviewed in Figure 2.6. These issues are leading to hotspot research issues related to energy efficiency in IoUT. The reviewed studies in the paper covered some challenging aspects, and most of them are depending on the developed clustering approach. Some of the reviewed studies presented the concept of delivering data from one UN to any other CH, so that data could be sent over multiple UNs in long hops which can consume more node energy, because each UN can participate in the transmission and rerouting process that leads to increased energy consumption (Coutinho et al., 2018)(Hu et al., 2022). Therefore, an open issue is to takes into account the mechanism of data routing and data exchanges between UNs. It may assume that no member UN within the cluster can be sent to any other CHs than its own, which helps to improve energy consumption by short hops approach within the cluster boundaries, taking into account the improvement of the routing mechanism between the CHs among themselves according to load traffic, CHs positions, and energy level (Hu et al., 2022).

One of the most important factors that leads to energy consumption in IoUT is the high routing overhead and link instability. These factors required an optimal solution to be avoided (Vani and Sunilkumar, 2021). The challenges and problems that are highlighted in this paper are expected to guide the researchers in future studies. Another considerations is the dynamic motion of UNs and UVs, which will make topology changes during IoUT operations and may lead to frequent packet drops which will significantly effect on the IoUT energy efficiency. The design of intelligent solutions for the mentioned issues are required to have a stable route and reliable transmission with low energy consumption (Poonam et al., 2022).

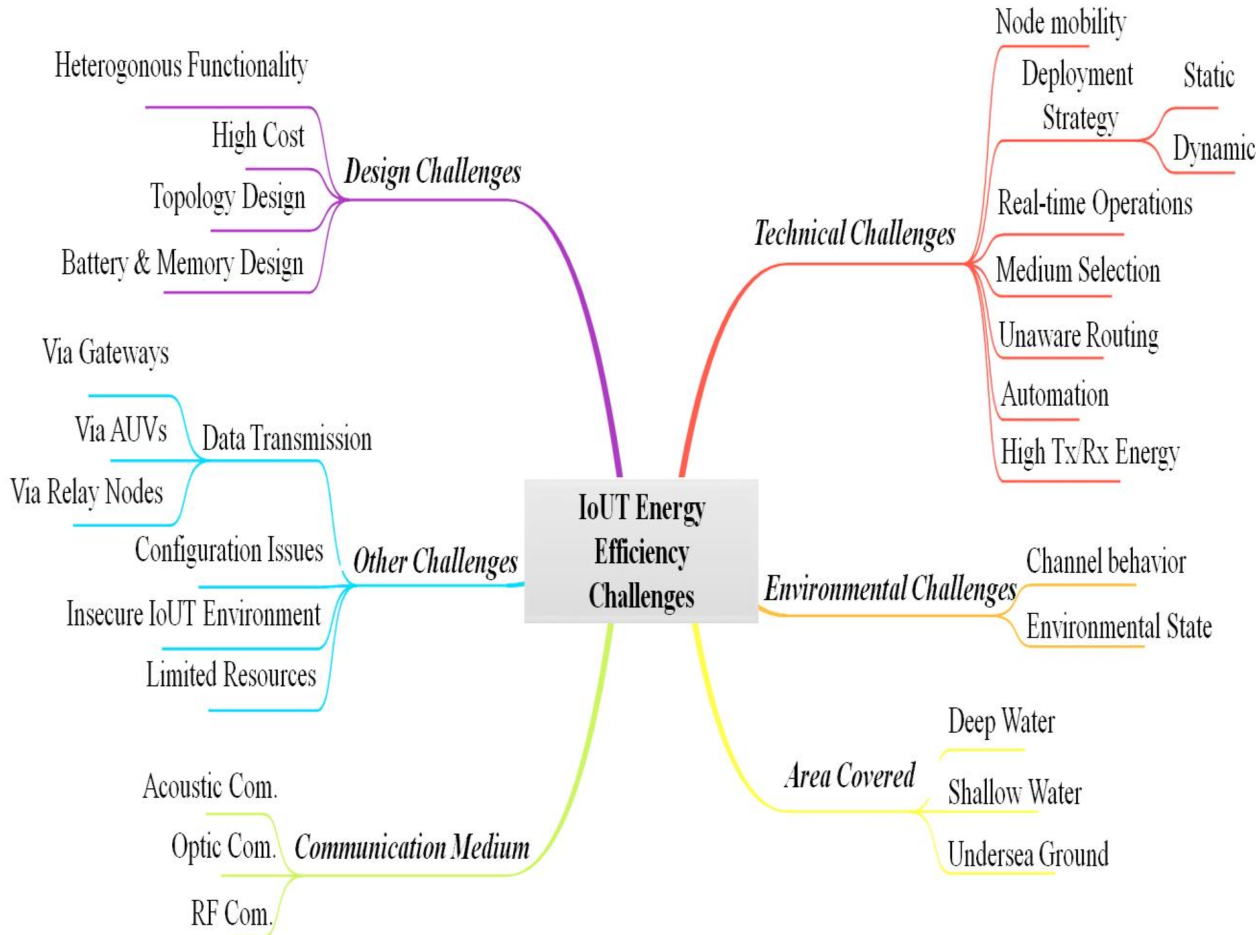


Figure 2.7. IoUT Energy Efficiency Challenges Taxonomy

Most of the new designed techniques suffer from routing overhead that can make network congestion and more energy consumption. The requirement in the design must consider the strategy to efficiently develop the shortest energy efficiency path planning for IoUT to reduce the process of route searching in addition to choosing the most stable one (W. Yu et al., 2020). However, the shortest route cannot give a reliable communication link and may not give high energy efficiency, in addition, cannot enable stable long rang communications. Accordingly, balancing between the shortest path and energy efficiency is required to deliver data accurately.

On the other side, the long commutation distance also can make a void node problem which will contribute more consumed energy, meanwhile, the clustering-based routing approach can solve the problem of void nodes effectively for long transmission distances (Sandeep and Kumar., 2017). The clustering method can encounter some problems with the selection of the CHs, if are not chosen optimally. Recently, different intelligent techniques are implemented to provide energy efficiency in IoUT. QL techniques are used in some studies to optimize the dynamic route adaptation corresponding to dynamic changes. QL can add a positive impact on the IoUT network by reducing the consumed energy in addition to achieving efficient QoS (Sandeep and Kumar., 2017)(T. Qiu et al., 2020). The energy efficiency-based QoS protocol is very important for most the real-time IoUT applications. According to what was discussed in this section, the following two research gaps (RGs) are considered the most important open research issues.

2.3.2.1 RG1: CHs Selection and Replacement Optimization

Usually, UNs and UVs are randomly deployed in a specific region. The election of UNs to become a CH depends on their types, energies, positions and environment. Accordingly, the CHs can be engaged with different functions, and have to handle commutations management of member UNs (T. Qiu et al., 2020). Other strategies can dedicate other UNs to serve as relay nodes (RNs) for many other CHs. Standard protocols used for IoT enabled WSN can enhance the CHs selection process based on high energy penalization avoidance approach depending on the residual energies of UNs such as distributed energy-efficient clustering protocol (DEEC) and stable election protocol (SEP) for heterogeneous networks. However, these protocol cannot be considered a good choice for IoUT, especially for a dynamic environments. However, possibly more modifications on DEEC and SEP to optimize the process of CH election to build cooperative communications between IoUT nodes or vehicles to improve energy efficiency.

2.3.2.2 RG2: Inter-clustering Routing Decision

The inter-cluster route decision process of the IoUT is important when the CHs that are far away from the SBS will communicate through the multi-hop CH route, however, the best inter-cluster route is an issue because the intermediate CH may not have enough energy to communicate (Nitin et al., 2019)(Chenthil and Jayarin,2022). The QL-based framework enable to optimize the route decision in inter-cluster communication. By QL, agents represent the CHs which they learn from the underwater environment to take transmission decisions (Deeksha et al., 2024). The optimal forwarding decision for transmitting packets between CHs and to SBS is achieved by using a QL framework combined with an SI algorithms.

2.3.2.3 RG3: Energy-Aware Stable Election Protocol

Clustering provides a suitable method to reduce energy consumption by grouping the UNs in the cluster and led by a CH, which aggregates the data and forward it to the next CHs or base station. The communications between CHs and the SBS depends on the routing topology (Nguyen et al., 2021). The gap is when and how to adopt the clustering approach for heterogeneous IoUT with considerations of residual energies for several kinds of UNs and UVs. Some protocols like SEP defined for heterogeneous networks by considering two energy levels. The CHs selected depending on weighed probability. Another protocols also are designed for considering four energy heterogeneity levels and others depend on multiple gateway architecture (Khan et al., 2018). But all attempts forget to consider the optimal selections of CHs with respect to different factors, such as UNs motion during underwater fluctuations or UVs mobility, depth, and overhead avoidance.

Furthermore, the heterogeneity of UNs/ UVs energies in IoUT networks leads to more complexity in designing clustering based routing protocols. Accordingly, there are several aspects those must be considered when designing IoUT routing protocols, such as the difference in energies, in addition to other effects from the global and local UNs/UVs environment (Chenthil and Jayarin,2022)(Khan et al., 2018). These considerations must be carefully analysed to developing intelligent energy efficiency-based clustering routing techniques for heterogeneous IoUT networks.

IoUT energy optimization is related to several performance criteria such as bandwidth, and network long lifetime, in addition to the percentage and speed of packet delivery, especially in real-time applications in which delays are not acceptable (Hassan et al., 2021). Also, QoS parameters are considered as one of the most important requirements for IoUT applications, with the improvement in energy efficiency (Saleh et al., 2022). The main gap in the literature review is that the studies did not consider all the influences that increase energy consumption such as the multiple UNs heterogeneity, their dynamics, locations, distances from the main station, and the amount of load on them, in addition to the topology used. The design of clustering protocols and IoUT modelling based on QL methods should contribute significantly to increasing the energy efficiency performance (Nguyen et al., 2021)(Saleh et al., 2022). Therefore, some limitations must be adopted in the development of protocols based on energy efficiency, and they are characterized by several different required characteristics, such as follows.

- ***First***: The protocol should be able to improve energy efficiency and extend the life of the network while maintaining reliability.
- ***Second:*** The protocol must be able to cover the area of the proposed network, especially that which relies on long-range communications, depending on the UNs distributions.
- ***Third:*** The long lifetime of the IoUT network, so that the protocol works to maintain the stability of the network for the longest possible period.
- ***Fourth:*** Ability to adapt the method of clustering management in dynamic IoUT scenarios.

Most of the recommendations provided by the discussed studies do not consider all the energy efficiency factors and criteria, in addition, a few researchers were considered the use of that specific techniques in IoUT such as bio-inspired and swarm intelligence since their results are accurate and give intelligent solutions (L. Huang et al., 2022). The most important studies based on such algorithms are conducted and reviewed in this chapter, however the justification of their cases forgets to address some of the parameters related to different underwater conditions and operations impacts. The recommendation is to provide more investigations to develop energy efficiency intelligent techniques considering the IoUT conditions, in addition to the factors of QoS to achieve a capability of significant IoUT services.

2.4 Chapter Summary

A comprehensive review of the literature is presented in this chapter focus on the critical issue of energy consumption in IoUT networks. Despite a great deal of study existing approaches do not adequately address all important impact factors in the energy optimized model highlighting the necessity of comprehensive strategy for energy efficiency. This review examines current developments and identifies promising protocols providing a roadmap for filling up research gaps and creating more efficient energy-saving solutions especially with intelligent and adaptable algorithms. The examination of current research highlights important research gaps and suggests future directions emphasizing how crucial it is to incorporate factors relate to the UNs/UVs and underwater environment into an integrated energy management framework for IoUT networks.

CHAPTER THREE

The Methodology of Energy Aware Stable Election Optimization

3.1 Introduction

This chapter discuss the methodology used to optimize the energy efficiency in IoUT. It discusses the stages of developing clustering-based approaches as a solutions to optimize the CH management and inter-cluster communication balance energy consumption and extend network lifetime. Because of to the challenges motivate this study is how to optimize the clustering based protocol to reduces high energy consumption and ensure QoS in large-scale deployments. The proposed methodology provides an optimized energy efficiency solution based on stable election scheme computations with adaptive strategy integrates hybrid optimization techniques to enhance both CH management and inter-cluster communication which is known as hybrid ABC and QL based energy ware SEP (ABCQL-EASE).

The chapter also proposed an intelligent method for UV selection to serve as relay in inter-cluster communication known as energy aware and QoS driven by UVs relaying integrated SEP (EQURI-SE). The use of UVs as mobile relays support efficient data forwarding, reducing transmission distances and energy consumption. The developed approaches discussed in two stage optimization strategy, first, hybrid ABC-QL with MCDM approach used for dynamically manages the CHs in addition to optimize inter-cluster routing decision, and second the hybrid NN-GA with MCDM used for intelligently selects the most suitable UVs as relays by predicting their status, optimizing relay, and ranking the best UVs to serve as relay between CHs. By integrates the adaptive CH management with predictive relay selection, this methodology significantly improves energy efficiency, network stability, and data delivery reliability in dynamic IoUT environments.

The proposed approaches are driven from the depth based SEP computations as a heterogeneous stable election scheme (Elmustafa et al., 2024)(Wang et al., 2023). For the underwater environment, different modifications have been done to add the characteristics of acoustic signals for underwater communications, considering the impact of water temperature, depth in addition to salinity. As shown in Figure 3.1, the IoUT network scenarios include various heterogeneous UNs that are positioned at random throughout IoUT environment. The most important variables, such as residual and average energies, depths, distances, motions, and signal quality, are the basis for the CH selection, dynamic replacement, and inter-cluster routing processes.

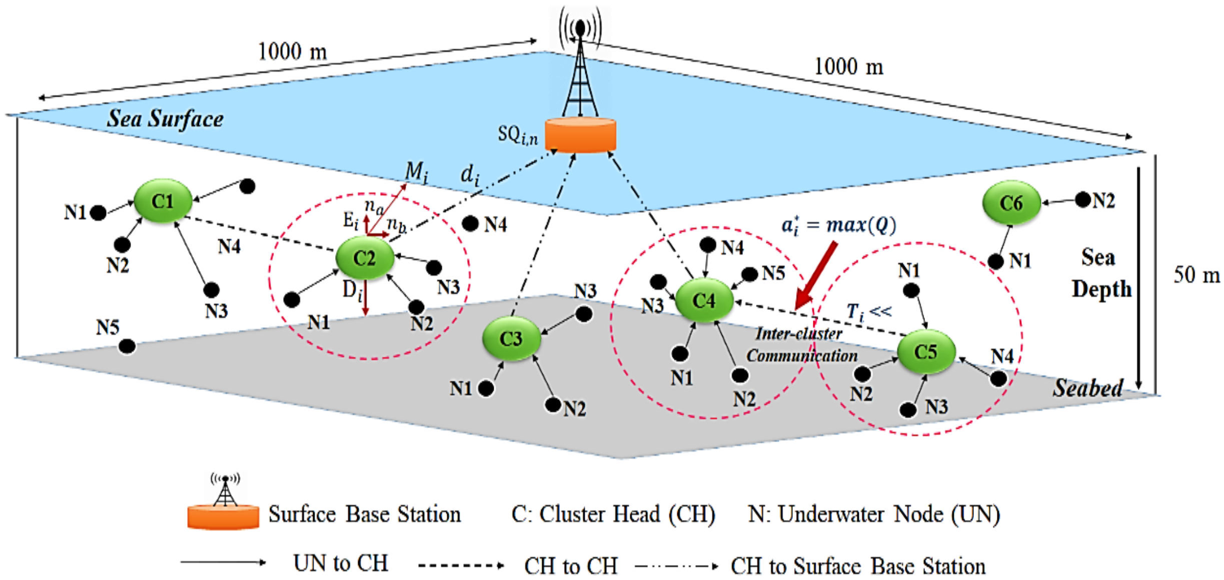


Figure 3.1. Proposed IoUT System Model

The proposed optimization approaches aims to provide stability, energy reduction, enhanced QoS, and network lifetime by optimizing the CHs management and inter-cluster routing approaches using the ABC-optimized QL and MCDM within the given IoUT network model. The methodologies are divided into two main section, the development of energy aware stable routing protocol, and the use of UVs as relay for inter-cluster routing decision by selecting the best UVs candidate to serve s relays.

3.2 Depth based Stable Election Protocol

A modified SEP for IoUT networks is provided by this chapter as a baseline protocol which intends to address the issues with energy efficiency by prolonging network lifetime and encouraging reduced energy consumption (Elmustafa et al., 2024). The IoUT is structured in clustering architecture, consists many CHs those are selected based on many variables which are UN distance to SBS, residual energy, as well as UN depth. The baseline protocol is named as depth based SEP which contribute to increasing the lifetime of the network and reduces energy consumption (Wang et al., 2023). This baseline protocol is further improved in the proposed methodology based on the current modification to SEP highlighted depth impact to enhance the computation compatibility to be suitable for IoUT based on UN positions (depth) enables to achievement of energy efficiency requirements and matching to underwater constraints (E. S. Ali, et al., 2023). Enabling the heterogeneity of UNs energy levels to maximize the energy utilization based on many parameters including the distance to the SBS, average and residual energies, and depths. The depth based SEP significantly improves energy efficiency in IoUT networks by improving the computation of SEP in both CHs selection and replacement process based on the UNs/CHs depths.

3.2.1 IoUT Communication Model

The communication reliability of modified SEP for IoUT is affected by the underwater environment and the influences that may occur on the channel (Domingos et al., 2025)(Ali, E.S et al., 2025). Therefore, channel models for underwater environments are reviewed to calculate the successful delivery rate of each link over the IoUT networks. This review helps to design reliable and effective communication protocols for such networks (Zhang et al.,2025). Communication models help to provide a systematic method for calculating communication reliability and successful delivery ratio in IoUT networks (Pabani et al., 2022). The method depends on studying the relationship between transmission energy and SNR or BER. The SNR (γ) denoted by γ and calculated by the following equation.

$$\gamma = S_{level} - T_{loss} - N_{level} + D_{index} \tag{3.1}$$

Where, S_{level} represents the source level which is known as the effective level of the acoustic signal, T_{loss} is a transmission level. N_{level} and D_{index} represent the noise level and directivity index respectively. All factors are in dB. The S_{level} can be calculated by the following equation (Villa et al., 2022)(Kao et al., 2017).

$$S_{level} = 10\ [\log(P) - \log(4\pi r^2) - \log(0.67\text{x}10^{-18})] \tag{3.2}$$

Where P represents transmitter power, r is the range that represents the radius of an imaginary sphere. And, the value $0.67\text{x}10^{-18}$ represents the hydrophones sound pressure expressed in units of micro-Pascal (1μPa) as an ambiguity in sound intensity.

In an underwater environment, the noise level (N_{level}) can be impacted by different sources like ship's movement, turbulence, and underwater waves. The approximated noise level can be calculated by the following equation (El-Banna et al., 2020)(Nayyar et al., 2019).

$$N_{level} = 50 - 18 \log f \tag{3.3}$$

The directivity index (D_{index}) is equal to zero because underwater hydrophones are often omnidirectional. For transmission loss T_{loss} the measure used to calculate the sound energy loss rate in the underwater environment over distance d in a specific frequency (Gosman et al., 2016). The T_{loss} can be expressed as follows.

$$T_{loss} = 20 \log d + \alpha\ (f) * d * 10^{-3} \tag{3.4}$$

Where $\alpha(f)$ represents the absorption coefficient in dB/km, and it can be calculated by using Thorp's formula as follows (E. S. Ali et al., 2023)(Mavromoustakis et al., 2018).

$$\alpha\ (f) = \frac{0.11\, f^2}{1 + f^2} + \frac{44\, f^2}{4100 + f^2} + 2.75 * 10^{-4} * f^2 + 0.003 \tag{3.5}$$

The relationship between the transmitter power and SNR (γ) can be expressed by substituting Equations (3.2), (3.3), (3.4), and (3.5) in Equation (3.1). In underwater environments, the usual modulation used is BPSK with acoustic communications. If consider the acoustic signals propagating in rayleigh fading channel which is a suitable model for shallow and deep water multipath effect, the bit error rate (BER (γ)) can be estimated over the communication channel when based on the SNR (γ) (Gosman et al., 2016)(Mavromoustakis et al., 2018). This estimation performed according to the given transmitter energy, distance, and frequency, helps to accurate model the IoUT.

3.2.2 Modified Stable Election Model

SEP is a routing protocol created for WSNs to increase network lifetime by distributing energy usage among sensor nodes. It improves the energy-efficient routing for WSN-based IoT. The use of SEP provides many characteristics such as reducing energy consumption by using the clustering-based approach (Yan et al., 2021). Taking the consideration of IoT network heterogeneity, improves the CH replacement, in addition to effectively routes and aggregates the exchanged data through the network. These characteristics are very important for achieving energy efficiency in IoUT. Hoverer, the SEP requires many modifications to be compatible and able to operate in an IoUT environment. These modifications are related to communication and energy model to represent SEP-IoUT protocol.

The SEP-IoUT heterogeneous protocol is based on two energy-level networks made up of basic UNs with initial energy (E_o) and advanced UNs with higher energy by (E_o(1+ α)). The advanced UNs are more likely to become CHs using the probabilistic equation (3.7), and α is chosen based on their initial energy (Yan et al., 2021). The percentage of advanced UNs is m. The probability that normal UNs (p_n) or advanced UNs (p_a) will develop into CHs in SEP provided by the following equations (3.6) and (3.7).

$$p_n = \frac{p}{(1+ \alpha \text{ m})} \tag{3.6}$$

$$p_a = \frac{p(1+ \alpha)}{(1+ \alpha \text{ m})} \tag{3.7}$$

For depth aware SEP, it's critical to identify the likelihood that normal and advanced UNs would develop into CHs depending on selection probability based on two keys variables, the energies residual energy as ($E_i(r)$), average energy as ($\overline{E_i(r)}$) and UN depth (d_i). The updated depth aware SEP probabilities becomes as follows.

$$p_n(IoUT) = \frac{p\ E_i(r)}{(1+ \alpha \text{ m})\overline{E_i(r)}\ d_i} \tag{3.8}$$

$$p_a(IoUT) = \frac{p\ (1+ \alpha)\ E_i(r)}{(1+ \alpha \text{ m})\ \overline{E_i(r)} d_i} \tag{3.9}$$

Where, $E_i(r)$ denotes the residual energy of UNs i in round r. And d_i is the depth impact between the surface base station and UNs. $\overline{E_i(r)}$ denotes the rth average energy of UNs at round r that can be calculated by the following equation.

$$\overline{E_i(r)} = \frac{1}{N}\ E_{total}(n)(1 - \frac{r}{R_{total}\ (l)}) \tag{3.10}$$

Where, $E_{total}(n)$ is initial energies of UNs, N total number of UNs, r is a simulation round and R_{total} (l) represents the total round of the network lifetime and can be estimated based on the total energy consumed in a round by the network (E_{round}) and total residual energy of all UNs in the network (E_{total}) at round r as follows.

$$R_{total}\ (l) = \frac{E_{total}}{E_{round}} \tag{3.11}$$

$$E_{round} = \text{k}\ (2\text{N}E_{elec} + \text{N}E_{DA} + E_{mp}\ {d_o}^4 + \text{N}\ E_{fs}\ {d_o}^2) \tag{3.12}$$

Where K is the packet size, E_{elec} the transmission energy, E_{DA} the data aggregation energy for acoustic communication, E_{mp} the multi-path fading energy, E_{fs} is the transmit amplifier energy for acoustic communication, and d_o the distance between the cluster head and the base station.

In equation (3.12) d_o is power by 2 with E_{fs} to represent the energy consumption associated with data aggregation and transmission, which is dependent on the square of the distance. However, because signal propagation in underwater acoustic communication is complicated and changeable, d_o is powered by 4 with E_{mp} to represent the mimic multi-path fading and transmit amplifier energy which displays a rapid decrease with the fourth power of the distance (Yan et al., 2021). By calculated for the characteristics and complexities of underwater communication networks, these distance factors produce more accurate energy consumption models. The d_o can be calculated by equation (3.13). The depth impact d_i between the surface base station and UNs is calculated based on the UN depth and number of waves (k) by the equation (3.14).

$$d_o = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3.13}$$

$$d_i = \frac{depth}{\sqrt{2\pi k}} \tag{3.14}$$

Based on the influence of the underwater environment on acoustic communication, the initial likelihood of normal and advanced UNs is based on IoUT networks in (Wang et al., 2023)(Yan et al., 2021). The conditions below can be used to determine the nodes' energy E_{node}.

$$E_{node} = \begin{cases} rand_{elec} \geq \ (\mathrm{mn}+1)\mathrm{p}_{\mathrm{acoustic}}; \ \ for\ normal\ nodes \\ rand_{elec} < \ (\mathrm{mn}+1)\mathrm{p}_{\mathrm{adv}_{\mathrm{acoustic}}}; \ for\ advanced\ nodes \end{cases} \tag{3.15}$$

Where, $\mathrm{p}_{\mathrm{acoustic}}$, represents the optimal election probability for normal UNs in acoustic communication. And $\mathrm{p}_{\mathrm{adv}_{\mathrm{acoustic}}}$ is the optimal election probability for advanced nodes in acoustic communication.

Each UN in the SEP-IoUT algorithm produces a random number between 0 and 1. This UN will act as the CH if this number is lower than a predetermined threshold that takes into account its initial energy and the number of rounds which it is not chosen as a CH (Wang et al., 2023)(Bhola et al., 2022). The following equations determine the threshold for each type of node as either a normal (T_n) or advanced (T_a). These thresholds depend on the updated selection probability given in Equation (3.16) and Equation (3.17).

$$T_n = \begin{cases} \frac{Pn}{1-Pn\left(r \bmod \frac{1}{pn}\right)} & ; \ if \ thre \ \in G' \\ 0 & otherwise \end{cases} \tag{3.16}$$

$$T_a = \begin{cases} \frac{Pa}{1-Pa\left(r \bmod \frac{1}{pa}\right)} & if \ thre \ \in G'' \\ 0 & otherwise \end{cases} \tag{3.17}$$

Where G' and G" are the sets of normal and advanced UNs that have not been elected as CHs in the last $\frac{1}{pn}$ and $\frac{1}{pa}$ epoch, respectively. Equations (3.16) and (3.17) are used in SEP-IoUT, to make a dynamic and adaptive threshold mechanism that considers the history of CH elections and the current context. This will optimize the CHs selection process to promote fairness and energy efficiency within the network.

After identifying the CHs, each UN joins the cluster of its nearest CH, and communication within each cluster is planned using the TDMA protocol in which each CH establishes a transmission schedule between its member nodes to avoid cohesion and conserve UN energy while waiting or idle (Bhola et al., 2022). The cluster heads use the CSMA protocol to interact with the base station to verify channel availability and ensure data transmission.

To represent SEP-IoUT energy model, Let E_{tx} and E_{rx} represent the energy spent by a UNs transmitter and reception circuits, respectively. To send a k-bit packet to a recipient M kilometers away, there are two channel models (Yi et al., 2023). Equation (3.18), provides the propagation and multipath fading channel models. In case the distance between a source UN and a SBS (M) is smaller than a predetermined threshold (d_o) the propagation channel model is employed, while in case the distance is larger than the predetermined threshold, the signal is amplified using the multipath fading channel model to prevent signal degradation. The consumed energy by a CH to receive a k-bit packet can be calculated by equation (3.19).

$$E_{tx} = \begin{cases} \text{k}\left(E_{elec} + E_{fs}\text{M}^2\right); & \text{M} < d_o \quad \text{(propagation channel)} \\ \text{k}\left(E_{elec} + E_{mp}\text{M}^4\right); & \text{M} > d_o \quad \text{(Multipath fading channel)} \end{cases} \tag{3.18}$$

$$E_{rx} = \text{k}\ (E_{elec} + E_{DA}) \tag{3.19}$$

The communication model for SEP-IoUT calculates for shallow or deep water using Thorp's equation. As a result, the following updates are made to both the multipath fading channel model and the underwater propagation channel model (Yi et al., 2023)(Climent et al., 2014). The equation (3.18) is updated as follows.

$$E_{tx} = \begin{cases} \text{k}\left(\left(\frac{E_{elec}}{U_i}\right) + \left(\left(\frac{E_{fs}}{U_i}\right)\text{M}^2 S_i\right)\right);\ \text{M} < d_o & \text{(propagation channel)} \\ \text{k}\left(\left(\frac{E_{elec}}{U_i}\right) + \left(\left(\frac{E_{mp}}{U_i}\right)\text{M}^4 S_i\right)\right);\ \text{M} > d_o & \text{(Multipath fading channel)} \end{cases} \tag{3.20}$$

Where, U_i stands for the subsurface impact as a normalized communication possibility factor, which estimated by Thorp's equation. For UNs with high motion, S_i represents the underwater dynamic motion impact factor as an energy multiplier. The U_i is computed as a heuristic channel quality index by the following equation.

$$U_i = \text{k B}\ log_2(1 + \frac{SNR_l}{KT}) \tag{3.21}$$

Where k is a packet size, B is the bandwidth of the communication channel (in Hz). SNR_l is a linear signal strength normalized by KT which presents thermal noise floor parameter.

The modifications on underwater free space and multipath fading channels for SEP-IoUT equations are created based on U_i which allows us to take into account the influence of the available communication bandwidth and signal quality as elements that affect energy consumption and consequently the stability of UNs elections in the protocol (Kao et al., 2017)(Draz et al.2021). The channel conditions, signal faults, and retransmissions caused by interference or a limited bandwidth can all be taken into account by considering U_i as a heuristic communication efficiency factor.

In IoUT, the UNs are also regulated by their depths, adding to the impact of depth during communication (Kao et al., 2017)(Al-Bzoor et al., 2022). According to the given equation (3.18) both the multipath fading channel model and the underwater propagation channel model are updated. The equation (3.20) is updated to model the depth factors as follows.

$$E_{tx}=\begin{cases} k\left(\left(\frac{E_{elec}}{U_i}\right)+\left(\left(\frac{E_{fs}}{U_i}\right)M^2S_i\right)\right); & \text{UN depth} < T_d \;;\; M < d_o \\ k\left(\left(\frac{E_{elec}}{U_i}\right)+\left(\left(\frac{E_{fs}}{U_i}\right)M^2S_iD_i\right)\right); & \text{UN depth} > T_d \;;\; M < d_o \\ k\left(\left(\frac{E_{elec}}{U_i}\right)+\left(\left(\frac{E_{mp}}{U_i}\right)M^4S_i\right)\right); & \text{UN depth} < T_d \;;\; M > d_o \\ k\left(\left(\frac{E_{elec}}{U_i}\right)+\left(\left(\frac{E_{mp}}{U_i}\right)M^4S_iD_i\right)\right); & \text{UN depth} > T_d \;;\; M > d_o \end{cases} \tag{3.22}$$

Where D_i is an energy multiplier for UNs below the depth threshold. S_i is the energy multiplier for UNs with high motion. Accordingly, the consumed energy by a CH to receive a k-bit packet that is given by equation (3.19), will be updated as follows for SEP-IoUT as follows.

$$E_{rx}=\begin{cases} \frac{k(E_{elec}+E_{DA})}{U_i}M^2S_i \;; & \text{UN depth} < T_d;\; M < d_o \\ \frac{k(E_{elec}+E_{DA})}{U_i}M^2S_iD_i \;; & \text{UN depth} > T_d;\; M < d_o \\ \frac{k(E_{elec}+E_{DA})}{U_i}M^4S_i \;; & \text{UN depth} < T_d \;;\; M > d_o \\ \frac{k(E_{elec}+E_{DA})}{U_i}M^4S_iD_i \;; & \text{UN depth} > T_d;\; M > d_o \end{cases} \tag{3.23}$$

Where M represents a constant distance value of UNs. d_o is a distance threshold value. (T_d) is the predefined depth threshold that represents the increased energy consumption per meter.

Under a variety of underwater environment conditions including residual energy values, depth, and CH selection threshold, the above set of equations shows the modelling of energy consumption in underwater communication UNs. These equations take into account the depth and dynamic motion-dependent acoustic channel influence of (S_i) and (D_i) as important factors in energy consumption in dynamic underwater environments.

3.3 Energy-Aware Stable Election Optimization

The proposed approach was developed during three main optimization stages based on depth based stable election protocol. CH management optimization, Inter-cluster routing decision optimization and energy aware QoS driven stable election optimization. Figure 3.2 shows the flowchart of proposed approach highlights the integrations of the three optimization algorithms. The following subsection discuss the modeling for each optimization stages, highlights the proposed solutions related to every problem formulation.

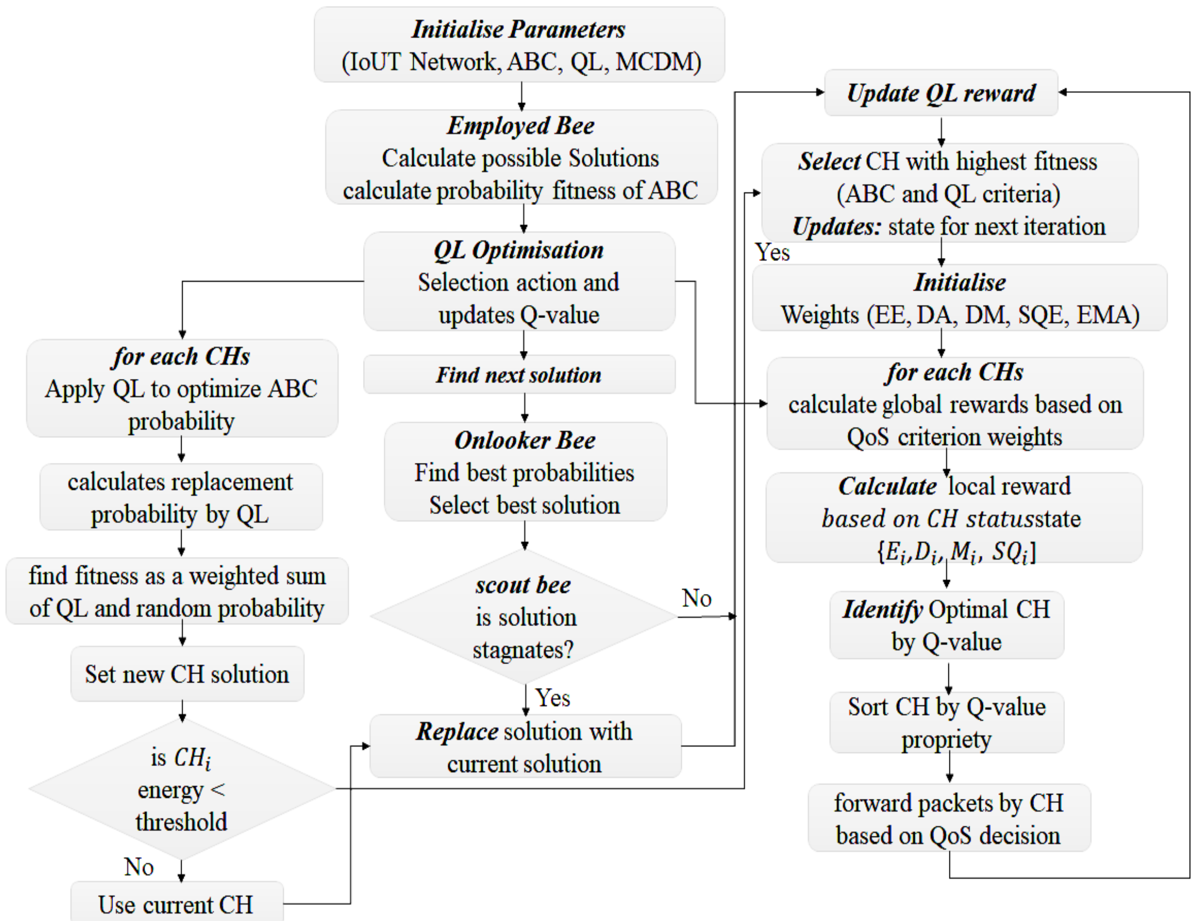


Figure 3.2. The Proposed Energy-Aware Stable Election Optimization Flowchart

3.3.1 CH Management by Using Hybrid ABC and QL

CH management criteria are based on five processes, network structure creation, UN type selection, energy dissipation setting, cluster management, ABC fitness evaluation, and CH selection probability calculations. The number of selected CHs determines the clusters that are created. The CHs were first chosen using the ABC approach for each UN's fitness estimate (Rahman el at., 2025)(Kaveripakam and Chinthaginjala, 2023). The likelihood of choosing an advanced or normal UN to become a CH is determined by ABC fitness values based on the ABC fitness function process as shown in Figure 3.3. Every UN that is closest to CH will be linked to join the cluster that the typical CH serves. The relationship between UNs and CH is based on energy-efficient standards as a function of CH's minimum distance. ABC algorithm is used to assess the fitness values and calculate the probability that a UN will become a CH (E. S. Ali et al., 2023)(Kaveripakam and Chinthaginjala, 2023).

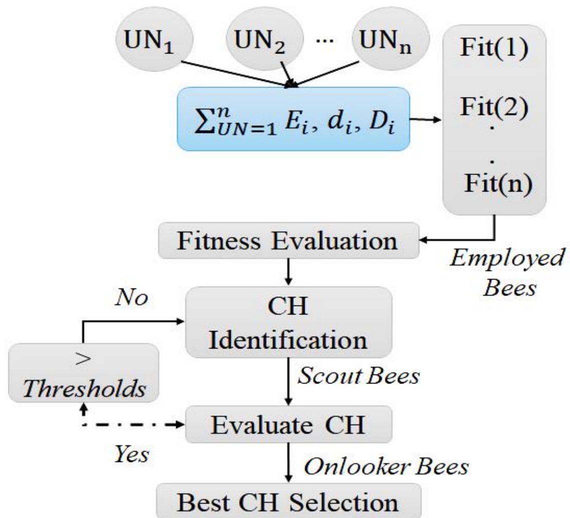


Figure 3.3. CH selection-based ABC Fitness Optimization

Another enhancement is to use an energy balancing scheme to improve the selection of CHs and balance the energy among CHs during the selection and replacement process using both ABC and a lightweight QL approach. According to ABC fitness and the state of the underwater environment as highlighted in Figure 3.3, UNs can modify their CH eligibility through ABC optimization (Tadele et al., 2024). Each UN state is used to determine the fitness. To help UNs make the best choices possible about the CH election QL is utilized. It maintains a balance between the exploration and exploitation of ABC and SEP fitness probabilities to balance energy and optimize long-term benefits associated with network longevity and energy efficiency. Factors like underwater depth affecting the consumption of energy, and UN motion affecting communication efficiency are included in the energy modelling for both approaches (Ahmad et al., 2019). CHs are dynamically replaced and adjusted throughout network operations in response to the UNs status based on their energy, depths, and distances from SBS. CHs optimize energy consumption while managing data collection and transfer to the SBS.

A proposed CH replacement approach known as ABC-based QL stable election (ABCQL-SE) is used as a method to replaces CHs based on the underwater environment conditions that affect UNs like residual energy, depths, distances, signal quality, and motions (Ye and Weili, 2024). The technique replaced the CHs precisely and adaptively using a lightweight QL optimization with ABC. Multi-hop communication between the CHs and the SBS is used while the IoUT network is operating (Ye and Weili, 2024)(E. S. Ali et al., 2024).

The CHs will be replaced by QL adaptations rather than every round. It depends on whether the UN's reward values are realized and whether the probability of selecting new CHs throughout the replacement process is met as shown in Figure 3.4. By using this method, the network will not have to replace the CHs every round, which will save energy (E. S. Ali et al., 2024). The CHs are continuous for several successive rounds, which will reduce the discarded energy in the process of creating new clusters.

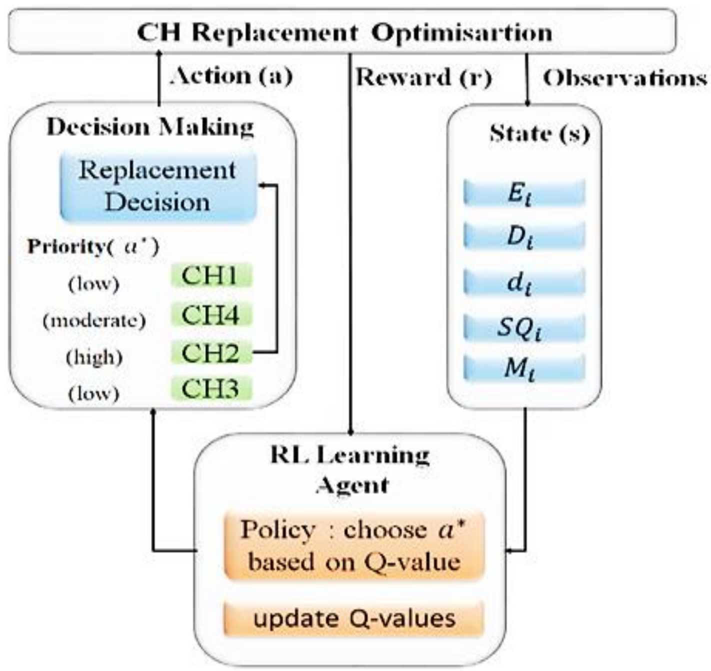


Figure 3.4. CH Replacement-based QL Optimization

To replace the CHs, the SBS updates the records of Q-value to the CHs' fitness on a regular schedule. The neighboring UNs receive the advertising message and TDMA scheduling from the new CH. They then send joint messages and turn on their acoustic models to receive the new TDMA scheduling (Anjan et al., 2025)(Ye and Weili, 2024). The CH uses low-frequency acoustic signals and dynamically modifies the intervals of the advertising message according to the network's condition. Given that the IoUT network is segmented into clusters and that each UN within a cluster has its own TDMA schedule (Ye and Weili, 2024)(E. S. Ali et al., 2024). During inter-cluster communication, CHs are run on a different TDMA schedule to connect with the SBS.

Based on their distance from the CH, UNs estimate the time for joint ACK, and joint messages are sent accordingly. By doing this, fewer unnecessary retransmissions are made, which can waste bandwidth and energy.

Prior high-energy CHs can continue to function till their Q-values decrease due to the CHs' replacement based on a QL. At the end of each round, CHs compute their residual energies, signal quality, depths, motions and distances. The current CH will either advance to the following round or be replaced based on the Q-values and ABC fitness of selection probability (Anjan et al., 2025)(Ye and Weili, 2024). Because of the significant energy reduction from this process, it is expected that the stability period may increase. According to Figure 3.4, Only CHs with lower fitness and energy levels are replaced based on the adaptive replacement mechanism which is driven by Q-values and ABC fitness. This will reduces energy dissipation during the development of new clusters and avoids excessive replacements (E. S. Ali et al., 2024). The following phases act as a basis for the CH management procedures that combine QL and ABC optimization for energy balancing and energy efficiency clustered-based routing protocols.

- Describe ABC's initial settings, QL, and the set of potential CHs.
- For CH selection, define a fitness function that takes into account energy levels and other significant criteria.
- To maximize the potential CH selection, apply the ABC algorithm (ABC-SE protocol).
- To balance the energy distribution among CHs during the selection process, use QL, which trades off the ABC probability and the random fitness probability (ABC-EB protocol).
- Optimize the ABC search capabilities using QL to adaptively update the CH replacement and selection procedures based on energy usage and network feedback (ABCQL-SE protocol).

A. CH Selection Process

This approach known as ABC-SE to select the best CH for routing the data between UNs and SBS. To set up the UNs and parameters, A group of UNs is initialized as a set of all UNs in the network is represented as UN_i,, where i=1, 2…, N. The coordinates of a UN in three dimensions are indicated by UN_i= (x_i,y_i,z_i). Each UN's initial energy level is denoted by E_i. R_i is the range of communication for each UN's. p_i is the initial CH election probability as the likelihood that a

UN will be elected as a CH (E. S. Ali et al., 2024). $thre_{CH}$ is the threshold probability of CH election. The symbol for the likelihood of choosing UN types as advanced or normal is $p_{n,type}$. The initial energy level E_i, of UNs can differ depending on deployment or initial conditions. The two energy levels of the UNs, normal and advanced, are dispersed at random. The following equation is how binary 0 and 1 represent the UN levels.

$$UN_{type}=\begin{cases} 1\ ; & UN_i\ for\ advanced\ UN \\ 0\ ; & UN_i\ for\ normal\ UN \end{cases} \tag{3.24}$$

The binaries 0 and 1 indicate the type UN_i. Equation (3.24) determines UN_i selection chance for being assigned to either the normal or advanced state (S. Kaveripakam, and R. Chinthaginjala, 2023)(E. S. Ali et al., 2024).

$$\mathrm{p_{n,type}} = \begin{cases} 1\ ; & \text{with probability } (\mathrm{p_{adv}}) \\ 0\ ; & \text{with probability } (1 - \mathrm{p_{adv}}) \end{cases} \tag{3.25}$$

Where, $\mathrm{p_{adv}}$, represents the initial probability that node UN_i, is a normal UN. The initial probability that UN_i is a typical UN is denoted by$\mathrm{p_{adv}}$.

Once the UNs are initialized, they are dispersed at random among two energy levels, creating a heterogeneous network. A subset of $\mathrm{UN_i}$ are chosen to be CHs, and the clusters are formed according to the original election probability ($\mathrm{p_{CH,type}}$). Based on the following probability by equation (3.26), the CHs elected might be either regular or advanced UN_i candidates (Bing et al., 2023)(Zhang et al., 2022).

$$P_{i,CH} = f\left(p_{CH,type}, \psi\right) \tag{3.26}$$

The symbol ψ represented as $\psi = \{D_i, E_i, d_i, SQ_i\}$, affects the CH election process. These factors include depth, energy levels, distance, and signal quality which are represented by, D_i, E_i, d_i, SQ_i respectively (Anjan et al., 2025)(E. S. Ali et al., 2024). According to the following equation (3.27), the CH election probability $\mathbf{p_{i,CH}}$ is compared to the CH threshold $thre_{CH}$ to determine whether it becomes a CH.

$$CH_{i,s}=\begin{cases} 1\ ; & UN_{type} = 1 \text{ and } p_{i,CH} > thre_{CH} \\ 0; & otherwise \end{cases} \tag{3.27}$$

When UN_i is elected as a CH based on its status, it is indicated by a binary indicator (0 or 1) in $CH_{i,s}$ set. Additionally, the UN_i normalized probability $\mathrm{p_{i,CH}}$, indicates whether it is a candidate for CH election. UN_i need to have a minimum $\mathrm{p}_{i,\mathrm{CH}}$ of fitness $\mathrm{thre}_{\mathrm{CH}}$ to become a CH. If $CH_{i,s}$ equal 1 and the distance d_i falls within the cluster communication range (R_i) then UN_i makes the transmission decision to send data to t

- **Lemma 1: Optimal CH Selection**

In a heterogeneous IoUT network where UNs are initialized with varying energy levels (E_i) and other attributes such as depth (D_i), distance$(d_{i,BS})$ and signal quality (SQ_i) the probability $(P_{I,CH})$ of UN_ibeing elected as a CH is directly proportional to its residual energy and inversely proportional to its distance from the SBS with motion (M_i). This lemma provides the optimal CH selection to ensure minimal total energy consumption (EC_T) while maximizing the fitness value $f(PS_i)$ across all candidate UNs.

- ***Proposed Solution 1***

The CH election probability is influenced by Lemma 1 factors ensuring that UNs with favorable attributes have a higher likelihood of becoming CHs. Minimizing (EC_T) requires reducing both transmission and reception costs. This achieved by selecting CHs that are closer to the SBS and their member UNs thereby minimizing distances $(d_{i,BS})$ and associated energy costs.

The ABC algorithm is used to improve the CH election process by identifying the optimal CHs that can be chosen from a group of candidates with varying random selection probabilities (Liu et al., 2022)(P.J. Sathish et al., 2023). The best-related solution that will select the optimal CH with higher residual energy, near distance and depth from SBS, high signal quality, and low UN motion will be found by calculating the fitness of the ABC algorithm for each initialized election probability (P.J. Sathish et al., 2023). By equation (3.28), ABC initializes the population of solutions (PS) with its residual energy, depth and distance.

$$PS_i = \begin{bmatrix} p_{i,CH_{11}} & p_{i,CH_{12}} & \cdots & p_{i,CH_{1M}} \\ p_{i,CH}S_{21} & p_{i,CH_{22}} & \cdots & p_{i,CH_{2M}} \\ . & . & . & . \\ p_{i,CH_{N1}} & p_{i,CH_{N2}} & \cdots & p_{i,CH_{NM}} \end{bmatrix} \tag{3.28}$$

Where PS_i represents N solutions in M dimensions as a N×M matrix. Following the initiation of potential solutions, the employed bee stage uses the existing solution PS_i to create a new solution, $\mathrm{V_i}$ calculated as follows.

$$V_i = PS_i + \phi_{i,j}(PS_i - PS_k) \tag{3.29}$$

Where j is a random dimension, k is a random index distinct from i, and $\phi_{i,j}$ is a random number in the interval $[-1,1]$. In this case, V_i is the new solution that is produced by calculating the current solution PS_i by equation (3.30) with a different randomly chosen solution (PS_k). The greedy selection technique is used to assess the fitness (f) to choose the optimal solution. The fitness function is denoted by $f(V_i)$ (E. S. Ali et al., 2024). Following this phase, the onlooker bee finds the likelihood probability $p_{i,ABC}$ of choosing a solution (PS_i) in equation (3.31). And finally, the best probability $p_{i,best}$ is given as follows.

$$PS_i = \begin{cases} V_i\,; & \mathrm{f}(V_i) > \mathrm{f}(PS_i) \\ PS_i; & \text{otherwise} \end{cases} \tag{3.30}$$

$$p_{i,ABC} = \begin{bmatrix} p_{i,ABC_1} \\ p_{i,ABC_2} \\ . \\ p_{i,ABC_N} \end{bmatrix} \tag{3.31}$$

$$p_{i,best} = \frac{\mathrm{f}(p_{i,ABC})}{\sum_{j=1}^{N} f(PS_i)} \tag{3.32}$$

The fitness function $\mathrm{f}(PS_i)$ to calculate the fitness value for each corresponding CH candidate is calculated by the following equation.

$$f(PS_i) = w_1 \frac{E_i}{E_{max}} + w_2\left(1 - \frac{d_{i,BS}}{d_{max}}\right) + w_3\left(1 - \frac{D_i}{D_{max}}\right) + w_4 SQ_i + w_5\left(1 - \frac{M_i}{M_{max}}\right) \tag{3.33}$$

The distance between UN_i and the SBS is denoted by $d_{i,BS}$, where E_i is the energy level of UN_i. For UN_i motions, M_i is indicated. Energy levels, distances, depths, and motions maximum values are denoted by the symbols $E_{max}, d_{max}, D_{max},$ and M_{max}. And, w_1 to w_5 are weighting factors between 0 and 1. By using the same procedure as in the employed bee phase, ABC creates a new solution V_i after determining the optimal probability, which is then assessed by the onlooker bee stage (Sathish et al., 2025)(E. S. Ali, et al., 2023). The scout bee stage determines whether a solution (PS_i) can be improved over a set number of cycles, at which point it is abandoned and a new solution is chosen randomly.

The steps previously mentioned are repeated by the algorithm until a maximum number of cycles is reached. Following the ABC generation of the potential best solutions, a lightweight QL algorithm begins with a stage that uses employed bees to drive the neighborhood exploration of related solutions, updating the search space with the best solutions (E. S. Ali et al., 2023). The best individuals from the search space are then chosen by the onlooker bee stage to take use of their neighborhood for more optimization.

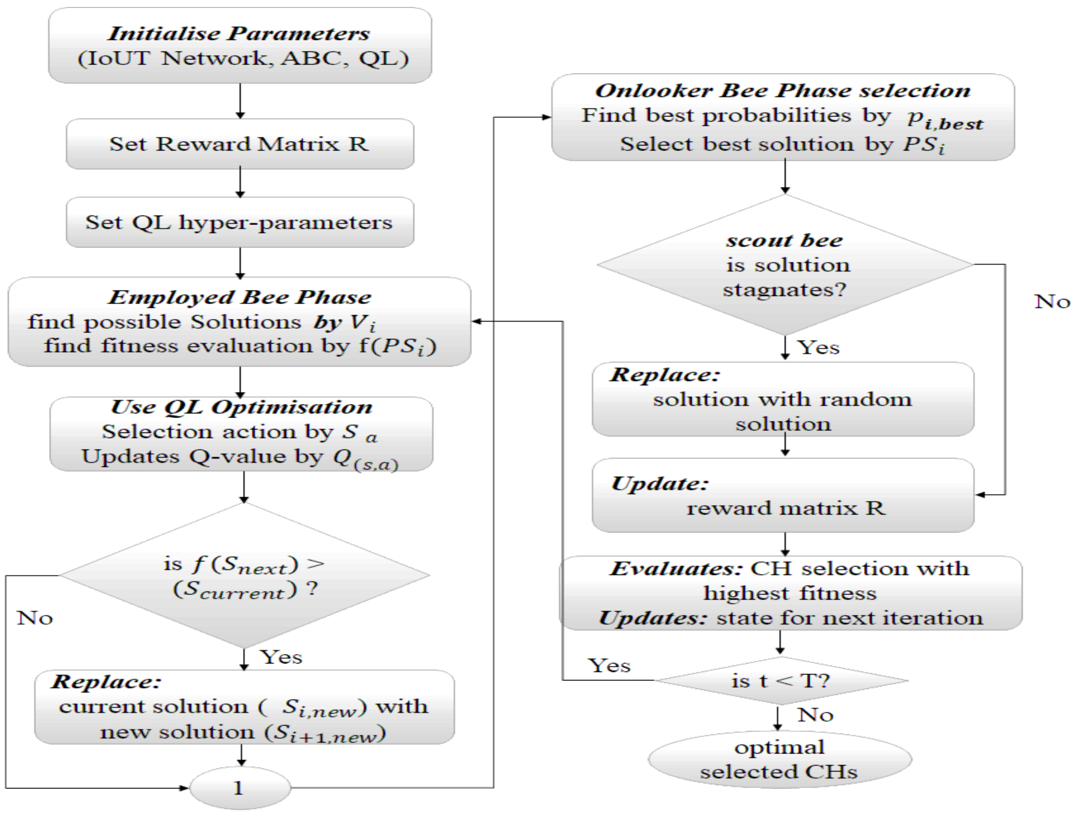


Figure 3.5. CH Selection Optimization Flowchart

The integration of QL and ABC for CH selection optimization is shown in Figure 3.5. In the proposed approach, the contributions are concentrated on the usage of a multi-objective fitness function that incorporates important underwater characteristics for the best CH, and applying a lightweight QL to increase ABC fitness (E. S. Ali et al., 2023). The major contribution of proposed solution 1 is the use of dynamic reward updates that adjust to real-time underwater network changes. To ensure dynamic adaptive CH selection, this method allows hybrid ABC-QL to discover the best solution. The purpose of utilizing QL together with ABC is to guide the ABC search in both employed and onlooker bee stages. By using the Q-function to estimate the expected cumulative rewards for executing a certain action in a particular state, the use of QL enables agents to learn about the ideal policy based on various UN_i status in an underwater environment (E. S. Ali et al., 2023)(Zhang et al., 2025). The agents then attempt to determine the optimal policy.

To update the Q_{value}, the QL agents investigate the underwater environment, which is represented by the impact state s_t of UN_i. They then take action (a) and monitor the outcomes of rewards and the subsequent state. The following equation is used to represent the Q_{value}.

$$Q_{value} = \begin{bmatrix} Q_{(s1,a1)} & Q_{(s1,a2)} & \cdots. & Q_{(s1,aM)} \\ Q_{(s2,a1)} & Q_{(s2,a2)} & \cdots. & Q_{(s2,aM)} \\ . & . & . & . \\ Q_{(sN,a1)} & Q_{(sN,a2)} & \cdots. & Q_{(sN,aM)} \end{bmatrix} \tag{3.34}$$

In this case, Q is N×M matrix that represents Q-values for M actions and N states. The Q_{value} are used to investigate future Q-values and show the estimated quality of activities in various UN_i impact statuses. In the UN_i impact parameters as D_i, E_i, d_i, and SQ_i, the impact (s_t) at the time (t) is represented (Zhang et al., 2025). Using the equation (2.5) as in chapter 2, the Q-values as $Q_{(s,a)}$ are initialized for every state (s_t) and action (a).

The rewards obtained for acting in specific states are represented by the reward matrix R. Additionally, equation (3.35) express the reward matrix with N states and M actions. Equation (3.36) shows the ϵ-greedy approach that forms the basis of the action selection policy (Ye et al, 2024).

$$R = \begin{bmatrix} \sum_{t=0}^{T} F_{a1}(t)\ exp(-\lambda_{a1} t) \\ \sum_{t=0}^{T} F_{a2}(t)\ exp(-\lambda_{a2} t) \\ \cdots \\ \sum_{t=0}^{T} F_{aM}(t)\ exp(-\lambda_{aM} t) \end{bmatrix} \tag{3.35}$$

Where, $F_a(t)$ represents the combined effect of energy, depth, signal quality, and motion for action a_i at time t. λ_a is a decay factor for a_1 to a_M , and T is the time period over which rewards are aggregated. According to equation (3.35), the reward matrix R provides the reward for each action (a_M) over time, and it is used in the Q-value update step as a temporal reward function that calculates the reward over time for taking a specific action.

$$S_{\ a} = \begin{cases} random\ action\ \{a_1, a_2\ , .., a_n\};\ p = \epsilon \\ arg\ max_{\ a}\ \ Q(s, a); \qquad\qquad p = 1 - \epsilon \end{cases} \tag{3.36}$$

Where, ϵ is the exploration probability, and p is the selection probability. Based on the process described, the e-greedy strategy is used to construct the action selection mechanism. The agent can either randomly select one action with an e-greedy probability or choose the best action based on the associated Q-value (exploitation) by ABC (Zhang et al., 2022). Exploration as well as exploitation is thus made possible by the e-greedy strategy. Actions from a_1 to a_n represent the non-optimized exploratory strategies performed by UNs related to their statuses.

According to the concept, QL agent in the employed bee phase of ABC guide the neighborhood search toward high-quality clustering configurations. At each iteration, the agent observes the current network topology state (s) and selects a structural modification action (a) using ϵ-greedy policy. This action generates a candidate solution (s′), which is evaluated using the multi-criteria fitness function (Zhang et al., 2022). . The agent then receives a reward signal (r), computed as the fitness improvement reinforcing actions that reduce energy consumption and improve depth and signal quality. The corresponding state-action value is stored and updated in a Q-table enabling the agent to recall past optimization experiences (Zhang et al., 2022)(Yao and Chen, 2024). Over successive cycles, the QL agent progressively biases the employed bees toward rewarding neighborhood structures, accelerating convergence toward energy-efficient CH layouts while preserving exploratory diversity to create a new solution ($S_{i,new}$).

B. CH Replacement Process

The proposed approach as ABC-EB considered into account the same factors as used in the process of CH selection to be involved in updating the probability of replacement criteria to characterize the CH replacement process using QL and ABC optimization. The QL update calculation, which modifies the Q-values for various activities according to rewards and state transitions, serves as the foundation for the replacement procedure (E. S. Ali et al., 2024). With this method, the proposed approach gradually learns the best CH replacement policies (Zhang et al., 2025). A fitness function is used by the ABC optimization process to assess the quality of solutions. The fitness function considers factors ψ= $\{D_i, E_i, d_i, SQ_i\}$. The CHs replacement condition is calculated by the following.

$$CH_i = \begin{cases} 1;\ if\ P = \dfrac{p_R}{1-p_R\ mod(r, round\ (\frac{1}{p_R})} \\ 0\ ; \qquad\qquad\qquad otherwise \end{cases} \tag{3.37}$$

Where P is the calculated number from probability fitness ranged between 0 and 1. The probability of replacement p_R equal to f ($argmax_x$ $fit_i(x)$) is based on the best solution found by the ABC algorithm that maximizes the fitness function in (E. S. Ali et al., 2024)(Zhang et al., 2025) where, $fit_i(x)$) represent the fitness function evaluated by ABC algorithm for each CHs probability. f (x) is the function that maps the best solution x^* to the optimal probability (p_R). The optimized value of p_R based on the best solution x^* is given by f (x^*). The x^* is equal to $argmax_x$ $fit_i(x)$.

- **Lemma 2: Optimal CH Replacement Policy**

In the CH replacement process optimal replacement policy is achieved by dynamically balancing the fitness value f_i of potential CH candidates and the optimized replacement probability (p_{new}) as determined by the integration of ABC and lightweight QL optimization. The replacement condition ensures that only UNs with high residual energy(E_i), suitable network features (D_i, d_i, SQ_i, M_i) and sufficient fitness scores are selected as new CHs thereby maintaining energy efficiency and prolonging the network lifetime.

The fitness value (f_i) helps to measure of how suitable a UN is for becoming a CH. UNs with higher (f_i) values are more likely to replace existing CHs. ABC algorithm iteratively searches for the optimal replacement probability ensuring that the replacement decision is guided by both energy efficiency and network performance QL algorithm updates the Q-values based on rewards and state transitions, enabling the system to learn optimal CH replacement policies over time (Yao and Chen, 2024).

- ***Proposed solution 2***

The replacement procedure is dependent on QL optimization which CHs will be replaced and by whom is decided by the activity. Equation (3.38) serves as the foundation for the action selection policy for new CHs. Based on ABC's computed fitness value and the updated probability (p_R), the other UNs are re-elected as CHs (E. S. Ali et al., 2024)(Alqahtani and Bouabdallah, 2023). The fitness value f_i for a potential CH replacement is calculated as a weighted sum of the probability $p_{CH,i}$ of selecting a UNs as a CH based on QL, and random factor (rnd_i) as an exploration term to introduce diversity in the selection. Accordingly, the fitness value (f_i) is calculated by the following.

$$f_i \ = w_{ABC}\, p_{CH,i} + \ (1 - w_{ABC})\, rnd_i \tag{3.38}$$

Where, $w_{ABC} \epsilon$ [0,1] represents a weight parameter balancing the influence of the QL output for the ($p_{CH,i}$) and the random factor (rnd_i).

The process of optimizing the CH replacement as proposed solution 2 is shown in Figure 3.6, showing that after calculating the fitness value (f_i), the ABC algorithm optimizes the probability (p_{new}) of replacing the current CH. The updated ($\mathrm{p_{new}}$) is obtained by applying the ABC optimization algorithm to the current probability ($p_{CH,i}$) and the fitness value (f_i) (Alqahtani and Bouabdallah, 2023). The ABC optimization algorithm searches for the optimal value of $\mathrm{p_{CH,i}}$ that maximizes the objective function $f(p_{CH,i}, f_i)$, which depends on the fitness value (f_i).

$$p_R = argmax_p\, f(p_{CH,i}, f_i) \tag{3.39}$$

To dynamically manage and replace CHs in the network and distribute energies among CHs to meet the energy balancing concept, the selection of alternative UNs to replace the existing CH is based on the integration of QL through fitness value calculation and ABC optimization through $\mathrm{p_R}$ according to equation (3.39). A combination of a random threshold and each UN's fitness value can be used to build the final representation for CH replacement (Yao and Chen, (2024). (Alqahtani and Bouabdallah, 2023). The new CH selection set S_{new} can be expressed as follows.

$$S_{new} = \begin{bmatrix} S_i \\ S_{i+1} \\ . \\ S_{n,} \end{bmatrix} \tag{3.40}$$

Where, $S_{i,new}$, represents the CH replacement decision for the i^{th} UN in the network. Each UN_i the decision to become a new CH depends on a random probability (p) to the optimized replacement probability $\mathrm{p_{new}}$, and the fitness value calculated from lightweight QL and ABC optimization. The decision $S_{i,new}$ for each UN_i can be formulated as follows.

$$S_{i,new} = \begin{cases} 1, & P \leq \ p_{new} \ and \ f_i \gg \\ 0 & Otherwise \end{cases} \tag{3.41}$$

According to equation (3.41), the UN replaces the current CH by setting $S_{i,new}$ equate to 1, if a randomly generated number is less than or equal to the optimized probability p_{new} as a threshold and the fitness value f_i is sufficiently high. Where decision set $S_{i,new}$ equal 0 to represent the UN remains a non-CH (Hussain et al., 2025)(X. Wei et al., 2022).

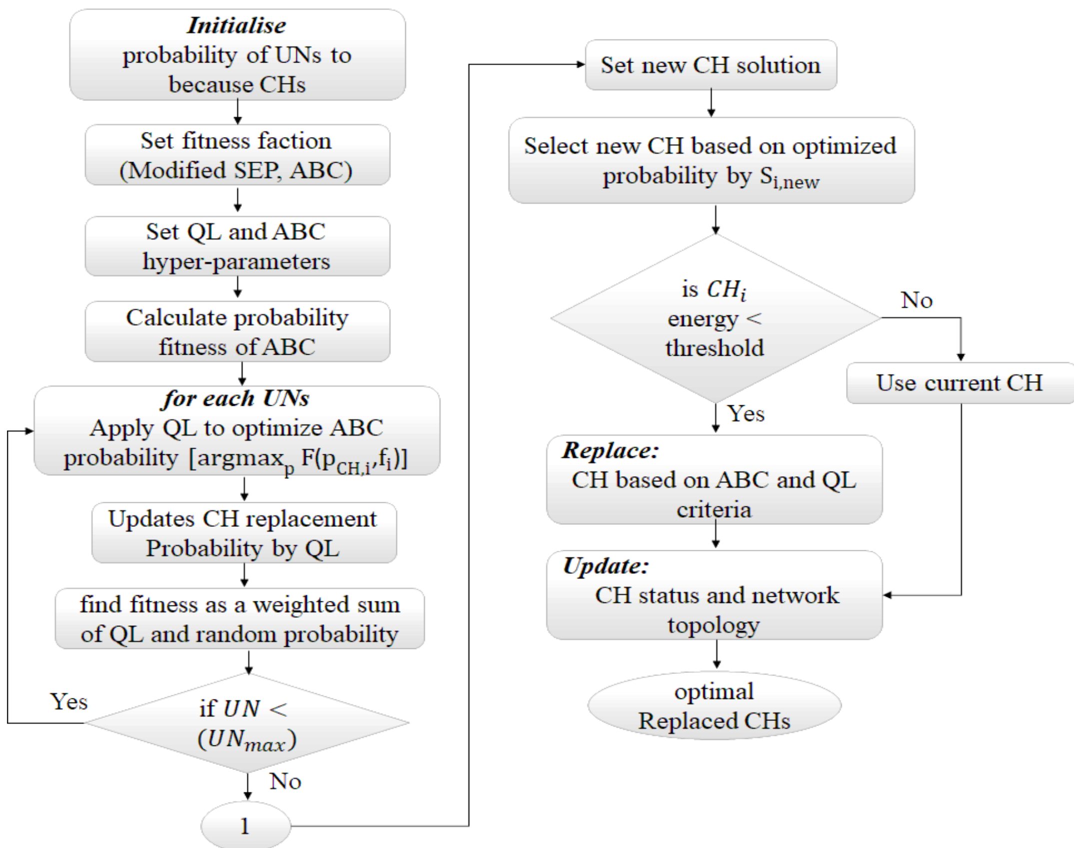


Figure 3.6. CH Replacement Optimization Flowchart

In proposed solution 2 ABC approach maximizes the CH replacement probability, while QL with ABC uses a hybrid fitness function to optimize the ABC probability. This helps to optimize the replacement decision-based energy balancing approach among CHs (Ye and Weili, 2024). Therefore, rather than changing the CHs in each round, the CHs are changed based on their current status using the ABC fitness probability that QL optimizes (Alqahtani and Bouabdallah, 2023). By extending the network lifetime threshold-based CHs replacement mechanism, the scheme makes it possible. This approach distributes energy around the network among CHs in an efficient manner (X. Wei et al., 2022). It controls the CHs to be replaced probabilistically based on ABC fitness probability optimization rather than randomly at each round, which will use less energy in the process of selecting the CHs and forming clusters.

3.3.2 Inter-Cluster Routing Decision by QL Optimization

Inter-cluster route decision process of the IoUT can be optimized by QL approach. The CHs that are far away from the SBS will communicate through the multi-hop CH route, however, the choice best inter-cluster route is an issue due to that the intermediate CH may not have enough energy to communicate (Zhang et al., 2022)(J. Gao et al., 2024). The QL-based framework consists of four main processes, the setting of discrete states, actions, the state transition probabilities, and rewards.

For the proposed approach as ABCQL-SE, agents represent the CHs which they learn from the underwater environment to take transmission decisions, and they can be described by $N = [CH_1, CH_2, \dots CH_i \dots\ CH_m]$, where the a_i represents the i^{th} CH and m is the total number of them. The sates (s) are equal to $[s_1, s_2, \dots \dots \dots s_i \dots . . s_m]$, which represents the states set of the network, the s_i is the data packets reach CH_i. If the packet is forwarded from CH_i to CH_{i+1} then the state of CH transfers from the s_i to s_{i+1} and so on for all other CHs and states (Zhang et al., 2022)(J. Gao et al., 2024).. Action (a) is equal to $[a_1, a_2, \dots \dots \dots a_i]$, denotes the set of exploration actions, where a_i is the CH_i that selected as the next hop forwarded successfully.

The reward $R_{s_i s_{i+1}}^{a_i+1}$represent the reward when an agent takes action a_i to make the state transfer from s_i to s_{i+1}. The reward factors considered by the function are the CH energy consumption, depth, distance, and signal quality. The transfer function probability $p_{s_i s_{i+1}}^{a_{i+1}}$denoted for the transition probability that CH_i takes the action a_i from state s_i to s_{i+1} and calculated as the ABC fitness function $f(PS_i)$ (J. Gao et al., 2024).

The QL enables finding the optimal policy to obtain the highest reward during iterations and evaluates the performance of action at a specific state with the aid of action value (Q_{value}). $Q(s_i, a_i)$ presents the expected discount reward to take an action (a_i) at state (s_i) [53](J. Gao et al., 2024).. The Q-value function is given by equation (2.5) in chapter 2. In the case of small QL discount factor, agents pay more attention to the immediate rewards, and if large it will pay more in future rewards. $r_i(a_{i+1})$ is the reward function enables to find the behavior and performance of action a_{i+1} at state s_i and can by formulated as follows (Anjan et al., 2025)(Zhang et al., 2022).

$$r_i(a_{i+1}) = \sum_{s_i+1} p_{s_i s_{i+1}}^{a_{i+1}} \times R_{s_i s_{i+1}}^{a_{i+1}} \tag{3.42}$$

When max Q-value function is found, an optimal policy can be obtained. The optimal action a_i^* at state s_i is given by the following.

$$a_i^* = \text{argmax Q } (s_i, a_i)_{a_i A(s_i)} \tag{3.43}$$

Where, $A(s_i)$ is the set of actions that a_i may be chosen at state s_i. Greedy QL process will choose the action with the highest Q-value to enable the packets forwarded from CH to the SBS via the best route (Yao and Chen, 2024)(J. Gao et al.,2024).

- **Lemma 3: Optimal CH Forwarding Decision**

In the inter-cluster routing optimization process the optimal forwarding decision for transmitting packets between CHs and to SBS is achieved by using a lightweight QL framework combined with an ABC-based fitness evaluation. The QL reward function ensures that UNs with higher residual energy, lower depth, shorter distances and best signal quality are prioritized as forwarders. QL iteratively updates the Q_{value} to converge to the optimal policy ensuring that the best forwarding decisions are made based on long-term rewards. CHs with larger Q-values have shorter holding times allowing them to forward packets preferentially and reducing energy wastage due to redundant transmissions.

- ***Proposed Solution 3***

The inter-cluster routing decision is based on two stages, the first is to select the subset of neighboring CHs that will transfer the packets to the SBS is made possible by the CH selection phase (S. Chinnasamy, et al., 2022). In addition to the payload data, the sender adds the unique ID of the candidate CHs to the data packet to identify the next forwarder CHs. As seen in Figure 3.7, the sender ID is part of a packet header that also includes the packet sequence number, distance, Q-value, CH depth, and void flag. The CHs as a packet receivers decide whether or not to be qualified by themselves to engage within the inter-cluster route (Anjan et al., 2025)(S. Chinnasamy, et al., 2022).

The second phase enables the CHs to work together to determine the forwarding orders and suppress redundant forwarding based on priorities. According to each neighbor CH's Q-value, the QL implemented with the holding time process assigned to each neighbor CH in the candidate set was designed to reduce energy usage. First, the top forwarders are chosen from among the CHs with the highest Q-value (S. Chinnasamy, et al., 2022)(Yi et al., 2023). To reduce energy usage, data transmission between CHs is based on Q-value.

The inter-cluster routing optimization process flow is displayed in Figure 3.8. The use of adaptive CH management for inter-cluster routing based on multi-factor CH prioritization, coordinated forwarding order by suppressing redundant forwarding packets, and ultimately optimizing the inter-cluster routing by holistic routing decision. To model the optimization concept, let CH_i represents the candidate CH of the current forwarder. The intermediate reward function $R_{s_i s_{i+1}}^{a_{i+1}}$ to take action a_i at state s_i is calculated as follows.

$$R_{s_i s_{i+1}}^{a_{i+1}} = \sum_i^{UN}(w_{EE}E_i + w_{DM}d_{i,j} + w_{DA}D_i + w_{EMA}M_i + w_{SQE}SQ_i) \quad (3.44)$$

Where E_i represents energy-related factor, and D_i as depth related factor, and $d_{i,j}$ is a distance factor, SQ_i is the signal quality factor, and M_i is the UN motion factor. $w_{EE}, w_{DA}, w_{DM}, w_{SQE}$, and w_{EMA} represent the weights of energy efficiency, depth adaptation, distance minimization, signal quality enhancement, and environmental motion adaptation respectively which are assigned to each factor to adjust their impact in the reward function. The D_i is calculated by the following (Anjan et al., 2025)(S. Chinnasamy et al.,2022)(Yao and Chen, 2024).

$$D_i = \frac{depth_{CH,i} - depth_{CH,j}}{R_{max}} \quad (3.45)$$

Where, R_{max} represent the maximum communication ranges between CHs. In general, during communication, CHs with the smallest depth tend to die quickly because of frequent packet data frequently (Lu et al., 2020). In the proposed methods, depth, motion, distance and residual energy consumption are represented in the reward function as basic factors.

In case of CH_i sends packet to CH_{i+1} successfully, the intermediate reward function $R_{s_i s_{i+1}}^{a_{i+1}}$ is an increasing function and its values is more than 1, otherwise, is a decreasing function with values between 0 and 1 denoting that the packets are filed to be transmitted (Yao and Chen, 2024)(X. Wei et al., 2022). The higher residual energy, lower depth, motions and distance factors have more rewards to be selected as a forwarder CH. Accordingly, the candidate forwarder with a larger Q-value will have a shorter holding time which is to relay the data packet preferentially. Upon receiving the data packet broadcasted by inter-cluster, CHs start to calculate the waiting time before forwarding. The waiting time (T_i) is for each CH_i can be calculated by the following equations (X. Wei et al., 2022)(Lu et al., 2020).

$$T_i = 1 - \frac{2}{\pi} - \ arctanQ(s_i, a_i)\, T_{max} \tag{3.46}$$

$$T_{max} = \frac{2R_{max}}{Vs} \tag{3.47}$$

Where Vs represents propagation speed of the acoustic signal, and T_{max} is a pre-defined maximum holding time. Each CH with a larger Q-value has the shortest waiting time will forwards the packets. The constant term (1-$\frac{2}{\pi}$) represents normalized baseline time offset. The T_i constrained between [T_{min},T_{max}] to avoid direct transmission and ensures collision aware scheduling .The UNs and CHs are impacted by the motion factor which will affect in replacement of CHs and inter-cluster route communication.

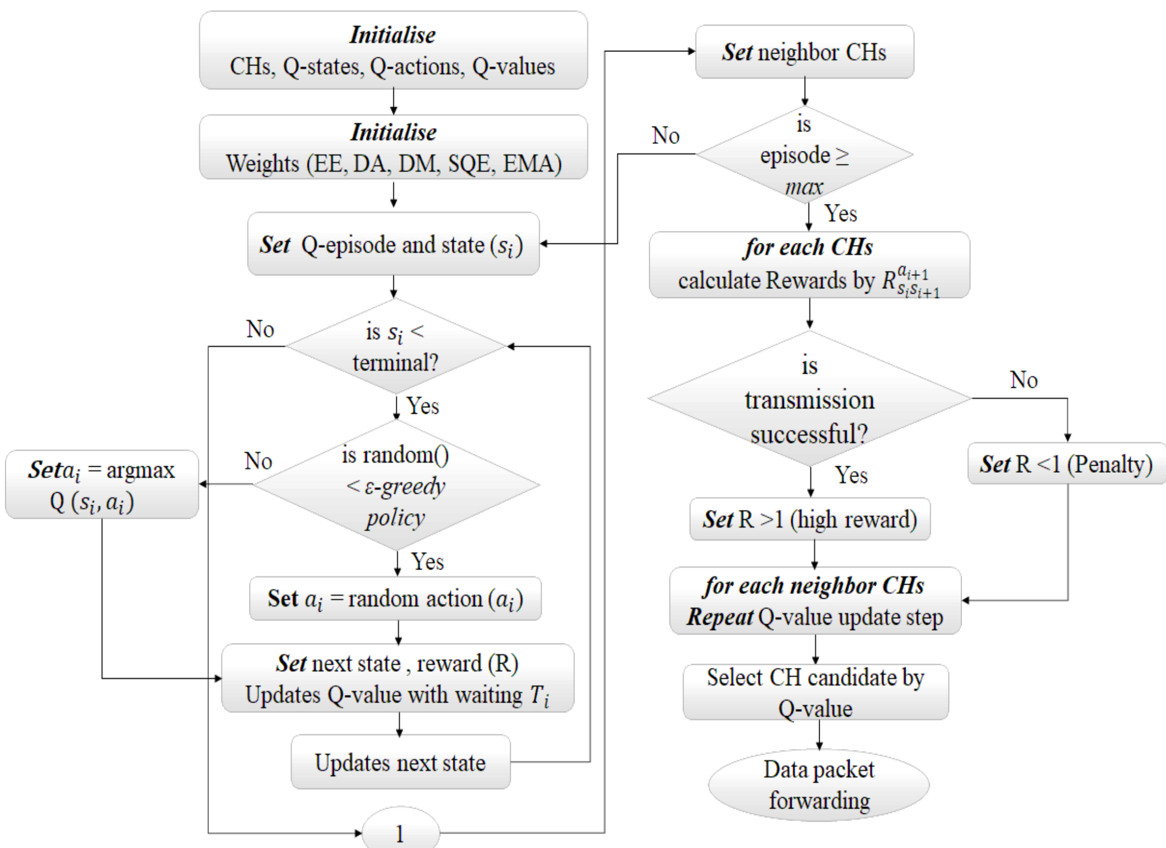


Figure 3.7. Inter-Cluster Route Decision Optimization Flowchart

As a scenario of this management optimization, a CH with a larger Q-value will have a shorter waiting time and thus gains forwarding priority as shown in Figure 3.8. As an example for this method, if CH_a broadcasts a packet and both CH_b and CH_c are candidate forwarders (Lu et al., 2020)(J. Gao et al., 2024). Also their Q-values are 3 and 1, respectively, and waiting times are 0.02s and 0.09s repressively. ConsequentlyCH_b forwards the packet first, and CH_c cancels its transmission upon overhearing the same packet to effectively preventing redundancy.

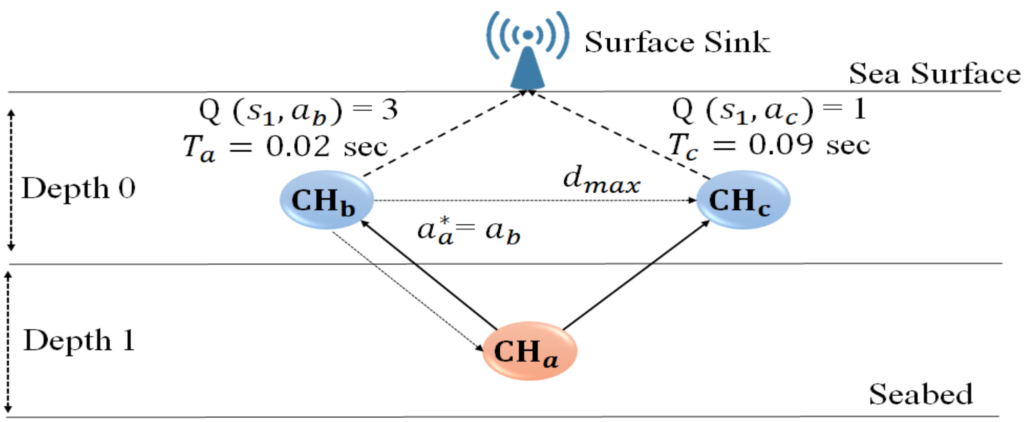


Figure 3.8. Inter-Cluster Routing Decision Process by QL

To represent the oscillatory motion of the CHs due to a meandering current (S. Chinnasamy et al., 2022)(Yao and Chen, 2024). The motion magnitude can be calculated based on the amplitude function m(t) at time (t)as follows.

$$m(t) = m_0 + Acos(ft) \tag{3.48}$$

where, m_0 is the initial amplitude of the current, which is a fixed starting value. A is an amplitude scaling factor that adjusts how strongly the current affects the UNs positions. f represents the frequency of the oscillatory behaviour, controlling how rapidly the current changes over time. And t is the current time (Lu et al., 2020)(J. Gao et al., 2024). Meander amplitude m(t) changes with time. As time progresses, the amplitude oscillates, affecting the motion of the underwater UN (Anjan et al., 2025). The flow dynamics of the UN at position (n_a, n_b) at time t can be calculated based on the accounting for the meandering current m(t) as follows.

$$f_{flow}(n_a, n_b, t) = -tanh\left(\frac{n_{b-m(t)\,sin(k,(n_a-ct))}}{\sqrt{1+}\,k^2\; m(t)^2\, cos^2((k,(n_a-ct))}\right) \tag{3.49}$$

Where, n_a, n_b current position of the CH in the x-axis and y-axis, respectively. K is a wave number that influences the strength of the current's effect on the CHs position. c is phase velocity. The function $f_{flow}(n_a, n_b, t)$ models the non-linear dynamics of the flow (Lu et al., 2020)(J. Gao et al., 2024). The numerator represents the difference between the CH position and the meandering current's effect, while the denominator normalizes this difference by taking into account the oscillatory nature of the flow (Anjan et al., 2025)(J. Gao et al., 2024). The total magnitude of the CHs motion can be calculated by combining the partial derivatives in the x- and y-directions based on the partial derivatives concerning n_a and n_b as follows.

$$M_T = \sqrt{(\frac{\partial f_{flow}}{\partial n_a})^2 + (\frac{\partial f_{flow}}{\partial n_b})^2} \quad (3.50)$$

Equation (3.50) shows a model of the underwater current dynamics using a meander amplitude and flow function. The approximated rate of change of the flow concerning the CH position is based on the derivatives in the equation (J. Gao et al., 2024). The reward of motion M_T is assigned based on how fast or slow the CHs are moving. The motion factor is the effect of the depth or CHs positions which is considered as a reward to compute the Q_{value}.

3.3.3 QoS Driven Energy-Aware by Using QL and MCDM

By integrating a QoS-driven metric into MCDM approach, the QL process will be enhanced. This approach as hybrid ABC and QL based energy ware stable election protocol (ABCQL-EASE) enables the QL feedback loop by incorporating an assessment of both local and global network parameters (S. Chinnasamy et al., 2022). Unlike traditional approaches that rely on single-criterion optimization, the proposed methodology evaluates multiple factors to optimize CH selection and inter-cluster route decision-making over time. While ABC and QL optimize CH management dynamically, the MCDM contribution adds a strategic layer that takes QoS priorities into account, resulting in a comprehensive strategy that integrates technical optimization with network performance objectives and resource restrictions (Aljanabi et al., 2022)(S. Chinnasamy et al., 2022). This result provides an optimization strategy that aligns with the varying conditions of the IoUT networks while adapting to environmental fluctuations, including multipath-induced distortions in channel capacity.

- **Lemma 4: QoS-Integrated Energy Optimization**

The integration of MCDM with lightweight QL and ABC enhance the decision-making process for CH management and inter-cluster route decisions. By use multiple QoS criteria such as energy efficiency, packet delivery ratio, network lifetime and network efficiency the QL reward function dynamically adapts to network conditions ensuring that decisions prioritize UNs with suitable attributes while aligning with overall system performance objectives.

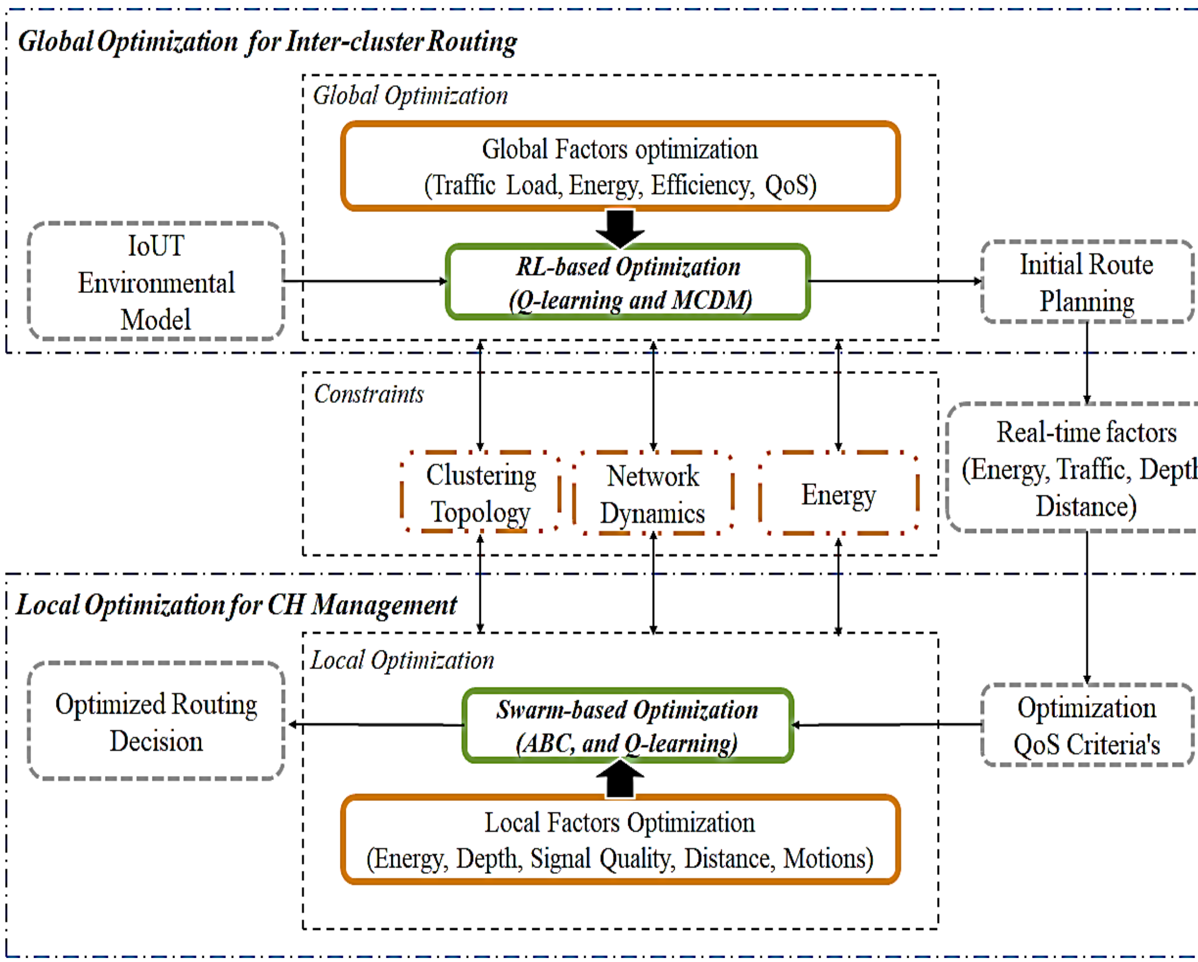


Figure 3.9. QoS Driven Stable Election Process

As in Figure 3.9, the inter-cluster routing decision is performed by a hybrid optimization framework combines local and global optimization methods to provide scalability, and energy efficiency. The framework combines swarm-based optimization as ABC and QL for specific CH management and routing decisions using QL and MCDM for global traffic load balancing, energy efficiency, and QoS management. In addition to taking into account limitations like clustering topology and network dynamics, this dual-layer strategy ensures that the system can dynamically adjust to real-time environmental elements including energy levels, depth, signal quality, and mobility.

- ***Proposed Solution 4***

To enhance the relevance of actions taken by the lightweight QL agent, and optimize multi-objective QoS, let's define lightweight QL space by $S = \{E_i, D_i, M_i, SQ_i\}$, represents the state of the UN characterized by multiple factors, where, D_i for UN depth, M_i for motion, E_i for residual energy, and SQ_i is for signal quality. A represents possible actions available to the UNs, like adjusting parameters and switching states (Aljanabi et al., 2022)(Yao and Chen, 2024). And R(s,a) represents the immediate reward received after taking action (a) in state (s). For MCDM, the method sets a criterion related to the defined multiple factors as $C = \{\mathrm{C}_1, \mathrm{C}_2, \mathrm{C}_3, \mathrm{C}_4\}$ represents the criteria for evaluating UN performance related to its residual energy, depth, motion, and signal quality as feedback to be taken in dynamic QL calculations. By setting weight vector $w = [\mathrm{w}_1, \mathrm{w}_2, \mathrm{w}_3, \mathrm{w}_4]$ where w_1 to w_4 are the weights assigned to each criterion. The reward function can be expressed in a more complex form that incorporates normalization, weighting, and penalty mechanisms for each criterion (Shah et al., 2024)(Ali et al., 2024).

$$R(s,a) = \sum_{i=1}^{4} w_i R_i\,(s) + R_{QoS}(s) \tag{3.51}$$

Where $R_i(s)$ is defined the different local rewards related to the residual energy $R_{RE}(s)$, depth $R_D(s)$, motion $R_m(s)$, and signal quality $R_{SQ}(s)$. And $R_{QoS}(s)$ represents the global rewards related to QoS. These rewards are calculated by the following equations.

$$R_{RE}(s) = \begin{cases} \left(\frac{E_i}{E_{max}}\right)^2; & E_i > E_{thre} \\ \frac{E_i}{E_{max}}\left(1 - \frac{E_{thre} - E_i}{E_{max} - E_{thre}}\right); & E_i < E_{thre} \end{cases} \tag{3.52}$$

Where, E_{max} represents the maximum energy level, and $\mathrm{E}_{\mathrm{thre}}$, the critical energy threshold.

$$R_D(s) = \begin{cases} -D_{penalty}\,; & if\ D > D_{thre} \\ 0\,; & if\ D < D_{thre} \end{cases} \tag{3.53}$$

Where, $D_{penalty}$ represents the penalty for being below the depth threshold, and $\mathrm{D}_{\mathrm{thre}}$is the depth threshold.

$$R_m(s) = \frac{1}{M_T} \tag{3.54}$$

Where the M_T is the motion magnitude threshold.

$$R_{SQ}(s) = \begin{cases} 1; & Q_{dB,norm\,>1} \\ 0; & Q_{dB,norm\,\leq 0} \\ Q_{dB,norm;} & otherwise \end{cases} \tag{3.55}$$

Where $Q_{dB,norm}$ represent the normalized value of Q_{dB} within the specified range $[Q_{min}, Q_{max}]$. The Q_{dB} represents the signal quality in decibels (dB), measured as a quality factor in underwater acoustic communication to reflect the impacts of attenuation, multipath fading, and Doppler effects present in the acoustic channel (Ali et al., 2024). It is calculated by $Q_{dB} = 10log_{10}\frac{|h(t)|^2 P_t}{N_o}$, where. $h(t)$ represents the small-scale fading coefficient, for multipath interference. N_o is the noise power, which includes ambient and thermal noise. The $Q_{dB,norm}$ is calculated by the following.

$$Q_{dB,norm} = \frac{Q_{dB} - Q_{min}}{Q_{max} - Q_{min}}; Q_{min} \in 0\,, Q_{max} \in 1 \tag{3.56}$$

Where the $Q_{dB,obs}$ be the observed signal quality in dB for a given UN, and calculated by the following.

$$Q_{dB,obs} = max(min(Q_{dB}, Q_{thr,max}), Q_{thre,min}) \tag{3.57}$$

The $Q_{thr,max}$ and $Q_{thr,min}$ are the thresholds of max and min acceptable signal quality that represent the excellent and poor signal quality.

$$R_{QoS}(s) = f(\overline{E_\iota}, \overline{PR}, \overline{NL}, \overline{NE}) \tag{3.58}$$

Where, $\overline{E_\iota}$ represent the average energy efficiency. $\overline{PR}$ is the average packet delivery ratio. $\overline{NL}$ is denoted for average network lifetime, and $\overline{NE}$ for network efficiency. These values are calculated as averages of each metric across nodes or episodes to reflect the overall system performance. By using PCM with criteria weights w_E, w_{PR}, w_{NL}, w_{NE}. Then the $\mathrm{R_{QoS}}(s)$ can be represented by each average term as follows (Aljanabi et al., 2022)(Ali et al., 2024).

$$R_{QoS}(s) = (w_E \frac{1}{N}\sum_{i=1}^{N} E_i) + (w_{PR} \frac{1}{N}\sum_{i=1}^{N} PR_i) + (w_{NL} \frac{1}{N}\sum_{i=1}^{N} NL_i) + (w_{NE} \frac{1}{N}\sum_{i=1}^{N} NE_i) \tag{3.59}$$

Where N represents the total UNs. E_i, PR_i, NL_i, and NE_i represent individual values of energy efficiency, packet delivery ratio, network lifetime, and network efficiency for each UN.

The MCDM using analytic hierarchical process (AHP) to compare each QoS criterion relative to the others, using a scale that reflects the importance or preference level. A set of QoS criteria C_i={C_1,C_2,…,C_n} where each C_i represents a specific QoS metric denoted before (Ali et al., 2024). A pairwise comparison matrix A where each element represents the relative importance of the criterion C_i to C_j, taken as an action of QL $a_{i,j}$. The pairwise comparison matrix is calculated as follows.

$$A = \begin{bmatrix} 1 & a_{1,2} & a_{1,3} & \cdots & a_{1,n} \\ \frac{1}{a_{1,2}} & 1 & a_{2,3} & \cdots & a_{2,n} \\ . & . & . & . & . \\ \frac{1}{a_{1,n}} & \frac{1}{a_{2,n}} & \frac{1}{a_{3,n}} & \cdots & 1 \end{bmatrix} \tag{3.60}$$

Where, each $a_{i,j}$ value is determined based on expert judgment, and can be calculated by.

$$a_{i,j} = \begin{cases} a_{i,j} > 1; & if\ C_i\ more\ important\ than\ C_j \\ a_{i,j} < 1; & if\ C_i\ less\ important\ than\ C_j \\ a_{i,j} = 1\ ; & if\ C_i and\ C_j\ equally\ important \end{cases} \tag{3.61}$$

By using the Eigenvalue Method, the criteria weights for each criterion are derived by finding the principal eigenvector of the matrix A, which corresponds to the largest eigenvalue λ_{max} of A and it can be represented by.

$$A_w = \lambda_{max} w_i \tag{3.62}$$

The result is a set of normalized weights {w_1,w_2,…,w_N}, representing the relative importance of each QoS criterion. The normalized weights $w_{N,i}$ are equal to $\frac{w_i}{\sum_{j=1}^{n} w_j}$. In QL, the reward function R(s,a) is critical for driving the agent's decisions. The reward function related to the MCDM is calculated by the following.

$$R(a_i)_{MCDM} = \sum_{i=1}^{n} w_{N,i}\, a_{i,j} \tag{3.63}$$

This reward function allows the lightweight QL model to prioritize different QoS metrics dynamically with the rewards of the first solution of the CH replacement and route decision scheme rewards, depending on their relative weights. Accordingly, the total reward of the developed lightweight QL is calculated by the following (Jiang et al., 2023)(Ali et al., 2024).

$$R(s,a)_{QL} = R(a_i)_{MCDM} + R(s,a) \tag{3.64}$$

Figure 3.10 shows the QoS driven Optimization, which represent three major improvement solutions. The usage of multi-criteria QoS reward computation, which acts as a global reward in the QL approach. The evaluating CHs' performance in the inter-cluster routing process, using an energy-aware and QoS-optimized technique to identify the best CHs for routing decisions (J. Gao et al., 2024). The packets routed among candidate CHs, which are prioritized using QoS-driven judgments and QL-driven dynamic CH replacement during the routing process.

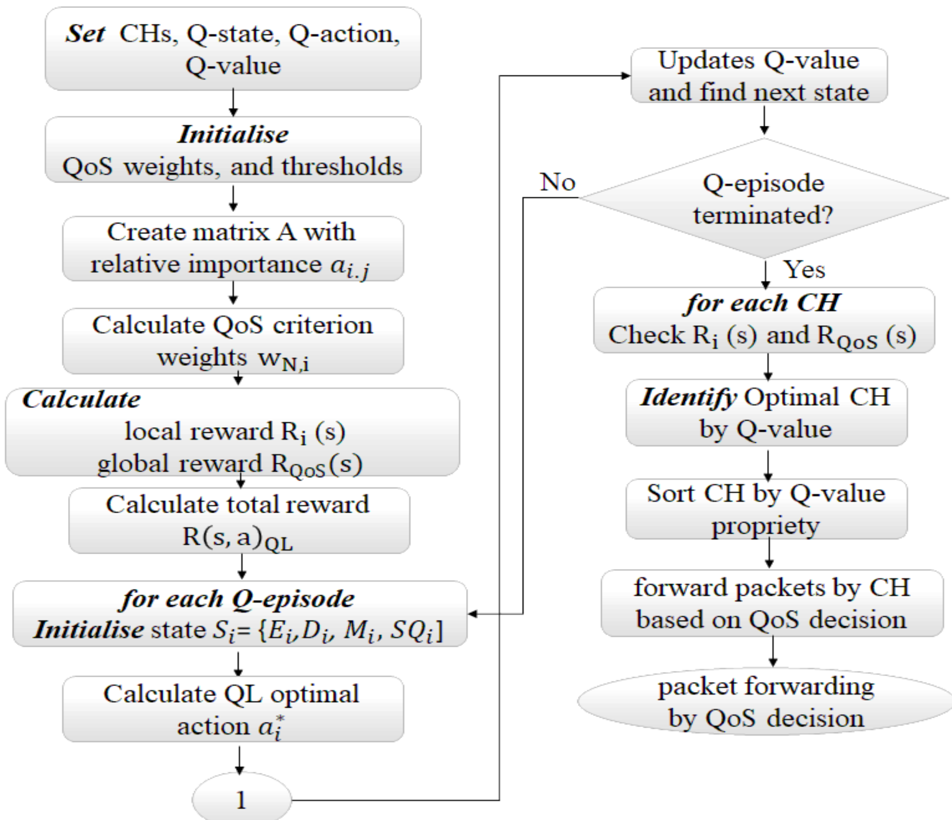


Figure .3.10. QoS Driven Optimization Flowchart

The energy-aware QoS optimization approach combines AHP method and lightweight QL to improve the performance of IoUT networks. It prioritizes energy efficiency and QoS by dynamically selecting CHs for inter-cluster routing (S. Chinnasamy et al., 2022)(J. Gao et al., 2024). The method calculates local and global rewards based on predefined QoS indicators and thresholds allowing adaptive decision-making. It uses QL to optimize CH selection through iterative state-action updates resulting in lower energy consumption and increased network stability (Jiang et al., 2023)(J. Gao et al., 2024). The MCDM component provides a comprehensive framework for achieving energy-efficient and QoS-driven data transmission by weighting decisions based on the relative importance of QoS criteria.

The proposed integration provides a more effective framework for decision-making in complex networks particularly those that require real-time and adaptive quality of service management (Aljanabi et al., 2022)(J. Gao et al., 2024). Adding MCDM to the QL model improves decision-making, optimizes the reward structure for faster convergence, and improves the model transparency and adaptability, making it ideal for real-world, multi-criteria situations. The proposed QL-based MCDM optimization strategy is shown in Figure 3.11.

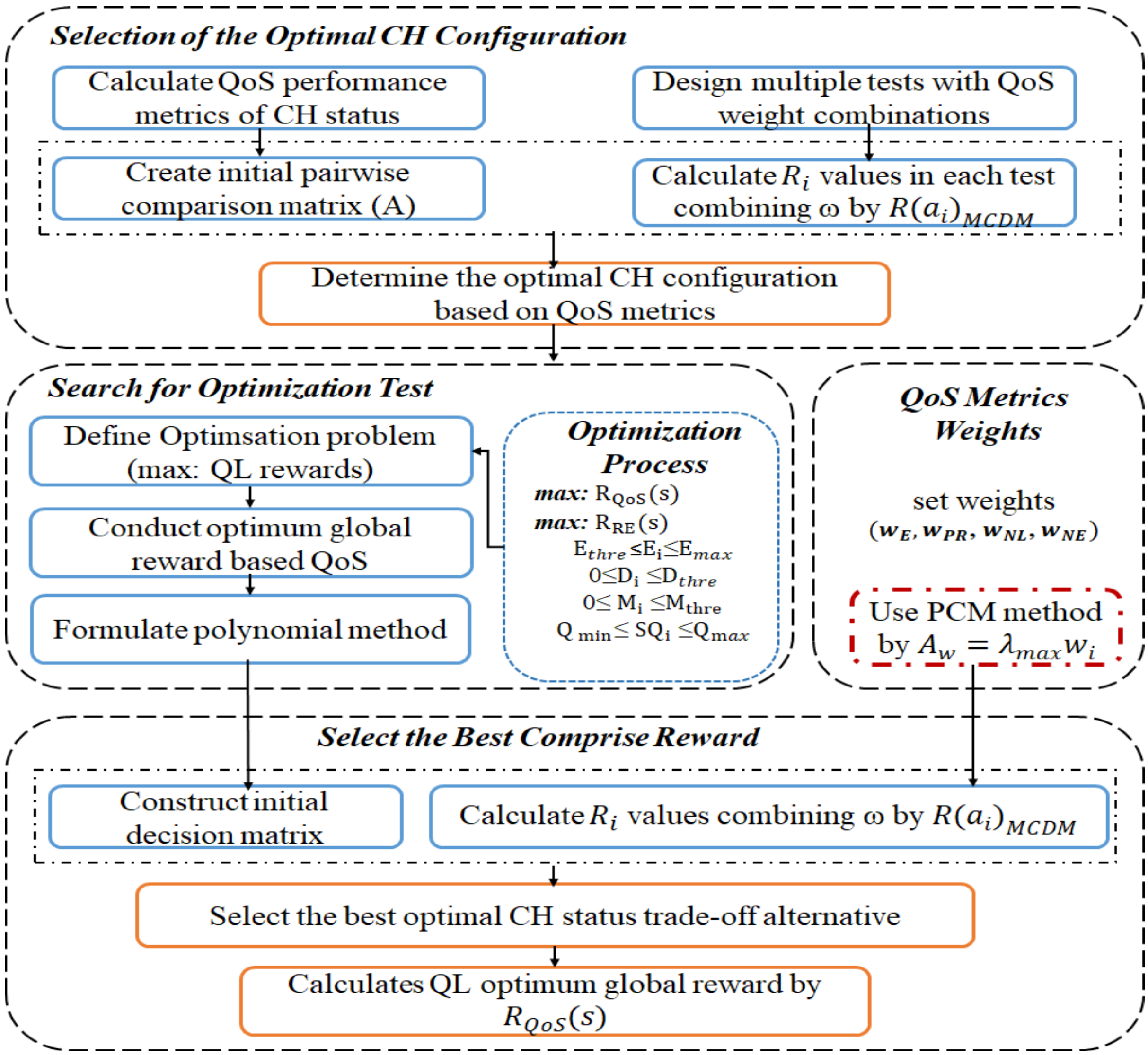


Figure 3.11. QL-based MCDM Optimization Strategy

Better inter-cluster routing decision-making promised by the hybrid MCDM-QL model, which effectively incorporates tactical CH replacement dynamically during route decision-making with strategic QoS goals (J. Gao et al., 2024). The proposed method is a feasible and long-term routing protocol for the difficulties of IoUT since it offers an energy-efficient scheme and intelligent inter-cluster routing by a responsive modification to QoS criteria. The QL with MCDM driven reward structure enable to guide adaptive decision-making for inter-cluster routing, it also offers an energy-conscious method that improves the QoS of IoUT networks while promoting energy-efficient operations.

3.4 Relay Selection for Inter-Cluster Routing

On inter-cluster routing communication, even long distances between CHs can increase the IoUT network energy consumption and reduces it efficiency (Shah et al., 2024). The primary objectives related to second stage of solution is based on how to minimize the energy consumption of the CHs during inter-cluster communication when long communication in occurred by selecting the best UVs to serve as relay. It's based on the strategy to maximize the communication reliability by considering the signal quality and distance between the CHs and the UVs relay (Ali Karkehabadi et al., 2024)(Rizvi et al., 2022).

According to the given energy concerns, the objective function for selecting the optimal set of relay UVs is formulated as follows.

$$Min_{EC} = \sum_{i=1}^{N} \sum_{j=1}^{M} (E_{ij,} EC_j) \tag{3.65}$$

Where E_{ij} represents the energy required by UV to forward data from CH. EC_j is energy consumption required by the CH for transmitting data to a UV. The selection of best UVs must consider several constraints. The energy constraint represents the energy consumed by each UV_i should not exceed its available energy E_i represented as follows (G. Xing et al., 2019).

$$E_{ij} \leq E_i \forall\ UV_i,\ \forall EC_j \tag{3.66}$$

The selected UVs must have sufficient signal quality (SQ_i) to ensure reliable communication based on the signal quality constraint described as follows.

$$SQ_i \geq SQ_{min}\ \forall UV_i \tag{3.67}$$

Where SQ_{min} is the minimum threshold for communication reliability. The distance constraint (d_i) represent the distance between CH and UV should be within communication range and not produce transmission delays or energy consumption. The depth constrains (D_i) ensures that the selected UVs operate within an optimal depth to maintain stable communication and energy efficiency (G. Xing et al., 2019)(Wang et al., 2025). These constraints are represented as follows.

$$d_i \leq d_{max} \; ; D_i \leq D_{max} \; \forall UV_i, \forall EC_j \tag{3.68}$$

Where d_{max} is the maximum allowable transmission distance. D_{max} is the maximum depth of UVs from the SBS. The developed objective function aims to reduce overall energy usage while maintaining strict limitations on signal quality, depth, distance, and energy availability. These limitations ensure that specific UVs function within optimal distances, minimizing energy loss and transmission delays.

By carefully selecting optimum UVs as relays the proposed approach energy aware and QoS driven UVs relaying integrated SEP (EQURI-SE) aims to optimize the relay selection procedure to improve communication between CHs (Sathish et al., 2025)(Z. Zhang et al., 2024). An MCDM strategy that combines hybrid NN-GA decision optimization with them is taken into consideration. The MCDM using technique for order preferences by similarity to ideal solution (TOPSIS) to rank UVs according to how close they are to an ideal solution considering variables like energy efficiency and the distance between and from CHs which have a direct impact on network stability and the quality of data transmission (Z. Zhang et al., 2024).

3.4.1 UVs Relay Based Model

Dynamic replacement, inter-cluster routing and CH selection are based on the most crucial characteristics including residual and average energies, depths, distances, motions and signal quality. The proposed approach selects the optimal UVs as relays for optimizing the inter-cluster routing strategies for IoUT network model with the goal of achieving stability, energy reduction, improved inter-cluster communication and network longevity (Subramani et al., 2022)(Ullah et al.,2024).

The environmental model as shown in Figure 3.12 for the proposed approach is based on many assumptions. All UNs and UVs are distributed randomly in the IoUT network environment. Each UNs can communicate only to its CHs. The UVs historical data related to their energies, positions, depths and distances are continually monitored by SBS. The UVs relay selection approach is performed by the SBS based on the registered UVs historical database. Each CHs can directly communicate to the UVs to relay data to SBS or other CH according to the inter-cluster route decision approach using multi-hop schemes directly (Ali, E. S et al., 2024).

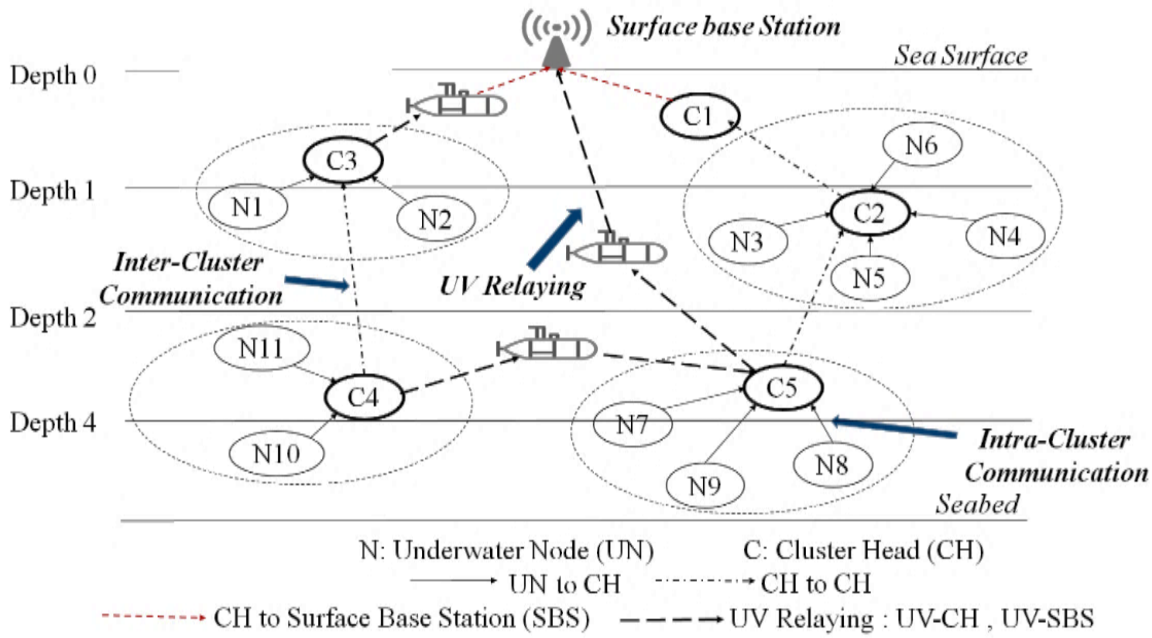


Figure 3.12. UVs-Relayed IoUT System Model

The mathematical model of the proposed framework is structured based on the UVs positioning and mobility modeling by considering the following (Liu et al.,2025).

- The set of all available UVs be denoted as V_i={V_1, V_2,… V_n}, where n is the total number of UVs available. The goal is to select a subset of these UVs as relay to assist in forwarding data between the CH or from CHs to SBS.

- Each UV is defined in a 3D coordinate space represented as horizontal position in meters and depth, constrained by a maximum depth D_{max} (S. Ali et al., 2024).

The initial position of each UV is randomly generated. Each UV moves with a velocity vector (v_i) where the speed constraint is given by 0 $\leq v_i \leq v_{max}$ and the direction is randomly generated. The UV position update over time is given by.

$$P_{next}(t) = P_i(t) + v_i\ \Delta t \tag{3.69}$$

The updated position of each UV is determined by its previous position P_i(t) and its velocity (v_i) over a time interval Δt ensuring dynamic movement within the defined constraints (S. Ali et al., 2024). The data from CHs will be transmitted to a selected relay V_i∈UVs based on certain criteria such as energy (E_i), distance (d_i) , signal quality (SQ_i) , and depth (D_i).

The energy consumption of each UV depends on its movement, communication, and depth. The total energy $E_i(T)$ of UV is given by.

$$E_i(T) = E_i(t) - E_{M,i} - E_{C,i} - E_{I,i} \quad (3.70)$$

Where, E_i the residual energy of UV_i at time t. $E_{M,i}$ is energy consumed by the UV during mobility (Subramani et al., 2022)(S. Ali et al., 2024). $E_{C,i}$ is the communication energy consumption, and $E_{I,i}$ represent the energy consumed due to underwater impact factors related to underwater attenuation, and temperature. The energy consumed due to UVs motions is given by the following.

$$E_{M,i} = C_1\, d_i + C_2\, D_i + C_3\, v_i \quad (3.71)$$

Where, d_i is distance traveled by UV_i in the given time interval. UV_i is the depth change of UV_i . v_i is the velocity of the UV_i during movement .C_1,and C_2, represent the energy per meter of distance, and depth changes, C_3 is energy per unit speed.

According to UVs positions, the signal quality is affected by depth, distance from SBS, speed, in addition to attenuation and temperature (Subramani et al., 2022)(S. Ali et al., 2024). The signal to noise ratio (SNR) is modeled as follows.

$$SNR_{UV} = SNR_i - \alpha\, D_i - \beta\, log_{\,10}(d_i) + \gamma\,(T_i - 20) + \delta\,(A_i - 35) - \rho\, v_i \quad (3.72)$$

Where, α, β, γ, δ, and ρ represent the impact coefficients corresponding to each impact factor. The SNR_{UV} relay in value as $SNR_{UV,min} \leq SNR_{UV} \leq SNR_{UV,max}$. T_i is water temperature and A_i represents salinity impact.

The UVs relay selection optimization is based on two objectives. Energy efficiency (EE) and communication quality (CQ). For energy efficiency, the objective function (f_{EE}) is based on the UVs energies and depth. The communication quality objective function (f_{CQ}) is based on the UVs signal quality and communication range (Gan et al., 2024). The two objective functions are given as follows.

$$f_{EE} = w_1\, E_i - w_2 D_i \quad (3.73)$$

$$f_{CQ}= w_3 SQ_i - w_4 d_i \tag{3.74}$$

Where, w_1 to w_4 be the balancing weights normalized between 0 and 1ensures a balanced trade-off between the various parameters for optimization process to fairly prioritize UVs based on both energy efficiency and communication reliability (Gan et al., 2024). The multi-objective optimization problem is given as follows.

$$max_{\forall \mathrm{i}} \ (f_{EE}, f_{CQ}) \tag{3.75}$$

The given multi-objective optimization problem is based on three main hypotheses that define the feasibility constraints.

- H_1, the energy constraint ensures that each UV maintains a minimum required energy level, expressed as $E_i \geq E_{thre}$ (Ertogan and Wilson, 2024).
- H_2, the signal quality constraint ensure that the signal quality of each UV remains above the acceptable threshold by $SQ_i \geq SQ_{thre}$.
- H_3, a depth constraint is imposed to ensure that UVs operate within a predefined depth range, given by $0 \leq D_i \leq D_{max}$ (Ertogan and Wilson, 2024).

3.4.2 UVs Relay Selection by Using Hybrid NN and GA

The proposed approach combines the prediction ability of the NN with the optimization strength of the GA to minimize energy consumption while maximizing relay selection score (Okereke, et al 2023). Figure 3.13 shows the workflow diagram of the proposed Hybrid NN-GA with MCDM Model. The energy consumption and relay selection score were approximate by NN trained on UVs dataset. The NN is designed as a Multi-Layer Perceptron (MLP) with back propagation learning. The input vector to NN is defined as N_i= [E_i, d_i, D_i, SQ_i, p_i], where p_i is the probability of successful acoustic communication (Liang et al., 2023)(Acarer, T., 2024).

The NN learns the objective functions are defined by N_L : $N_i \in (f_{EC}, f_{SS})$ where, f_{EC} and f_{SS} represent the objective functions of predicted energy consumption and relay selection score respectively. The NN structure is shown in Figure 3.14. The training optimization algorithm used is gradient descent to obtain an output layer with two outputs represent the predicted energy consumption and relay selection score (Acarer, T., 2024). For each hidden layer, the forward propagation is given by the following equation.

$$h_m = \sigma\,(W_m\, N_i + b_m) \tag{3.76}$$

Where, W_m is the weight matrix of layer m. $b_m$the bias vector of layer m, and σ is the activation function. The target output layer uses a linear activation function is calculated by Y_T=W_o h_M + b_o, where h_M represent total number of hidden layers.

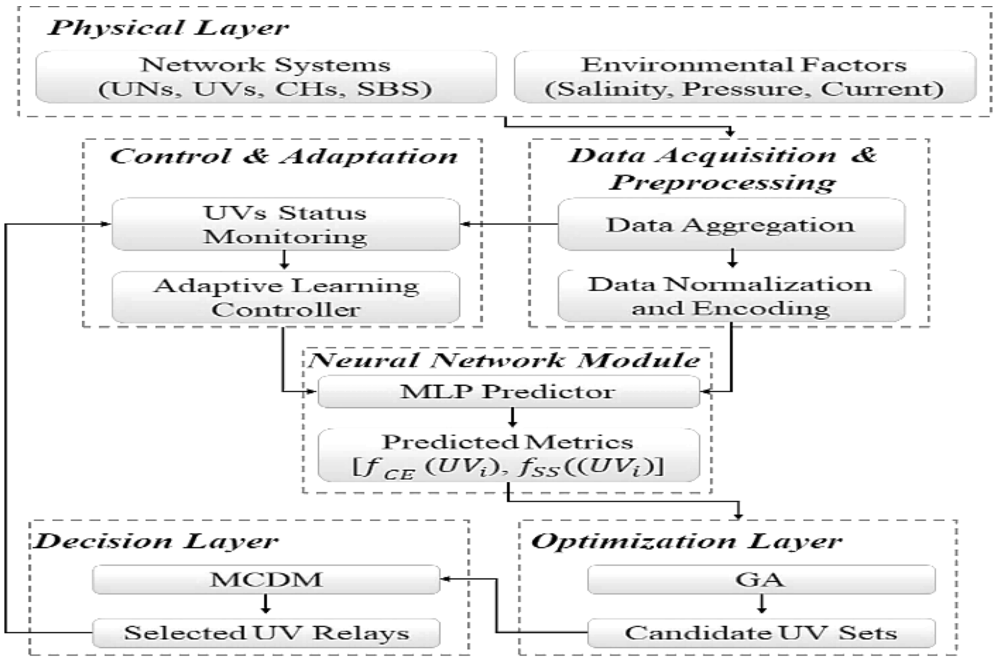


Figure 3.13. Hybrid NN-GA with MCDM Model

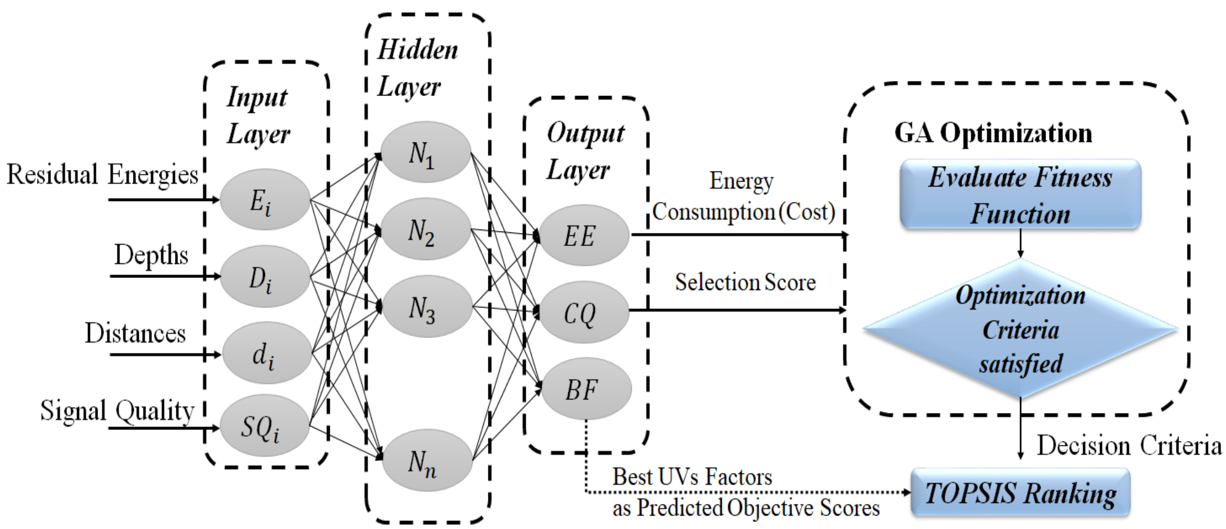


Figure 3.14. NN-GA approach for UV-Relay Selection

- **Lemma 1: NN-GA optimization**

The NN enables us to accurately predict both the energy consumption $f_{EC}(N_i)$ and relay selection score $f_{SS}(N_i)$, reliably estimates the objectives for each UV, facilitating accurate relay selection and energy optimization (Acarer, T., 2024)(Yu et al., 2023). The NN-GA will effectively approximate the objective functions, ensuring its utility in the hybrid framework. The predicted energy consumption and relay selection score are used as the input for the GA (Yu et al., 2023). The NN approximates the objectives as follows.

$$f_{EC}(N_i) = W_{o,1}\ h_M + b_{o,1} + \lambda_1\ \alpha_i + \lambda_2\ \beta_i \tag{3.77}$$

$$f_{SS}(N_i) = W_{o,2}\ h_M + b_{o,2} - \gamma_1 \frac{1}{SQ} + \gamma_2 \log(1+p_i) \tag{3.78}$$

Where, β_i and α_i represent, mobility and Environmental noise factors respectively. λ_1 and λ_2 are the environmental noise and mobility weighting factors. γ_1 and γ_2 are the weighting factor for signal quality and successful acoustic communication. The NN is trained using a mean squared error (MSE) loss function which is represented by the following equation (Yu et al., 2023).

$$\mathrm{L} = \frac{1}{N} \sum_{i=1}^{N} [\left(f_{EC}(N_i) - f_{EC}^{true}(N_i)\right)^2 + \left(f_{SS}(N_i) - f_{SS}^{true}(N_i)\right)^2] \tag{3.79}$$

Where, f_{EC}^{true} and f_{SS}^{true} are ground-truth labels. N is the number of training samples. The weights and biases are updated using gradient descent as follows.

$$W^{t+1} = W^t - \eta \frac{\partial \mathrm{L}}{\partial \mathrm{W}} \tag{3.80}$$

$$b^{t+1} = W^t - \eta \frac{\partial \mathrm{L}}{\partial \mathrm{b}} \tag{3.81}$$

Where, η represent learning rate. The GA optimizes UV selection as relay by minimizing the objective function for energy consumption and maximizing the objective function for relay selection score (Yu et al., 2023)(Bing et al., 2023). The process of GA is first set a chromosome C_i represents a selected UVs according to the NN input vectors (E_i, d_i, D_i, SNR, M_i), where each parameter is encoded as a gene. After generating the initial a set of 50 populations each chromosome is evaluated by $f(C_i) = w_1\ f_{EC}(C_i) - w_2\ f_{SS}(C_i)$. The selection mechanism as GA parents $P(C_i)$ is by roulette wheel selection which calculated by the following equation.

$$P(C_i) = \frac{\mathrm{F}(C_i)}{\sum_{j=1}^{P} \mathrm{F}(C_j)}(1 - \epsilon\, \delta(C_i)) \tag{3.82}$$

Where, $\delta(C_i)$ represents the penalty factor for chromosomes that violate constraints, and ϵ is scaling coefficient. And after GA termination, the best chromosome C^* of GA completion represents the optimal selected UVs and represented by the following.

$$C^* = \arg min_C f(C_i) \tag{3.83}$$

For final selected UVs, C^* represent the optimal relay set by ensuring the best performance in terms of energy consumption and network reliability (Bing et al., 2023).

The strategy focuses on two primary objectives, identifying UVs with the highest possible energy efficiency, and stable signal quality (Anderlini et al., 2019). UVs are ranked using a variety of factors using TOPSIS. The optimal solution, which is defined mainly by the highest energy efficiency, the best signal quality, in addition to the shortest distance and lower depths, is the elevation at which TOPSIS assesses each UV. The definition of the dual-objective optimization problem is as follows.

- **Objective 1: Maximize $(\mathbf{f_{EE}})$**

Prioritizes energy efficiency which is important for increasing the operational lifetime of UVs. In equation (3.84), the term $w_{\mathrm{E}}\, E_i$ emphasizes the importance of maintaining high residual energy levels, while $w_{\mathrm{D}} D_i$ penalizes deeper UVs due to their higher energy consumption for communication and mobility. Accordingly, the optimized f_{EE} can by calculated as follows.

$$f_{EE}=w_E \frac{E_i}{E_{max}} - w_D \frac{D_i}{D_{max}} + w_\alpha \frac{\alpha_i}{\alpha_{max}} \tag{3.84}$$

Where, E_{max} D_{max} and α_{max} represent the maximum threshold for energy, depth, and environmental noise.

- **Objective 2: Maximize $(\mathbf{f_{CQ}})$**

Balances signal quality and proximity to the SBS. In equation (3.85), the term $w_{\mathrm{SQ}} SQ_i$ rewards UVs with better communication capabilities, while $w_{\mathrm{d}} d_i$ encourages shorter distances to minimize propagation loss and improve data transmission reliability (Sen et al., 2023). Accordingly, the optimized f_{CQ} can by calculated as follows.

$$f_{CQ}= w_{SQ}\,\frac{SQ_i}{SQ_{max}} - w_d\,\frac{d_i}{d_{max}} + w_\beta\,\frac{\beta_i}{\beta_{max}} \tag{3.85}$$

Where, SQ_{max} d_{max} and β_{max} represent the maximum threshold for signal quality, distance, and mobility. After generating candidate solutions using the GA and NN, the final ranking of UVs is performed using the TOPSIS method (Anderlini et al., 2019)(Sen et al., 2023). TOPSIS ranks alternatives based on their proximity to the positive ideal solution and distance from the negative ideal solution. For TOPSIS decision making, the decision matrix(DM) is defined as follows.

$$\mathrm{DM} = \begin{bmatrix} E_1 & d_1 & SQ_1 & D_1 \\ E & d_2 & SQ_2 & D \\ . & . & . & . \\ E_\mathrm{n} & d_\mathrm{n} & SQ_n & D_\mathrm{n} \end{bmatrix} \tag{3.86}$$

By normalize DM each element represented by X_ij is scaled to a range between [0, 1]. The normalized value r_ij is calculated by r_ij = $Xij/\sqrt{\sum_{i=1}^{n} X^2{}_{ij}}$, updates the DM to ensure an equal comparison of several UV characteristics, including depth, energy, distance, and signal quality, which have distinct scales and units.

The TOPSIS technique ranks alternatives based on the normalized values, which are subsequently utilized in weighted computations and the identification of the best option (Anderlini et al., 2019)(Sen et al., 2023). The normalized decision matrix (DM_N) is consists of normalized values for each UVs monitored factors by r_ij for example, r_ij $=Ei/\sqrt{\sum_{i=1}^{n} E^2{}_i}$. Where each criterion j is assigned a weight (w_j). The weighted normalized value v_ij is equal to $w_\mathrm{j}{\cdot}r_\mathrm{ij}$ which are used to assess the alternatives relative to the ideal solutions, ultimately guiding the decision-making in the TOPSIS method.

- **Lemma 2: Optimality of Dual-Objective Decision**

By maximizing both energy efficiency (f_{EE}) and signal quality(f_{CQ}), the dual-objective optimization technique ensures that the UVs chosen are the best for relaying communication in the IoUT network (P. Sun and A. Boukerche, 2018). In TOPSIS, the best-performing options are selected for the relaying data by choosing UVs with the highest relative proximity coefficient (C_i), which yields the optimal solution (Sen et al., 2023)(P. Sun and A. Boukerche, 2018). Accordingly, after weight normalizing, the decision is based on positive and negative ideal solutions which represent the best and worst possible values for each criterion. The dual objective criteria (c_{obj}) can be found according to the following equation.

$$C_{\text{obj}} = \begin{cases} {A_j}^+ = \max(v_{\text{ij}}), {A_j}^- = \min(v_{\text{ij}}) \;\; for\ best\ value \\ {A_j}^+ = \min(v_{\text{ij}}), {A_j}^- = \max(v_{\text{ij}}) \;\; for\ worst\ value \end{cases} \tag{3.87}$$

The C_{obj} identify the best and worst values for each criterion. These ideal solutions serve as benchmarks for assessing the performance of each UVs (P. Sun and A. Boukerche, 2018). The L2 norm of each UV_{i} to the positive and negative ideal solution is calculated as follows.

$$L2_{\text{norm}} = \begin{cases} {D_i}^+ = \sqrt{\sum_{j=1}^{m}(v_{ij} - {A_j}^+)^{2} + 6(v_{ij} - {A_j}^-)^{2}} \\ {D_i}^- = \sqrt{\sum_{j=1}^{m}(v_{ij} - {A_j}^-)^{2} + 6(v_{ij} - {A_j}^+)^{2}} \end{cases} \tag{3.88}$$

Where, 6 represents the deviation factor. The $L2_{\text{norm}}$ distances quantify how close or far each UVs is to the best and worst possible solutions, forming the basis for determining the relative closeness coefficient in the TOPSIS method. The relative closeness coefficient (C_{i}) measures how close an alternative is to positive ideal solution compared to negative ideal solution is given by $C_{\text{i}}= {D_i}^-/{D_i}^+ + {D_i}^-$ (Anjan et al., 2025)(P. Sun and A. Boukerche, 2018). Where, $C_{\text{i}}\in[0,1]$, Higher (C_{i}) indicates better performance. Alternatives are ranked in descending order of (C_{i}). The best alternative has the highest (C_{i}). The better rank of (C_{i}) is based on the UV_{i} characterization by a set of parameters related to equation (3.89). The decision on selecting the best UVs is set as $X_{\text{i}}=\begin{cases} 1, & if\ UV\ is\ selected \\ 0, & otherwise \end{cases}$.

The dual-objective optimization should fulfill the condition in equation (3.89), and the constraints of . $E_i \geq E_{thre}$, $D_i \leq D_{thre}$, $d_i \leq d_{thre}$, while $X_{\text{i}} \in \{0,1\}, \forall i \in \{1,2,\ldots,N\}$ which indicates whether is UV_{i} is selected, where the final ranking decision to selecting UVs (S_{RD}) is calculated as follows.

$$S_{RD} = \text{Max} \sum_{i=1}^{N} X_{\text{i}} \, [fit\,(C_{\text{i}}) + \sigma \log\,(1+C_{\text{i}})] \tag{3.89}$$

Where, σ is the scaling factor for logarithmic enhancement of closeness coefficient. According to equation (3.89), the optimization objective for selecting the best UVs in the network is achieved. The $fit\ (C_{\text{i}})$ is the fitness function applied to the relative closeness coefficient (C_{i}) which measures how close each selected UV is to the ideal solution (P. Sun and A. Boukerche, 2018). By maximizing this sum the objective is to select the UVs that contribute the most to the network overall performance ensuring that those with the highest C_{i} values are prioritized. This optimization process directly impacts the selection of UVs which will effectively relay communication between CHs and SBS, enhance network efficiency and stability by ensuring the best-performing alternatives are chosen for the task.

3.4.3 Relay UVs in Inter-Cluster Ccommunication

The UVs mobility plays an important role in finding the efficiency of data relaying within IoUT networks. Due to the dynamic nature of underwater environments UVs must navigate through different depths, currents and distances to enable stable communication links between CHs and the SBS (Subramani et al., 2022)(Sathish et al., 2025)(P. Sun and A. Boukerche, 2018). Therefore, modeling both the mobility behavior and the associated relay cost is essential for optimizing energy usage and prolonging network lifetime. To reflect realistic underwater conditions, UVs are assumed to follow a meandering current mobility model, which simulates the natural drift caused by oceanic flows. This model is governed by the following equations (P. Sun and A. Boukerche, 2018).

$$x_i\ (t+1) = x_i\ (t) + u_{x,i}\ \Delta t + A_o \sin\left(k_k\ u_{x,i}\ t + f_f\ t\right) \tag{3.90}$$

$$y_i\ (t+1) = y_i\ (t) + u_{y,i}\ \Delta t + m_o \cos\left(f_f t\right) \tag{3.91}$$

Where, $x_i\ (t)$, $y_i\ (t)$ are the current coordinates of UV_i. $u_{x,i}$ and $u_{y,i}$ are the velocity components along x and y axes. A_o is Amplitude of lateral oscillation. k_k is Wave number. m_o Mean width of meander. f_f is angular frequency of oscillation, and Δt Time interval between position updates (Sen et al., 2023)(P. Sun and A. Boukerche, 2018).

This mobility feature ensures that UVs ensures smooth underwater communication and, enhancing their ability to serve as mobile relays while minimizing abrupt changes in direction or speed that could disrupt acoustic signal quality (Subramani et al., 2022)(Sen et al., 2023). The mobility cost $E_{M,i}$ is calculated based on distance traveled d_i , depth change ΔD_i , and velocity v_i as follows.

$$E_{M,i} = C_1 d_i + C_2 \Delta D_i + C_3 v_i \tag{3.92}$$

Where, $C_1, C_2, and\ C_3$ are empirically derived coefficients that represent energy consumption per unit of distance, depth variation, and speed respectively.

The relay cost is affected by UVs energy for receiving packets from CHs, in addition to aggregation and preprocessing costs. To ensure fair usage and prevent premature exhaustion of specific UVs, a dynamic cool-down mechanism is applied based on residual energy and frequency of use by the following function.

$$G_i = \text{round}\left(\frac{\exp(\beta\ M)}{\max(0.1\ \frac{E_r}{E_i})}\right) \tag{3.93}$$

Where, G_i is the cool down value for UV_i . M is the number of mobile relays in the network. β is scaling factor controlling penalty growth. E_i and E_r represent the initial energy and current energy level of UV respectively (Subramani et al., 2022)(Bing et al., 2023). This cooling-off process discourages the reuse of low-energy or frequently used UV as relay, thus distributing the relay load across available resources.

In the proposed approach UVs and UNs do not communicate directly. Instead, UVs serve primarily as mobile relays for inter-cluster communication. They enable data transfer between CHs and from CHs to the SBS reducing the high energy cost of long-distance underwater communication (Bing et al., 2023)(P. Sun and A. Boukerche, 2018). Equation (3.94) defines the transmission energy in the energy dissipation model for acoustic communication which mathematically guides this function. UVs are placed strategically to provide relay-assisted transmission, in which a CH sends its aggregated data to a neighboring UV which subsequently forwards it to the SBS (Anderlini et al., 2019)(P. Sun and A. Boukerche, 2018). The total energy for this two-hop path is as follows.

$$E_{relay} = E_{CH-UV} + E_{UV-SBS} \tag{3.94}$$

By using Equation (3.94), each communication hop is calculated based on the distance d_{CH-UV} . A UV is only chosen as a relay when the following conditions are met.

$$E_{relay} < E_{direct} \quad ; \quad E_j^{Er} > E_{CH-UV} \tag{3.95}$$

Based on the residual energy (E_j^{Er}) of the UV this ensures both energy efficiency and viability. Additionally the depth energy multiplier factor is used in the simulation to reflect depth-dependent energy penalties which result in higher energy costs for CH/UVs below a certain depth threshold (Anderlini et al., 2019)(Chen et al., 2024). This highlights how signal attenuation and propagation loss grow with depth. According to equation (3.93) the UVs themselves are controlled by a cooling mechanism that controls their reusability. Accordingly, the UVs serve as energy-aware, depth-aware and mobility-aware inter-cluster relays significantly reducing the energy limitations on CHs and extending network lifetime (Hussain et al., 2025).

Based on the proposed approach UVs role in inter-cluster communication will serve as mobile relays connecting CHs and the SBS. This ensures reliable intra-cluster communication which reduces network overhead and control complexity and avoids inefficient handoffs caused on by UV mobility. By selecting the best number of UVs as relays, it expected able to locate strategically placed and provides energy-efficient UVs that reduce network energy consumption. UVs are strategically positioned according to residual energy, depth, signal quality and proximity to CHs/SBS. This ensures that relays are chosen in the best possible way improving IoUT network performance overall.

3.5 Chapter Summary

The proposed approach provides a number of enhancement to overcome latency issues. Transmission delays caused by weak CHs are minimized by the dynamic selection of CHs, which ensures that UNs with higher residual energy, better signal quality, and lower depth are given priority to act as CH. Additionally, the solution minimizes the distance between CHs and the SBS, as well as the distance between CHs in inter-cluster communication in order to optimize the communication route. Furthermore, UVs are used as relay between the CHs to avoid long distance between CHs in inter-cluster communication. The integrating of MCDM provides solution to balances energy efficiency, packet transmission, and network lifetime by allocating weights to competing objectives related to latency. In addition, it’s used to ranks the selected UVs relay based on their energy efficiency and selection score.

The data aggregation combines correlated data from multiple UNs to the CHs based on QoS driven optimized inter-cluster route decision which enable to minimizing redundant transmissions, long communication distances which significantly reduces the overhead in CHs and energy consumption, in addition to extends the network's operational lifetime. According to the improvements given by the discussed developed solutions, the developed approaches enable to ensure high energy utilization performance for large scale IoUT scenarios.

CHAPTER FOUR

Simulation Results and Discussion

4.1 Introduction

In this chapter, the detailed simulation analysis of the proposed energy aware stable routing protocol and UVs relay based approaches are discussed. To evaluate the performance of both the approaches, the UNs are deployed randomly in network area and every individual UNs acts as a data source to generate data packets as well as a forwarder. All UNs are heterogeneous. The position of the SBS as a sink is static during the simulation course. The SBS is positioned at the water surface and at the center of the network area with coordinates. The chapter evaluates the performance of two developed approaches in different stages, starting from the main modifications in SEP by using the intelligence of meta-heuristic approaches, optimization performance of QL approach and finally propose energy-aware stable election protocol and the UVs relay based protocol.

4.2 Simulation Settings and Scenarios

To evaluate the proposed approaches Figure 4.1 shows the general simulation environment with a set of UNs, in underwater network area, where the IoUT UNs are deployed. The IoUT consists of one SBS which can communicate with different numbers of UNs/CHs with different energy levels and depths. The underwater network area is 1000 x1000 m and the maximum depth of the seabed is 50 meters for general cases and 70m for UVs relay scenario. The general network simulation parameters is shown in Table 4.1. The evaluates is considering different metrics such as number of dead UNs, average residual energy, energy consumption, network efficiency, QoS score, and network throughput. The simulation assumptions of this study are highlights as follows.

- The UNs/UVs are distributed randomly throughout at varying depths ranging from the SBS to a maximum depth for evaluating depth-dependent energy dynamics.

- Although UNs are considered fixed after deployment, but their relative positions changed over time due to water displacement caused by sea flows.

- The UNs cannot directly connect to the SBS. All data transmissions must be routed through CHs forming a multi-hop hierarchical network structure where CHs act as relays to forward aggregated data toward the SBS.

- Each UN/UVs has location awareness by pre-deployment configuration and knowledge of its depth, residual energy, and distance to neighboring UN/CHs and the SBS, enabling informed decision-making during CH management and routing phases.

- Acoustic communication parameters are used like frequency, bandwidth, and propagation speed set to reflect real-world underwater channel constraints.

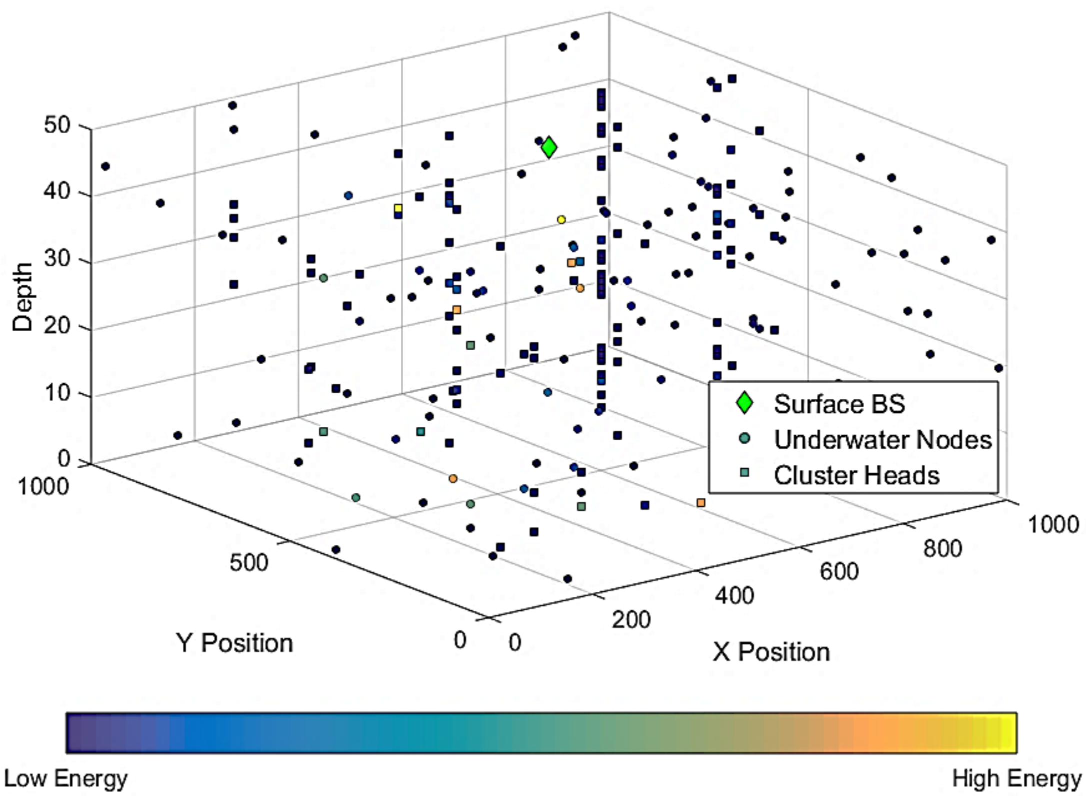


Figure 4.1. General Simulation Environment

Table 4.1. IoUT Network Simulation Parameters

Parameters	Values with Description
IoUT network area	1000 ×1000 m^2
SBS	1
UNs (General Scenario)	80 (depth based SEP)
	120 (Proposed Approaches)
UNs (Density Scenario)	50, 100, 150, 200, 250 (Meta-Heuristic)
	60, 120, 180, 240 (Proposed Approaches)
UVs	10
Max depth (General Scenario)	50 m
Max depth (UVs Relay Scenario)	70 m
Distances between UNs	10 m
Initial energy of UNs ($E_{i,UN}$)	5J (depth based SEP)
	400 J (Proposed Approaches)
Initial energy of UVs($E_{i,UV}$)	900 J
Tx/Rx energy (E_{elec})	55 nJ/bits
E_{mp}	0.0015 pJ/bit/ m^4
E_{DA}	6 nJ/bit/signal
E_{fs}	12 nJ/bit/m^2
d_o	10 m
Packet Size	512 Bytes
Tx frequency	200 KHz
ABC and GA Populations	50
ABC Cycles (limits)	5
Q-learning rate (α)	0.5
Q- discount factor (γ)	0.9
Q- exploration factor (ϵ)	0.2
QL episodes	50
NN hidden layer	15
GA crossover fraction	0.7
Fraction of the advanced UNs	0.5
Times more energy than normal UNs	1.5
Fraction of the advanced UNs	m=0.2, m=0.3
Times more energy than normal UNs	a=1.5, a =3
Max simulation iterations	2500 (Meta-Heuristic)
	5000 (proposed Approach)

The following points highlights the evaluation scenarios briefly.

- **Scenario 1:** The evaluation comparison of depth based SEP with standard SEP and modified SEP-IoUT.

- **Scenario 2:** Evaluates the performance of meta-heuristic approaches such as ACO, PSO, GA and ABC to electing the best CH in addition to the impact of QL optimization.

- **Scenario 3*:*** Evaluates the performance of proposed energy-aware stable election protocol optimized by ABC and QL approaches (ABCQL-EASE) compared with baseline approach and benchmarking.

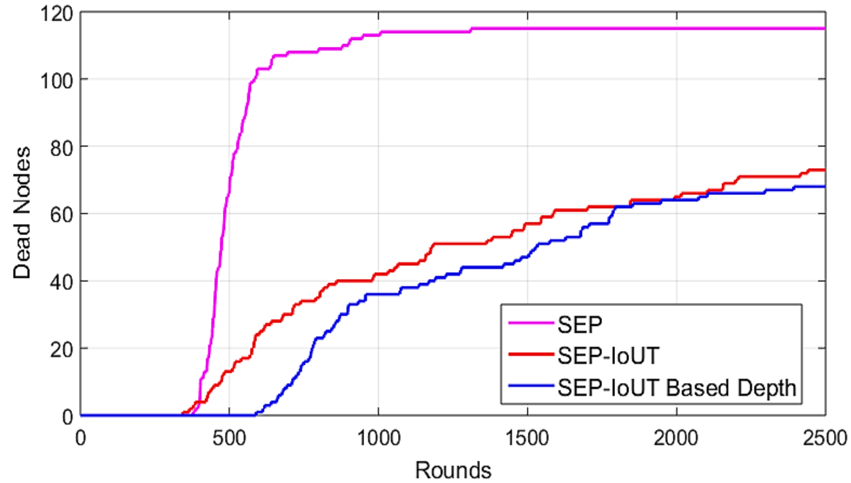
- **Scenario 4:** Evaluates the proposed energy-efficient QoS driven by UV relaying integrated stable election protocol (EQURI-SE).

For evaluating the proposed approaches compared to baseline, all simulation were runs repeated 30 times by Matlab2023a to simulate the proposed approaches with IoUT network consists UNs/UVs distributed randomly at the start of each simulation. In addition, to compare the proposed approaches they are runs 15 times by the related works setting to have benchmarking comparison.

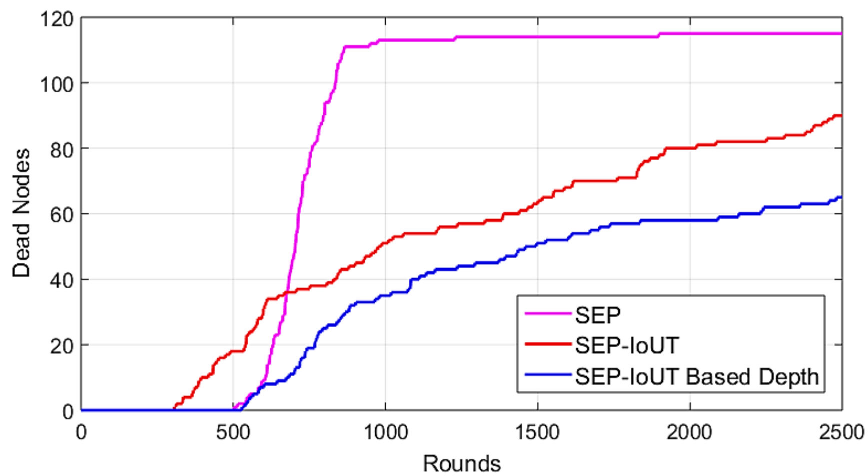
4.3 Performance of Depth based Stable Election Protocol

The performance results of proposed depth aware SEP highlighted as SEP-IoUT based depth are presented in this section, along with a comparison to conventional SEP and modified SEP-IoUT. With the results of counting the number of selected CHs and network efficiency, the performance is assessed using several performance metrics, including the network lifetime, throughput, residual energy, and CH overhead.

Figure 4.2 shows the performance comparison of depth based SEP-IoUT against standard SEP and SEP-IoUT with a variety of heterogeneous parameter cases. In Figure 4.2(a) the performance with m=0.3 and α = 1.5 show that the first dead UN dies for depth based SEP-IoUT at 569 rounds, while the other SEP-IoUT and SEP die in rounds 342 and 253 respectively. This indicates the depth based SEP-IoUT gives better performance. Furthermore, during rounds increases, the number of dead UNs are less when compared to SEP and SEP-IoUT. It's also observed that the standard SEP have a low lifetime and most of the UNs die quickly between rounds from 0 to 500 because it is not able to interact well with the underwater conditions and is frequently exhausting due to underwater channel modelling and parameters. However, the SEP-IoUT deals better reaming to keep UNs alive for a long time, and by taking the depth impact the network will enable maintain efficiently energy utilization.



(a) Dead UNs with parameters (m=0.3, α =1.5)



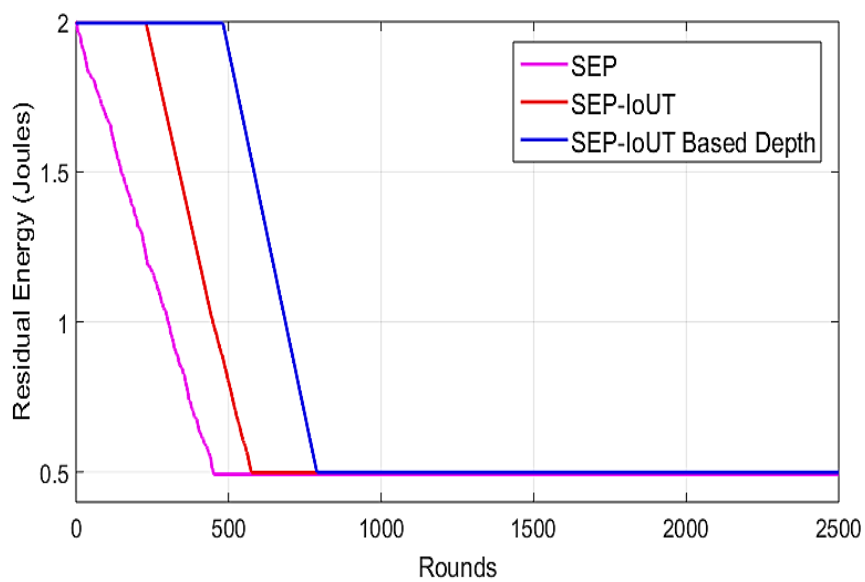
(b) Dead UNs with parameters (m=0.2, α =3)

Figure 4.2. Performance of Network lifetime (Underwater Dead UNs per Rounds)

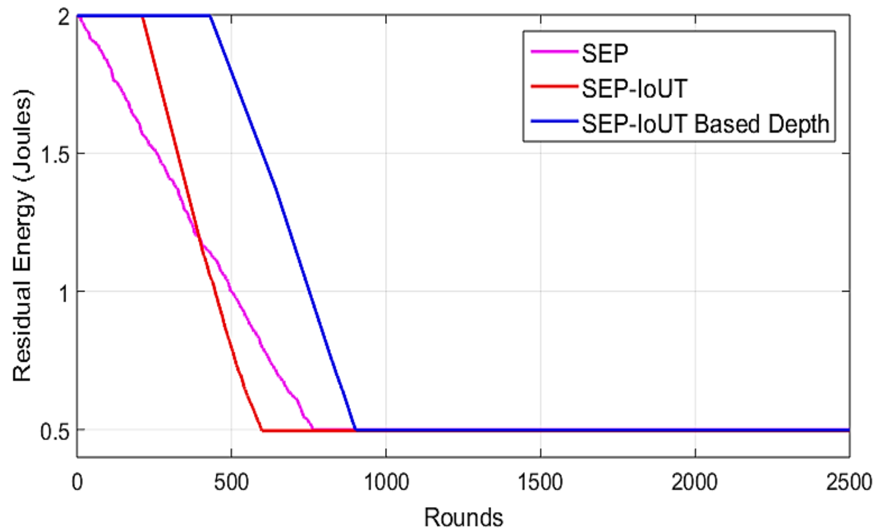
In Figure 4.2 (b), the heterogeneous parameters as m= 0.2 and α = 3 show that the first UN dies in standard SEP, SEP-IoUT and depth based SEP-IoUT at rounds 442, 298, and 551 respectively. It seems at first that, the SEP is better when the first dead UN dies later than in other SEP-IoUT and depth-based approach, this is because with parameter α =3 more advanced UNs will be considered to act as a CHs remains quick dead UN at early rounds. This means that the increase in α value will let more UNs with higher energy levels be selected as CHs. However, during rounds increased, the SEP-IoUT and depth-based approach maintain the energy balancing because they dynamically replace the CHs based on the UNs residual energy and network average energy makes the network stably consume the energy. At rounds more than 1000 rounds, the depth based SEP-IoUT gives better performance than the others, which indicates it has the best lifetime with a stability period. The depth based SEP-IoUT has a stability period of 25% and 14.2% better than SEP and SEP-IoUT repressively.

Figure 4.3 show that depth based SEP-IoUT has a larger total residual energy by alive CHs than the other protocols. This indicates that with depth based SEP-IoUT the network can continue to operate for a longer period because of more balanced the CH residual energy. UNs with higher energy can be chosen as CHs more frequently than UNs with lower energy taking into account the depth of the selected CHs. This is because, CHs with higher energy and appropriate depths are favored to leading to more even distribution of energy-consuming roles.

The depth based SEP-IoUT with greater residual energy indicate that they can balance the distribution of energy between CHs and contribute to a longer network lifetime. Therefore, the IoUT network can operate for longer periods without suffering from high energy consumption or UNs/CHs failures. The protocol optimizes CH selection by taking depth, energy levels and distance from SBS into account. As a result, the network becomes more efficient because the CHs are selected from UNs that can interact more effectively at their various depths.



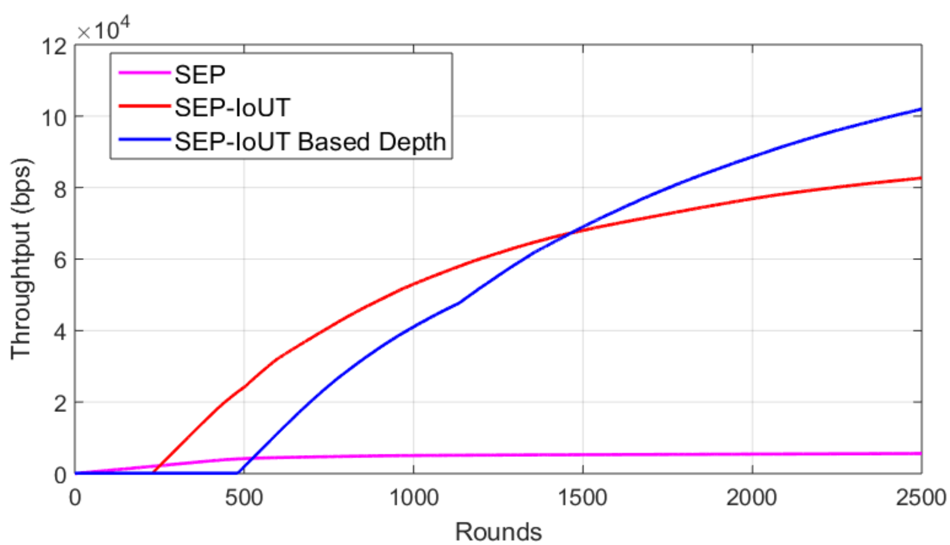
(a) RE with parameters (m=0.3, α =1.5)



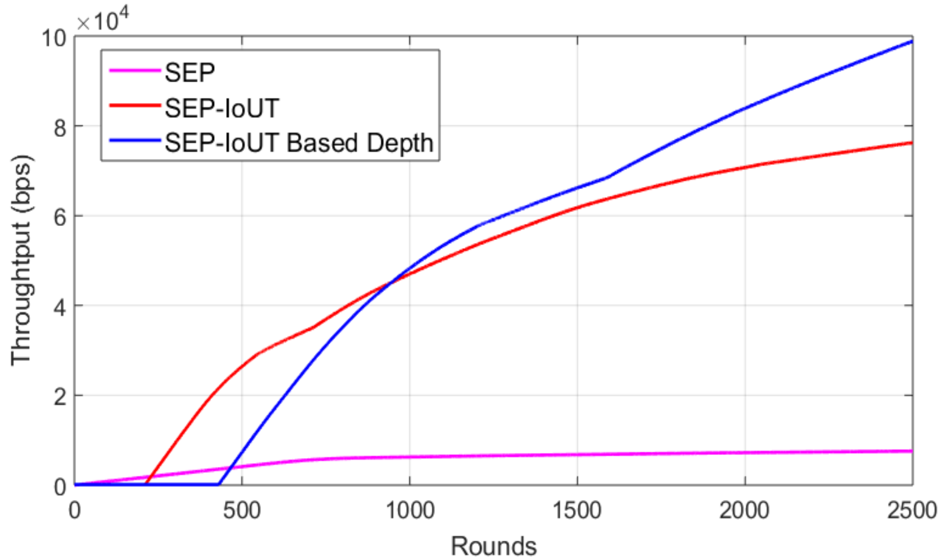
(b) RE with parameters (m=0.2, α =3)

Figure 4.3. Average CHs Residual Energy per Rounds

From the Figure 4.4, it's observed that depth based SEP-IoUT gives higher throughput when compared to other protocols. With heterogeneity parameters consideration, the standard SEP and SEP-IoUT at round 2500 shows 89.4% and 15.73% decrease in average throughput respectively compared with depth-based SEP when the ratio of advanced UNs is α =1.5. When the α ratio increased to 3, their average throughput decreased by by 87.5% and 12.5%, respectively. According to these results, depth based SEP-IoUT adopts more logical CH selection mechanism and the UNs have a longer survival duration. Its enable to aggregate more data than other protocols.



(a) Throughput with parameters (m=0.3, α =1.5)



(b) Throughput with parameters (m=0.2, α =3)

Figure 4.4. Network Throughput in Proportion to Rounds

4.4 Performance of Meta-Heuristics with QL Optimization for CH Selection

This section discusses the performance of different meta-heuristic approaches to enhance the CH selection process. Then the best approach is evaluated after optimized by QL approach. The evaluation is taken under IoUT network with 80 UNs as a general scenario, and with different UNs dense with max iterations of 1000 to provide a comparative of how each optimization approach performs regarding CH selection.

Figure 4.5 shows that ABC frequently outperform other methods when managing cluster sizes. Comparatively to PSO, ABC tends to choose fewer CHs. This cautious method of choosing a CH fits well with desire to prevent intense intra-cluster communication when many CHs are selected. The possibility of congestion within clusters can be decreased with smaller clusters making ABC a preferable option for this particular requirement. PSO may outperform ABC in terms of mean selection performance. However, ABC consistently achieves a modest performance that is frequently adequate for real-world network operation. ABC focuses on balancing between controlled cluster sizes and network performance. It aims to provide a stable and reliable network compared to PSO's potentially higher but less controlled performance.

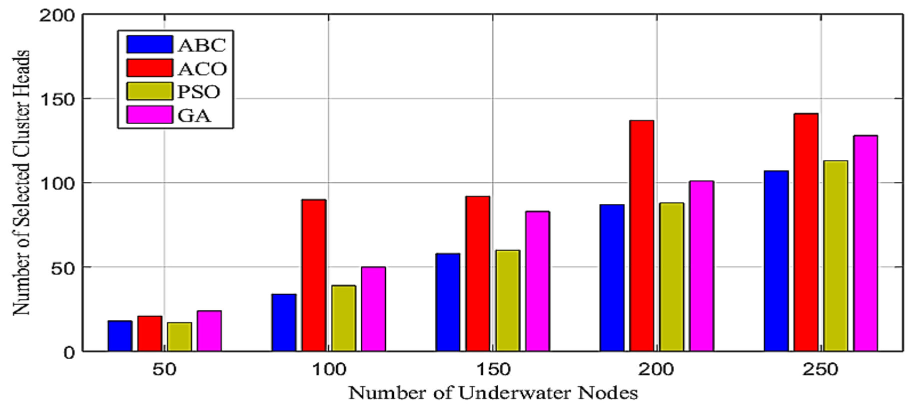


Figure 4.5. Performance of Swarm Algorithms for Selecting CHs

Additionally, ABC is known for being reliable and performing well across iterations. Network stability is essential for reliable communication to continue in unexpected underwater environments. The network's stability in performance is a result of ABC which kept operational even in the worst-case scenarios due to ABC's reasonable minimum performance level maintenance. This dependability is crucial for mission-critical applications since network outages or performance deterioration might have negative effects.

Figure 4.6 shows the performance in terms of the number of best selected CH. The results show that the ABC-QL selects a higher number of best CHs compared to ABC in low iterations. The ABC-QL selects approximately 17.5 % of the total number of UNs at early iterations from 200 to 400 serve as CH according to adjusted selection parameters. However, it remains low in higher iterations according to optimization in selecting the CH with a stable clustering size. At later iterations, its select approx. 13.5 % in a high iteration with 1000 after QL optimization which means it has fine-tuned to select the best balance between exploration and exploitation.

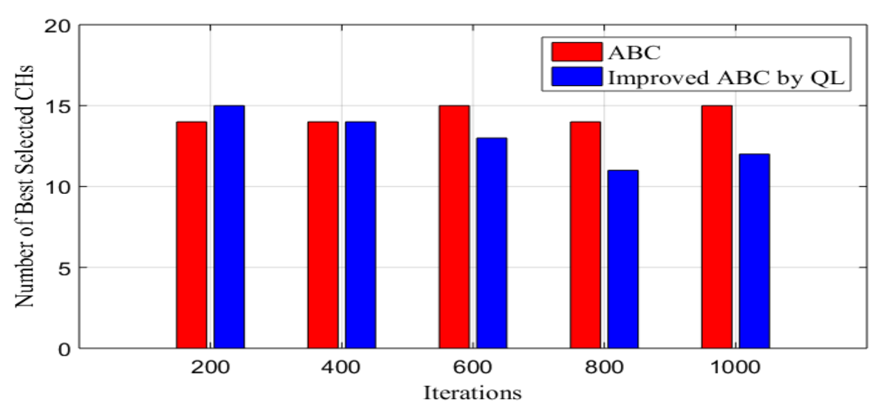


Figure 4.6. Performance of Hybrid ABC-QL vs. ABC on CH Selection Process

The QL enables adjusting the exploration and exploitation parameters based on the UN state. It also helps to explore a broader solution space early in the process to identify potential CHs while exploiting promising solutions and convergence quickly. This indicates that ABC-QL offer better coverage or more efficient CH selection, potentially improving network performance. According to these metrics, ABC-QL enables maintenance of a better average best selection cost lower than conventional ABC, which can benefit energy efficient CH selection.

Figure 4.7 shows the efficiency of the improved ABC-QL algorithm in terms of the dead UNs. The results show that the ABC-QL outperforms the conventional ABC by having significantly fewer average dead UNs by 18.5 % than Dead UNs by ABC in the initial iterations from 200 to 600. This show that a more stable network setup was initially attained via ABC-QL. While the ABC-QL continues to improve slightly, the ABC performed marginally better with fewer dead UNs through iterations up to 600. ABC-QL reduced the number of exhausted UNs iteration 1000 by 27.3 %, respectively.

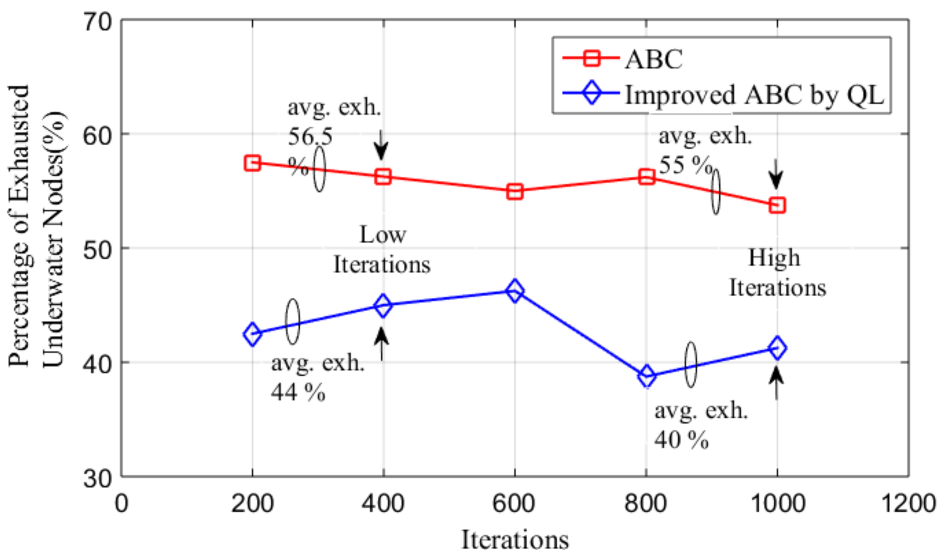


Figure 4.7. Number of Dead Nodes for Hybrid ABC-QL vs. ABC

These results show that ABC-QL performed better regarding the number of dead UNs in the initial iterations, show its ability to construct a more stable network configuration. According to the results, ABC-QL gives more advantages in configuring a stable IoUT network. It focused on early iterations while adjusting algorithm parameters by incorporating heuristics and prioritizing stability in the initial stages and become more stable in more iterations.

4.4.1 Impact of UNs Density

Figure 4.8 shows the percentage of dead UNs, which indicates the number of dead UNs concerning network size for both ABC-QL and ABC. Both approaches shows an increase in dead UNs as the network size grows. However, ABC-QL consistently shows fewer dead UNs over various network sizes than ABC. This indicates that ABC-QL tends to deliver a more optimized CH selection, resulting in a more stable network with fewer dead UNs. As the network size grows, the ABC-QL continues to perform better than ABC by 20.4% reduction in dead UNs.

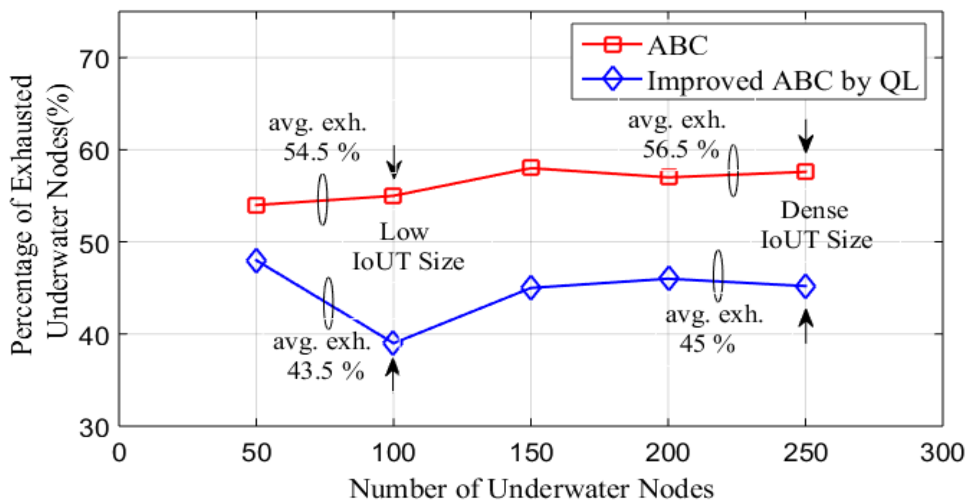


Figure 4.8. Performance UNs Lifetime Based on Network Size Variation

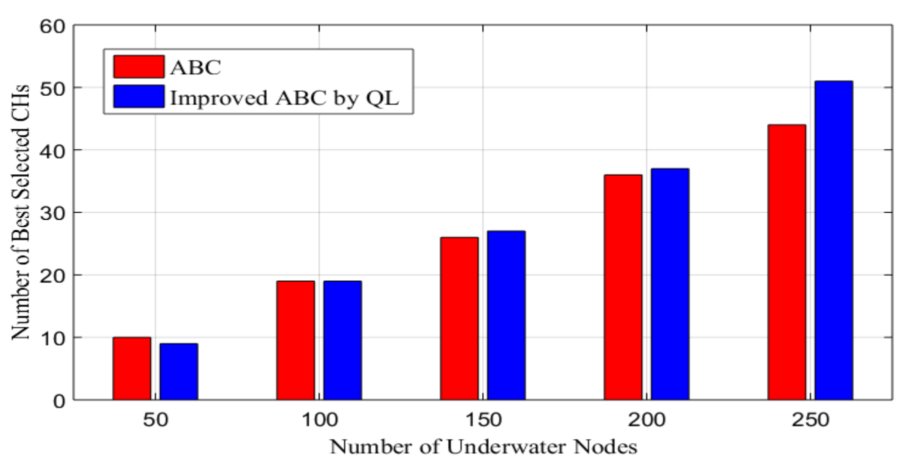


Figure 4.9. Performance of CH Selection Process Based on Network Size Variation

As in Figure 4.9, the number of best CH increases for both approaches as the network size grows. ABC-QL gives lower number of best CH compared to ABC with low UN dense. This because ABC-QL is more sensitive when selecting CHs, concentrating on the most stable UNs to be the best CHs. When the UNs increased, it selects more CHs to balancing the clustering size.

The improvement in ABC-QL's selectivity is due to the QL. The QL enable to learn and modify the CH selection process taking into account previous UNs experiences and the state of the network. As a result of best selection, CHs are distributed more optimally, potentially enhancing network efficiency and stability while reducing the unwanted increase in the number of selected CHs.

The use of QL approach allows to learn from previous iterations and make more informed CH selection decisions. It focuses on UNs that contribute the most to network performance and gives the proposed algorithm the capacity to change its CH selection method depending on historical data and network conditions resulting in a more optimal CH distribution. This selective strategy may result in improved network stability and efficiency because it reduces the number of selected CHs while maintaining a strong network.

4.4.2 Key Insights and Performance Highlights

The results shows the effectiveness of integrating QL with the ABC for CH selection. ABC-QL achieves more energy-aware CH selection, which directly translates into fewer dead UNs compared to standard ABC. In temporal evaluation over iterations, ABC-QL reduces the percentage of exhausted UNs by 18.5% during early rounds average over iterations 200 to 600 and by 27.3% at iteration 800 to 1000, indicating faster stabilization and better energy distribution. Although both protocols converge toward similar exhaustion levels by iteration 1000, ABC-QL maintains a consistent advantage in network longevity. More importantly, under increasing network density from 50 to 250 UNs, ABC-QL shows superior scalability. At the largest scale it reduces UNs exhaustion from 56.5% by ABC to 45.0% by ABC-QL. This confirms that ABC-QL’s adaptive CH selection mechanism preserves UN energy more effectively in dense IoUT deployments, thereby enhancing network connectivity, reliability, and operational lifetime.

- **Key Insight 1:** Faster Network stabilization by adaptive learning

ABC-QL achieves superior early-stage performance. When network topology is most volatile, it reduces the percentage of exhausted UNs which indicating rapid convergence toward stable clustering. By more iterations it reflecting QL’s ability to learn optimal CH policies and avoid premature energy depletion in critical nodes.

- **Key Insight 2:** Proven scalability in dense networks

ABC-QL demonstrates robust scalability under increasing network density. As the number of UNs grows from 50 to 250 the algorithm adapts its CH selection strategy to prevent overload in dense regions. This confirms that ABC-QL's learning-driven mechanism effectively balances load distribution even in highly congested environments.

These results validate that ABC-QL is provides incremental improvement and shift in CH selection for resource-constrained underwater networks. By fusing global search of ABC with local policy of QL it achieves a self-optimizing clustering framework that enhances network connectivity, reliability, and operational lifetime.

4.5 Performance Evaluation of Energy Aware Stable Election Protocol

This subsection is evaluates the proposed ABCQL-EASE with developed step by step baseline approaches driven from depth based SEP protocol, and also evaluated with related works as benchmark. The simulation results are obtained after evaluating the proposed approach in different scenarios as follows.

- The proposed ABCQL-EASE is evaluated compared to baseline approaches are ABC-SE, ABC-EB and ABCQL-SE during optimization as a general case scenario with 120 UNs and with different UNs as 60, 120, 180, and 240 as a UNs dense scenario.
- Evaluate the exploration and learning rates of a QL optimization and their impact on the performance of the ABCQL-EASE protocol in the IoUT network.
- Compare the performance of the proposed ABCQL-EASE protocol with baseline and benchmark approaches proposed by (Sathish et al., 2025)(Tian et al., 2024)(Çiğdem et al., 2024)(Kaveripakam et al., 2023)(Usman et al., 2020).

4.5.1 General Case

The proposed protocol in this case was evaluated with 120 UNs in various iterations ranging from 0 to 5000. The performance of ABCQL-EASE in comparison to other baseline approaches in terms of network lifetime and energy efficiency. In addition, the proposed ABCQL-EASE performance is evaluated in comparison to some existing protocols. These protocols are improved LEACH, EEUMC, EBREC, K-means RL, and SEP-ACH², TEEN-ACH², DEEC-ACH² approaches.

A. **Network Lifetime**

As shown in Figure 4.10 the ABCQL-EASE is the most successful compared to other baseline approaches, reduces the number of dead UNs during simulation rounds. The high performance of ABCQL-EASE is a result of combined optimization methodology for adaptive CHs selection and replacement by QL in addition to effective inter-cluster routing based on the integration of QL with MCDM. ABC-SE and ABC-EB show limits when they relate to the network lifetime and ABCQL-SE performs better because of adaptive optimization.

According to Table 4.2 the ABC-SE performs moderately in the early rounds with a steady rise in dead UNs. However, as rounds increase, it becomes unable to adjust to network dynamics, which results in a rapid increase in average dead UNs. After 3000 rounds, it shows the weakest performance, with the highest average dead UNs up to 20. In the early rounds, ABC-EB outperforms ABC-SE by a small margin due to its energy balancing technique, which results in 108 average alive UNs as opposed to 100 average alive UNs for ABC-SE. Both ABCQL-SE and ABC-EB give a close number of dead UNs before 4000 rounds then ABCQL-SE reduces the dead UNs, however, they are unable to maintain these advantages over time, and the number of dead UNs increases rapidly compared to ABCQL-EASE.

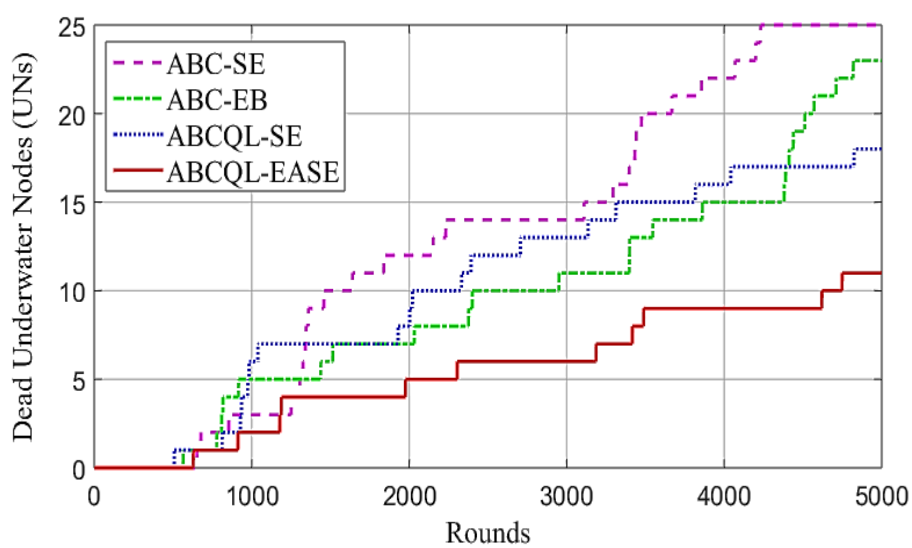


Figure 4.10. Performance of ABCQL-EASE in Terms of Dead UNs

Due to dynamically adjusting CH selection and replacement, the ABCQL-SE performs better by reducing the rate of average UN deaths with 12 dead UNs. However, the inter-cluster route is not optimized, which limits its performance over the long term. ABCQL-EASE performs noticeably better than other approaches gives fewest dead UNs are up to 4 and the most average alive UNs are up to 114. This because the inter-cluster routing process was optimized using MCDM and QL which minimizes energy consumption and reduces dead UNs by dynamically adapting to the network status. Better energy efficiency and stability throughout the IoUT network lifetime are ensured by the simultaneous optimization of CH selection, replacement and inter-cluster routing decision.

Table 4.2. ABCQL-EASE Average Dead UNs and CH Management

Algorithms	Normal Dead UNs	CH Replacement
ABC-SE	20	38
ABC-EB	12	36
ABCQL-SE	12	37
ABCQL-EASE	4	34

The performance of the proposed protocol concerning CH replacement events is shown in Table 4.2. ABCQL-EASE performs the most efficiently and fairly. It's able to efficiently find best CHs and replaced by the 34 which is close to the highest value seen with ABC-EB. Furthermore, with just 34 CH replacement events, ABCQL-EASE has the fewest network conflicts and the highest operating stability. A lower frequency of CH replacement events in ABCQL-EASE indicates that the selected CHs have a longer lifetime, which lowers energy overhead and enhances network performance. This excellent performance achieved because of the integration of adaptive decision-making by QL and MCDM techniques with ABC. The algorithm selects stable CHs, minimize replacement events, manage energy resources efficiently, and optimize the inter-cluster routing process.

Compared to related works, Figure 4.11 shows the percentage of dead UNs across all evaluated approaches, normalized to reflect relative network longevity. The results shows clear trade-off between energy efficiency and network lifetime. Protocols that prioritize aggressive data transmission such as SEP-ACH², TEEN-ACH² and DEEC-ACH² shows significantly higher UNs death rates between 84.43% and 100.00% indicating rapid depletion of energy resources due to frequent CH selection and high communication overhead. In contrast, protocols like EEUMC, K-means RL and Improved LEACH achieve moderate Dead UNs percentages between 14.37% to 37.13% by minimizing UNs participation and prolonging individual lifetimes, that at the cost of reduced throughput. Notably, EBREC shows a relatively high UNs death rate despite moderate throughput shows inefficient energy allocation.

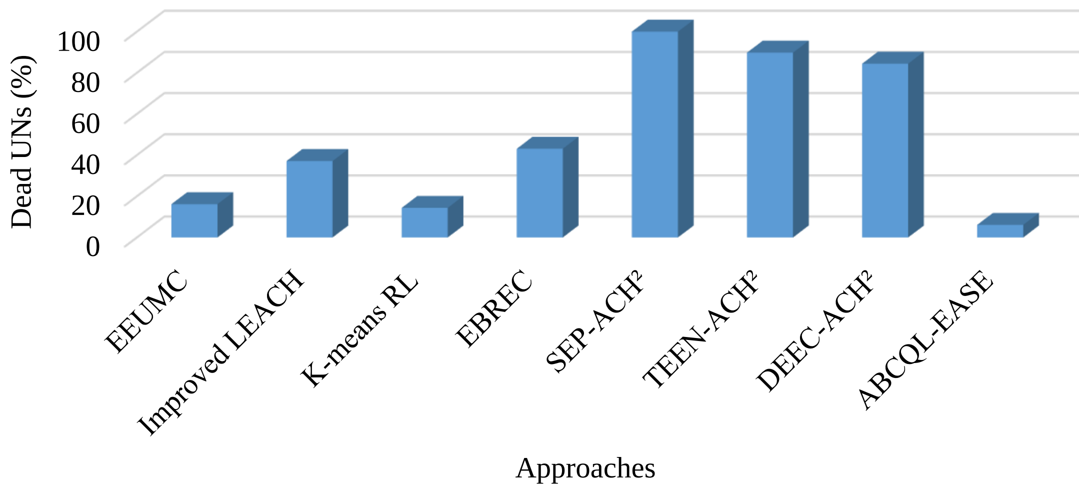


Figure 4.11. Dead UNs of ABCQL-EASE vs. Benchmark Studies

The proposed ABCQL-EASE approach achieves the lowest Dead UNs percentage shows superior network longevity. This outcome stems from its QL-based clustering mechanism, which dynamically manage the optimal CHs based on residual energy, distance, depth and network load. Thereby preventing premature UNs exhaustion and ensuring balanced energy consumption across the network. By intelligently adapting to changing conditions in ABCQL-EASE it avoids the overuse of critical UNs observed in baseline methods reflect its ability to more sustainable and resilient network topology.

The results show that the ABCQL-EASE able to provides an efficient energy-aware stable dynamic CH management. The hybrid ABC-QL method detects dead UNs and CH replacement before total failure by continuously monitoring residual energy levels and network stability parameters. Moreover, using MCDM-based next-hop selection together with multi-hop inter-cluster routing ensures stability in forwarding paths. Neighboring CHs are dynamically evaluated using QoS parameters like signal quality, depth, and mobility. The QL agent then selects a best link. Because mobility and connection stability are specifically identified as state variables in the QL module, ABCQL-EASE reduces the effects of excessive mobility through real-time state updates. The Q-agent monitors new states as CH positions change and modifies actions for route selection and replacement appropriately, ensuring that choices take into account the dynamics of the network at the time.

B. **Energy and Network Efficiency**

Figure 4.12 compares ABCQL-EASE's energy consumption patterns to other baseline approaches. Its highlights the average residual energy by alive CHs. ABCQL-EASE provides greatest average CHs residual energy shows the most gradual reduction in residual energy. This indicates better CHs energy management which is explained by its sophisticated CH replacement and selection methods that combine energy-aware stability upgrades and QL. ABCQL-EASE reduce the energy consumption compared to ABCQL-SE's and non-QL protocols such as ABC-SE and ABC-EB highlighting the contribution of QL and MCDM to increased energy efficiency. QL makes dynamic optimization possible by adaptively selecting CHs according to real-time network status, including distance, motion, signal quality, residual energy, and depth. This approach reduce energy overhead and improves network stability by ensure that CH replacements are only carried out when required.

While ABCQL-EASE and ABCQL-SE both use QL, ABCQL-EASE provides extra advantages due to the addition of energy-aware stability upgrades. Through the use of MCDM with QL, the energy-aware stability enhancements mechanism ensures that CHs stay operational for extended periods of time with multi-hop inter-cluster routing and that replacements are carried out in an energy-efficient manner. This is based on QoS network dynamic evaluation, and due to this fewer CH will be replaced during routing and provides more reliable energy savings.

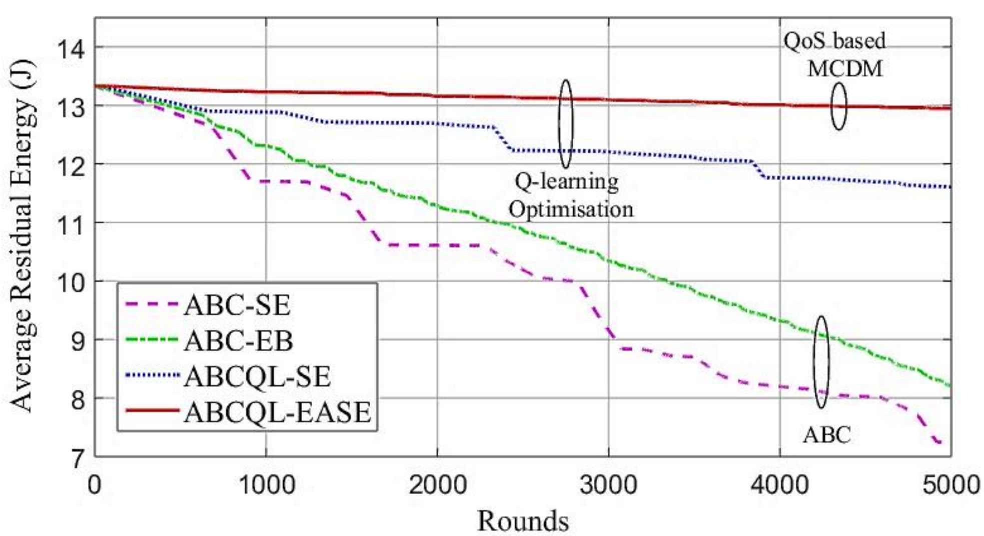


Figure 4.12. Performance of CHs Average Residual Energy by ABCQL-EASE Vs. Baseline Approaches

Table 4.3. Performance Evaluation of ABCQL-EASE in Terms of Total Energy Consumption, and Network Efficiency

Algorithms	Total Energy Consumption (J)	Efficiency (%)
ABC-SE	154.12	89.82
ABC-EB	114.04	93.72
ABCQL-SE	113.80	93.61
ABCQL-EASE	57.49	95.95

In terms of network energy consumption and network efficiency Table 4.3 compares ABCQL-EASE's performance to that of other baseline approaches. A significant improvement in energy efficiency is shown by the ABCQL-EASE algorithm which has the lowest energy consumption at 57.49 J. Its adaptive QL and energy-aware processes efficiently optimize CH selection and replacement while reducing the energy expenses. ABC-SE uses the highest amount of energy indicating inefficiencies resulting on by its static and non-adaptive CH management strategy. A moderate improvement is provided by ABC-EB at 114.04 J and by ABCQL-SE at 113.80 J. While ABCQL-SE is more appropriate than ABC-SE and ABC-EB due to its QL optimization capabilities, however, ABCQL-EASE outperforms all algorithms.

Efficiency measures a protocol's ability to make efficient use of resources while fulfilling its operational objectives. With an efficiency of 95.95% the results show ABCQL-EASE performs better than the other approaches highlighting its superior architecture in achieving a balance between reliable network operation and energy consumption. With an efficiency of 93.72%, ABC-EB and ABCQL-SE at 93.61% show improvements in CH selection more than ABC-SE. ABCQL-EASE trades off QoS with energy efficiency and network lifetime, and this trade-off can be justified when energy constraints are a dominant factor, as is often the case in IoUT networks.

Figure 4.13 presents the normalized percentage of energy consumption across selected approaches which shows their relative efficiency in resource utilization. The results shows a significant disparity in energy management strategies. Improved LEACH shows the highest energy consumption which indicating excessive overhead due to frequent cluster formation, inefficient routing and unbalanced load distribution which leads to rapid depletion of UNs energy and network failure. In contrast, EEUMC and EBREC achieve moderate energy consumption levels between 25 and 30%, reflecting their design focus on energy-aware clustering and reduced communication costs, though they fall short in balancing throughput and longevity.

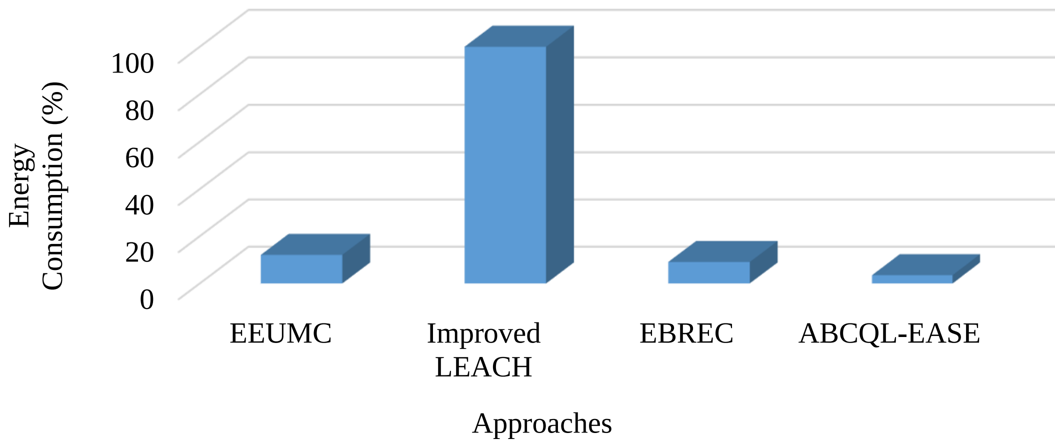


Figure 4.13. Energy Consumption of ABCQL-EASE Vs. Benchmark Studies

The proposed ABCQL-EASE approach achieves the lowest energy consumption demonstrating exceptional energy efficiency. This outcome is attributed to its adaptive QL-based mechanism with ABC and QoS driven approach by MCDM, which dynamically optimizes CH management and inter-cluster route decision. By intelligently distributing the communication load and avoiding overuse of high-energy UNs ABCQL-EASE ensures balanced energy dissipation across the network. Thereby it extending overall network lifetime. The high reduction in energy consumption compared to Improved LEACH ensures the effectiveness of QL in enabling intelligent and context-aware decision-making, making ABCQL-EASE a highly efficient solution for large-scale wireless sensor networks.

4.5.2 Underwater Nodes Density

The density of the UNs determines how well the proposed protocol performs in this situation. Results show how the performance of the ABCQL-EASE is impacted by additional UNs. The impact of different network sizes on the IoUT network model is evaluated by varying the simulated IoUT network scenarios from 60 to 240 UNs.

A. Network Lifetime

Figure 4.14 shows the total number of dead UNs for all approaches at different network sizes ranging from 60 to 240 UNs. All approaches gives close performance at small network sizes. However, the ABCQL-EASE approach performs significantly better than the others because of its energy-aware methodology. ABC-SEP starts to show increased UNs death as the network grows to 120 UNs due to its static optimization, whereas ABC-EB and ABCQL-SE better manage energy through stability and balancing energy methods. By dynamically adjusting energy consumption and inter-cluster routing the developed ABCQL-EASE approach proves to be the most efficient.

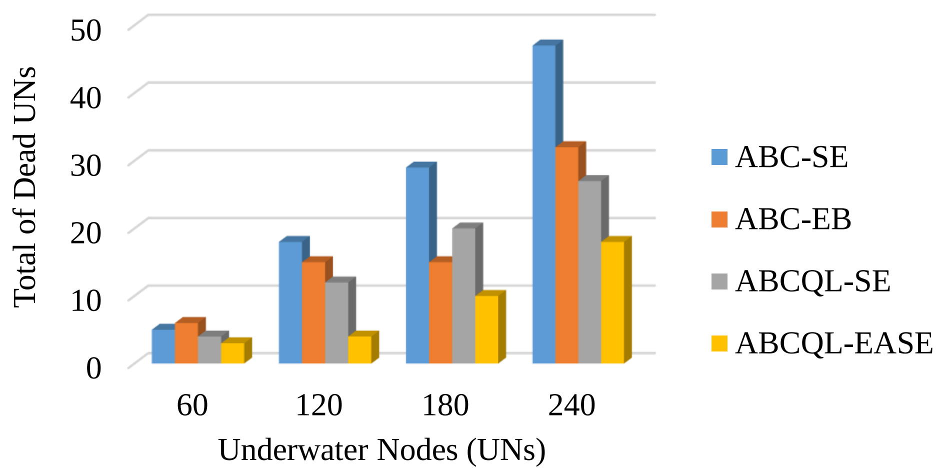


Figure 4.14. ABCQL-EASE in Total Dead UNs in Different Network Dense

The developed approach sustains the lowest UNs death rate by effectively use QL and MCDM for adaptive energy management. This ensures effective resource utilization particularly in massive networks. Overall, results show that developed approach is the most energy-efficient and scalable solution which overcoming the less adaptive and static options in IoUT networks.

Table 4.4. Lifetime Performance of ABCQL-EASE with Different IoUT Network Size

Network Lifetime	Total UNs	ABC-SE	ABC-EB	ABCQL-SE	ABCQL-EASE
Dead UNs	60	5	6	4	3
	120	20	12	12	4
	180	29	15	20	10
	240	47	32	27	18
Alive UNs	60	55	54	56	57
	120	100	108	107	116
	180	151	165	160	170
	240	193	208	213	222

According to the previous discussion and Table 4.4 the results highlight ABCQL-EASE approach has better performance in preserving network sustainability and extending network lifetime. ABC-SEP shows the highest number of UN deaths with the increase of UNs to 140 gives 47 Dead UNs out of 193 alive due to its static nature also ABC-EB provides moderate improvements by using energy balancing with 208 alive UNs. ABCQL-SE further improves by keeping 213 alive UNs at the dense network size by utilizing QL for increased stability in CH management. The ABCQL-EASE approach gives high performance because it dynamically combines MCDM and QL to optimize energy usage and provide adaptive CH management and consistently showing the greatest outcomes. The scalability and effectiveness of ABCQL-EASE are because of ability to managing energy constraints and network dynamics are shown by the fact that at 240 UNs it maintains 222 alive UNs and the lowest dead of 18 UNs. These results highlight how ABCQL-EASE greatly improves network lifetime and stability in addition to maximizing throughput especially in large-scale IoUT networks.

B. Energy Consumption and Network Efficiency

Figure 4.15 shows how each protocol controls energy efficiency for varying UN densities. The energy consumption of ABC-SEP is highest, and as network density rises, its works inefficiently in the selection and replacement of CHs. Although ABC-EB is slightly more energy efficient than ABC-SEP, it performs less well in complex network scenarios due to a gradual increase in energy consumption as UN density rises. ABCQL-SE shows better energy management since QL is used which improves CH management decision-making. Nevertheless, because inter-cluster routing optimization is not present in ABCQL-SE its energy consumption continues to rise with UN density.

The most energy-efficient method is in developed approach, which consistently uses the least amount of energy among all UN densities. Because QL and MCDM work together energy-aware CH management during the inter-cluster routing process and effective resource utilization even in high-density scenarios are made possible resulting in this higher performance. These outcomes confirm that developed approach superiority in lowering energy consumption while maintaining reliable performance in changing underwater conditions.

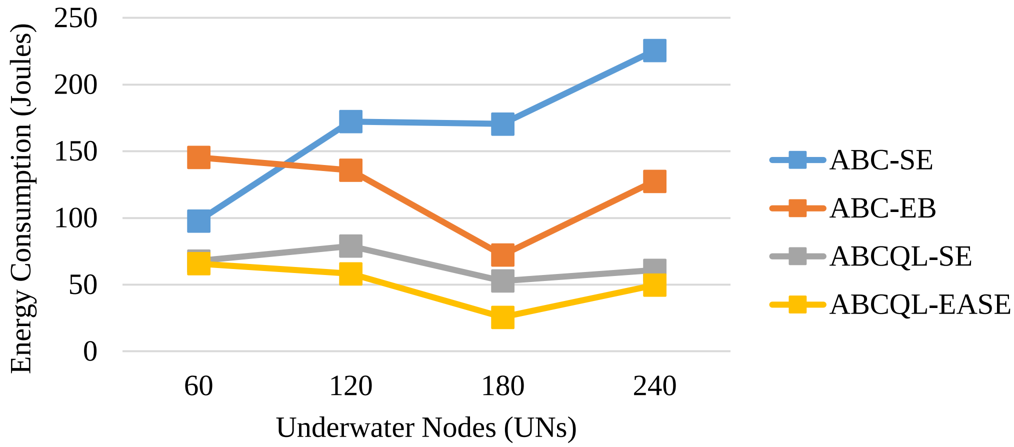


Figure 4.15. Impact of Different UNs on Energy Consumption by ABCQL-EASE

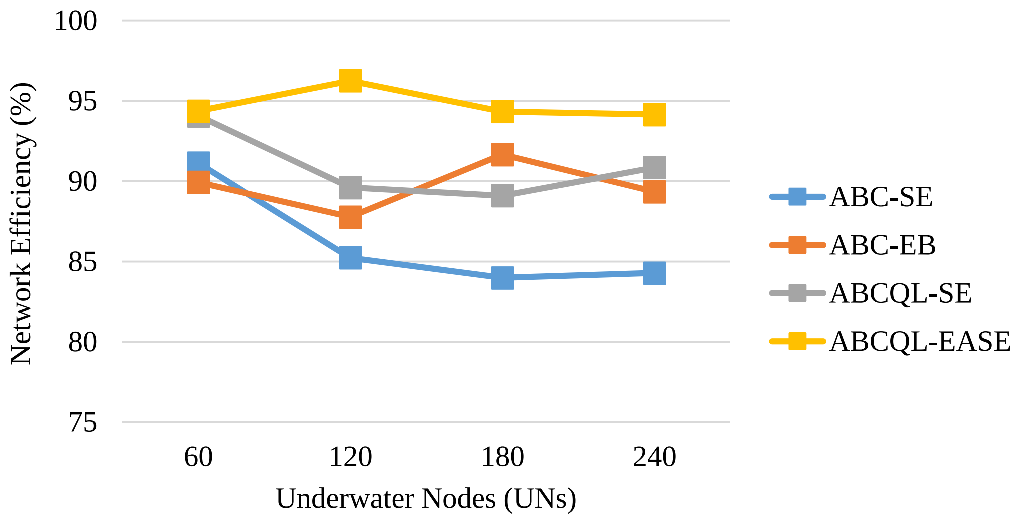


Figure 4.16. Impact of Different UNs on Network Efficiency by ABCQL-EASE

Network efficiency for the ABC-SEP, ABC-EB, ABCQL-SE, and ABCQL-EASE approach across different numbers of UNs are shown in Figure 4.16. Across all UN densities, ABCQL-EASE approach continuously exceeds the other approaches in terms of network efficiency, maintaining an efficiency above 95%. This stability shows how well the proposed approaches optimize CH management while reducing the consumption of energy. Particularly at lower UN densities ABCQL-SE performs competitively with efficiency stabilizing below developed approach. As the network grows ABC-SEP shows an obvious decline in efficiency highlighting its inability to sustain strong performance in denser IoUT networks. While maintaining a somewhat greater efficiency and showing an improvement in energy balance, ABC-EB has a similar performance to ABC-SEP.

4.6 Performance Evaluation of UVs Relay

This subsection evaluates the use of optimum UVs relay to optimize the inter-cluster communication in the developed ABCQL-EASE protocol. The evaluation is given in two scenarios, first evaluates the impacts of using UVs as relay in ABCQL-EASE, and the second scenario is evaluated the integrated UVs relay based approach as a EQURI-SE protocol with different baseline approaches.

4.6.1 Impact of UVs Relay

The network was deployed with 120 static UNs. A hybrid model combining the depth based SEP with QL, ABC and MCDM-based routing was implemented as a baseline approach. UVs acted as mobile relays, selected based on their distance, depth, signal quality, and residual energy. The NN and GA were trained on 500 sample to optimize relay selection. Each simulation ran for up to 5000 iterations to ensure convergence and stable performance metrics.

Table 4.5. Performance of UV Relay Based Protocol vs. Non Relay Based Protocol

Approach	Dead UNs	Network Efficiency (%)
Non – Relay Scheme	9	92
2 UVs	7	93
3 UVs	7	94
4 UVs	5	95
5 UVs	6	94
6 UVs	7	93

After simulating the proposed approach, table 4.5 show how well the proposed UV-relayed IoUT scheme is able to lower CH consumption by switching long-distance transmissions to mobile UVs. Nine dead UNs with 92% efficiency are shown applying the baseline approach as non-relay scheme. The configuration with 4 UVs gives 95% efficiency. It also reduces the number of dead UNs to 5 which is a 20.7% improvement. This shows that UVs that reduce transmission costs and distribute the communication load throughout the network, improving the operational lifetime of CHs and saving their residual energy.

With the 4-UV architecture, the network efficiency which is measured as the ratio of live UNs to total UNs over time gives 95%, whereas the baseline models is 92%. This approximately 2% improvement highlights how the proposed relaying approach can balance energy consumption and connectivity to increase network lifetime since the advantages of more relays are mitigated by higher coordination overhead and possible redundancy, the efficiency reduced at 5 and 6 UVs shows that having more relays does not always gives high performance.

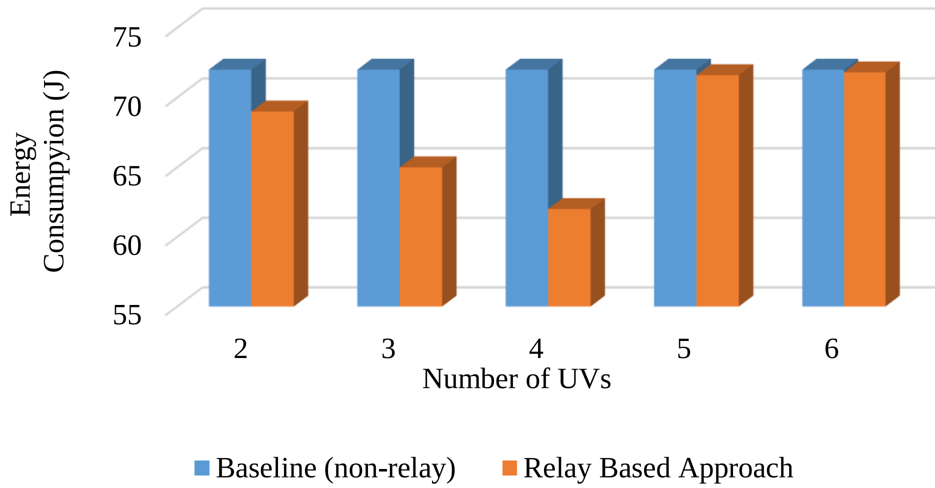


Figure 4.17. Energy Consumption of UVs relay vs. Baseline Approach

Figure 4.17 shows that the configuration with 4 UVs uses the least amount of energy by 61.91 J, which is 14.1% less than the baseline that gives 72.08 J. This ideal performance is due to the hybrid NN-GA-MCDM framework, which efficiently selects UVs that balance the communication load throughout the network and reduce transmission costs, thus increasing the operational lifetime of and saving UNs/CHs residual energy.

In final analysis, UVs' role in inter-cluster communication shows that they only serve as mobile relays connecting CHs and the SBS. This approach ensures reliable intra-cluster communication, reduces network overhead and control complexity and avoids inefficient handoffs caused on by UV mobility. The highest performance at 4 UVs shows that UVs as relays are able to locate strategically placed, energy-efficient UVs that reduce network energy consumption. UVs are strategically positioned according to residual energy, depth, signal quality and proximity to CHs/SBS. This ensures that relays are chosen in the best possible way which improving network performance overall.

4.6.2 Integrated Energy-Aware Protocol

The proposed EQURI-SE is evaluated compared with ABCQL-EASE and other baselines approaches. The total number of UVs are 10. The best selected UVs served as relay are 4 and 5 UVs during all runs according to the simulation results.

Figure 4.18 shows the performance comparison of the EQURI-SE protocol in terms of the number of UNs showing the cumulative number of dead nodes over 5000 simulation rounds as representing the high energy efficiency and longevity of the network. The figure shows that the EQURI-SE protocol highlights an extremely slow death rate, maintaining less than 20 dead UNs even at around 4000, and reaching only around 18 dead UNs by round 5000. All other protocols have higher death rates. The standard DEECP and Depth-Based-DEECP protocol reaches 120 dead UNs before round 1000, while the standard-SEP protocol sees an increase in dead UNs after round 3500, eventually reaching over 110 dead UNs by round 5000. The developed ABCQL-EASE protocol shows a higher death rate than EQURI-SE, and stabilizing at around 20 dead UNs, but with a higher rate than EQURI-SE.

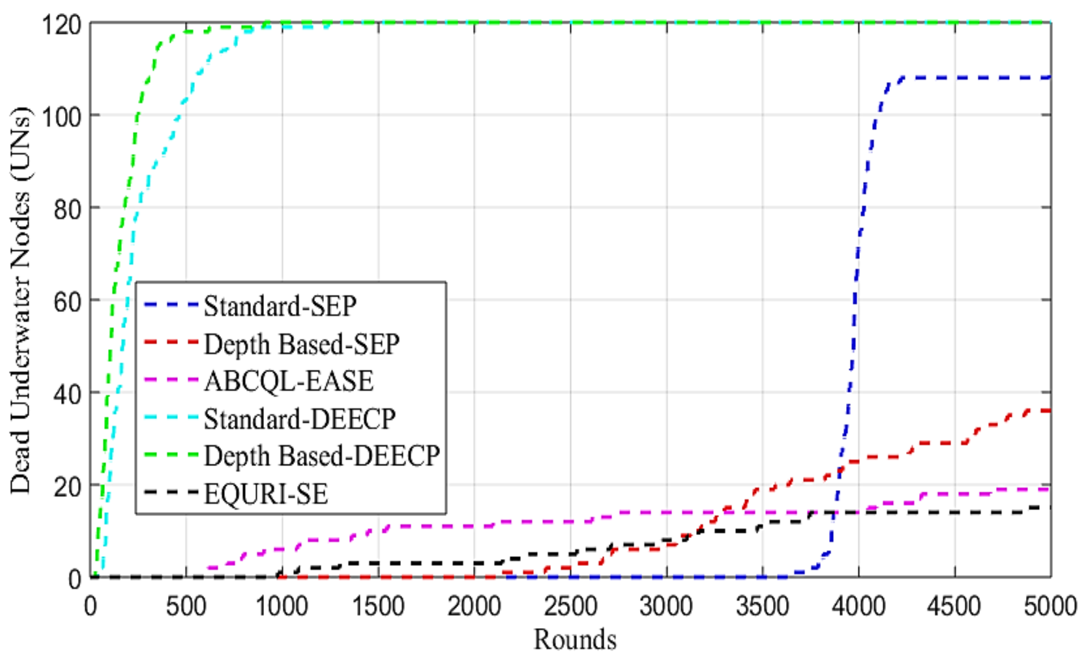


Figure 4.18. Performance Comparison of EQURI-SE in Term of dead UNs

This significant difference highlights the critical importance of integrating UVs as smart relays into the ABCQL-EASE framework. The EQURI-SE protocol uses UVs to transmit long-distance acoustic transmissions between CHs and to the SBS which significantly reducing the energy consumption of UNs. By acting as mobile intermediaries, UV enable shorter communication paths, reducing the high energy costs associated with long-distance routes and ensure long network lifetime. The performance of EQURI-SE also validates the effectiveness of the multi-stage optimization process used to select UVs. By use GA-optimized NN and MCDM the protocol ensures that UVs are chosen based on a holistic evaluation of factors such as residual energy, distance, signal quality and depth. This ensures optimal relay placement and prevents any single UV from being overused, thus distributing the energy load and increases the operational life time.

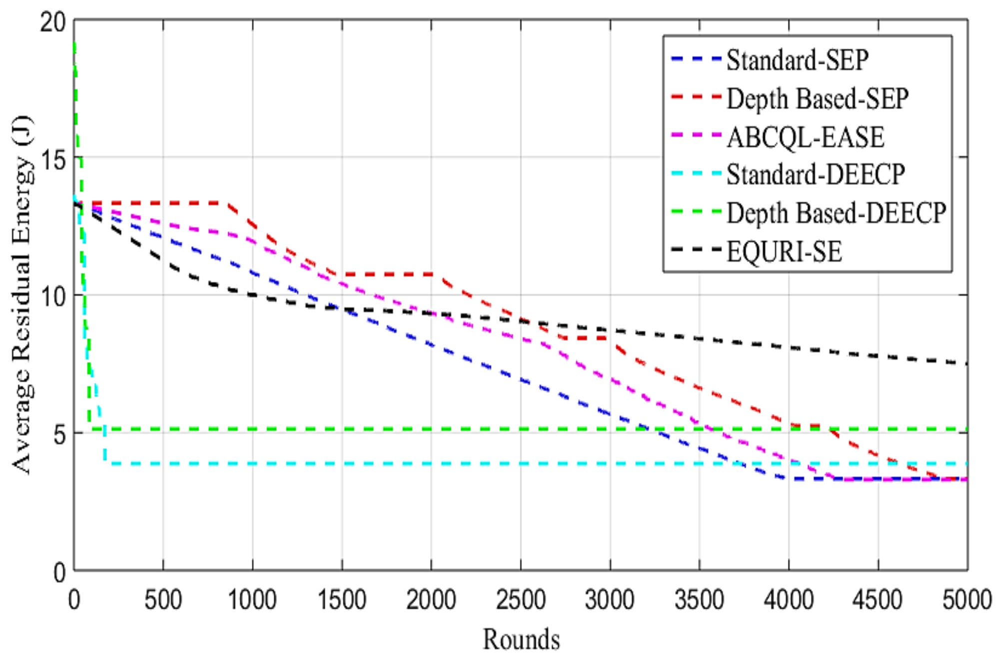


Figure 4.19. Performance Comparison of EQURI-SE in Term of Residual Energy

Figure 4.19 shows the energy performance of EQURI-SE reflected by calculating the average residual energy per alive CHs at each rounds. It shows that the EQURI-SE maintains the highest average residual energy across all 5000 rounds and stabilizing at approximately 8.5 Joules after round 3000, while all other protocols experience significantly higher energy depletion. Depth-Based-DEECP shows an extremely rapid drop in energy, falling to around 5.0 J within the first 1000 rounds and remaining flat thereafter which indicating early consumption of energy resources. Similarly, Standard-SEP and Standard-DEECP show steep declines, with both dropping below 5.0 J before round 4000. The ABCQL-EASE performs gives an acceptable stabilizing but less that than EQURI-SE which is still lower than the 8.5 J achieved by EQURI-

SE. This difference highlights the impact of integrating UVs as smart relays into the ABCQL-EASE framework, which significantly reduces the energy consumption on fixed UNs.

Table 4.6. Other Performance Metrics for EQURI-SE Compared with Other Approaches

Approaches	Energy consumption (J)	Total Dead UNs	Packets to SBS (count)	Packets to CHs (count)	Network Throughput (kbps)	Network Efficiency (%)
Standard SEP	161.2	22	27464	457466	5.8	81
Standard DEECP	460.2	40	393532	12701	2.82	66
Depth based DEECP	648	113	19046	5395	2.8	5
Depth based SEP	89.5	10	190820	147909	13.1	91
ABCQL-EASE	**62**	**9**	**171700**	**258800**	**13.8**	**93**
EQURI-SE	**32**	**6**	**169138**	**234676**	**13.63**	**95**

The performance comparison shown in Table 4.6 provides overall evaluation of the proposed ABCQL-EASE and EQURI-SE protocols against other baseline approaches across six critical network performance metrics. A key observation from the table is the exceptionally low energy consumption achieved by the EQURI-SE protocol, consuming only 32 J, significantly lower than all other methods with network throughput by 13.63 kbps. In contrast, the Depth-Based-DEECP protocol shows highest energy consumption at 648 J followed by Standard-DEECP by 460.2 J and standard-SEP by 161.2 J which all have low network throughput between 2 to 5 kbps. Even the relatively efficient Depth-Based-SEP protocol consumes 89.5 J, more than double that of EQURI-SE however it have close network throughput. This significant reduction in energy consumption underscores the effectiveness of integrating UVs as smart relays between CHs and SBS.

This superior energy efficiency for ABCQL-EASE and EQURI-SE directly related to improved network longevity as evidenced by the total number of dead UNs. EQURI-SE records only 6 dead UNs during the entire simulation period which lowest among all protocols. Depth-Based-SEP closely follows with 10 dead UNs and ABCQL-EASE with 9, while Standard-SEP reports 22 dead UNs. Both DEECP versions perform poorly as standard-DEECP recording 113 dead UNs and depth-Based-DEECP gives 40 dead UNs. EQURI-SE's hybrid architecture which combines adaptive CH management with dynamic UVs relaying enables sustainable network operation under challenging conditions.

In terms of data delivery to the SBS, EQURI-SE sends 69,138 data packets to the SBS lower than other approaches such as Depth-Based-SEP by 190,820, ABCQL-EASE by 171,700 and especially Depth-Based-DEECP by 393,532. However, this reflects a more conservative and energy-conscious transmission strategy where data aggregation and selective forwarding reduce duplicate transmissions. Notably, the extremely high number of packets reported by Depth-based DEECP occurs at the cost of worst energy consumption gives only 7% of the network's efficiency indicating unsustainable operation.

EQURI-SE achieves its data delivery goals while maintaining optimal energy levels shows a balance between performance and sustainability. Regarding intra-cluster communication measured by packets sent to CHs EQURI-SE shows robust balancing by 234,676 packets outperforming standard-DEECP by 12,701, Depth-Based-DEECP by 5,395, and standard-SEP by 457,466 while remaining competitive with depth-Based-SEP by 147,909 and ABCQL-EASE by 258,800. This indicates effective cluster formation and reliable data aggregation within clusters ensures that sensory data is efficiently collected before being relayed through UVs to the SBS.

Finally, the network efficiency highlights the superiority of the EQURI-SE protocol achieving 95% as the highest among all protocols. This outperforms ABCQL-EASE of 93%, depth-Based-SEP by 91% and Standard-SEP by 81% while significantly outperforming the DEECP variants between 7% and 13%. Network efficiency measures the ratio of active UNs to total UNs over time reflect the protocols ability to maintain connectivity and functionality. EQURI-SE's high score confirms that its combination of AI-powered CH selection and dynamic UV relaying with multi-criteria optimization creates a resilient and self-adaptive system capable of maintaining high performance in the face of environmental challenges such as UNs movement, depth variation and signal degradation.

4.7 Discussion

The results from the evaluation sections are further summarized in Table 4.7 which compares the proposed approaches across four core metrics. The EQURI-SE gives in energy consumption reducing by 32.82J and network longevity with only 6 dead UNs, while provides excellent network efficiency by 95.08%. Although ABCQL-EASE delivers higher throughput by 13.81, it does so at the cost of increased energy use and reduced lifetime. The EQURI-SE represents a superior solution especially when extended operation under energy constraints is critical. Table 4.8 highlights the improvements achieved during the developing the proposed approaches.

Table 4.7. Performance Summary of the Proposed Approaches

Algorithms	Energy Consumption (J)	Dead UNs	Throughput (kbps)	Network Efficiency (%)
EQURI-SE	**32↓**	**6 ↓**	13.63	**95 ↑**
ABQL-EASE	62	9	**13.81 ↑**	93
Depth-based SEP	89.5	10	13.1	91

According to the analysis the evaluation shows the validation of ABCQL-EASE and EQURI-SE outstanding performance. The most significant improvement observed is in energy consumption where the EQURI-SE shows a substantial reduction which consuming approximately 47.2% less energy than ABCQL-EASE. The energy consumption reduction is primarily because of the strategic use of UVs as relays. By offloading long-distance transmissions between CHs onto nearby UVs the EQURI-SE minimizes the high energy costs associated with multi-hop acoustic communication over large distances. This design effectively creates a dynamic mechanism that reduces the transmission load on fixed underwater UNs leading to a more balanced and sustainable energy distribution across the entire network.

Table 4.8. The Advantages of Proposed Approaches

Improvement Aspect	Approach	Advantages
CH management	Hybrid ABC and QL	▪ Adaptive CH replacement
Inter-cluster route optimization	Hybrid multi-decision based QoS by QL and MCDM	▪ Optimizes the inter-cluster route decision
Multi-objective UV relay selection	Hybrid GA-NN with MCDM	▪ Optimizes the UVs selection
UVs as Relays for energy efficiency	UVs relaying between CHs driven by dynamic cooldown method to prevents overuse	▪ Reduce transmission distance ▪ Increase relay lifetime and fairness

This superior energy management directly reflected by the enhanced UNs/CHs lifetime by a 33.3% decrease in the number of dead UNs. The UV relay-based protocol maintains a higher population of functional UNs for a longer duration which is a direct consequence of the reduced energy heavy load per round by 3.29%. This indicate that the EQURI-SE is more effective at utilizing the available network resources ensuring that a greater proportion of UNs remain active and contribute to data collection and forwarding thereby maximizing the utility of the deployed infrastructure.

Importantly, these gains in sustainability are achieved without compromising core network functionality. Both approaches shows nearly identical performance in network throughput with values around 13.7 kbps. This parity confirms that the UVs as relay provides an efficient alternative path for data delivery. The stable throughput promise the reliability of the hybrid QL and ABC algorithm used for CH management, which maintains optimal network structure even under the dynamic conditions introduced by the moving UVs. The UV relay-based ABCQL-EASE protocol represents a strategic advancement which successfully balancing the trade-offs between energy efficiency, increase network lifetime and data delivery performance. It validates the effectiveness of integrating mobile relays with adaptive, AI-driven clustering strategies, positioning it as a highly promising solution for the next generation of resilient and long-lived IoUT deployments.

The integration of UVs as mobile relays with ABQL-EASE as proposed EQURI-SE introduces additional system complexity including the need for dynamic relay selection, coordination between CHs and UVs and management of UV energy and cooldown periods. This increased complexity reflected by multi-stage decision-making process by GA-based NN and MCDM for optimal UV selection. However, this added overhead is fully justified by the substantial performance gains achieved most notably a 47.2% reduction in energy consumption which significantly reduces dead UNs and extended network lifetime. Despite the mobility-related overhead associated with UV movement and communication the energy they consume is far outweighed by the savings realized through shorter transmission routes. By serving as intermediate relays between CHs and the SBS UVs eliminate the need for long-range acoustic transmissions, which are highly energy-intensive in underwater environments.

Thus, while the UV-assisted architecture increases operational complexity, the trade-off is strongly favorable, since the energy saved at the sensor UNs vastly exceeds the energy consumed by the UVs, leading to a net gain in network efficiency and sustainability. This makes the approach feasible and highly advantageous for long-term, mission where network lifetime and data delivery reliability are important.

4.8 Chapter Summary

This chapter presents a comprehensive simulation-based evaluation of two clustering protocols for the IoUT. ABCQL-EASE, an energy-aware stable election protocol optimized by integrating ABC with lightweight QL and MCDM and EQURI-SE which enhanced variant that incorporates UVs as intelligent relays between CHs. The performance of both protocols is rigorously assessed against different baseline approaches across a wide range of key performance indicators including energy consumption, network lifetime, throughput, packet delivery, and overall QoS. The results shows that the proposed protocols significantly outperform all baselines.

The ABCQL-EASE protocol achieves superior energy efficiency and network stability compared to baseline and benchmark approaches and reducing energy consumption approx. by 30.5%. The EQURI-SE protocol which extends ABCQL-EASE by integrating UVs as mobile relays selected via a GA-based NN model and MCDM shows more high performance. EQURI-SE reduces energy consumption by up to 47.2% compared to ABCQL-EASE, extends network lifetime and delivers higher throughput. The ABCQL-EASE and EQURI-SE provide network efficiency approx. by 92 to 95% respectively compared to baseline. This dramatic improvement is due to the strategic use of UVs to offload long-distance acoustic transmissions, thereby minimizing the energy cost associated with direct CH-to-CH communication as a major bottleneck in IoUT networks.

CHAPTER FIVE

Conclusion, Limitations and Recommendations

5.1 Conclusion

This thesis presents a developed approach for IoUT network energy optimization by addressing critical challenges related to energy efficiency, network longevity and QoS in dynamic underwater environments. The proposed framework introduces two protocols, ABCQL-EASE and EQURI-SE. These protocols integrate ABC, QL, MCDM and mobile UVs relay infrastructure to achieve intelligent, adaptive and sustainable clustering and data transmission strategies.

The ABCQL-EASE gains the global search capability of the ABC algorithm combined with the adaptive decision-making driven by QL to dynamically balance exploration and exploitation during CH management. This hybrid approach enables the protocol to respond to changing in network conditions such as UNs mobility, residual energy levels, depth variation and signal quality by continuously enhancing its CH election policy. As shown through comprehensive analysis ABCQL-EASE outperforms conventional and depth-based variants of DEEC and SEP in terms of energy consumption, throughput and network efficiency.

Based on this foundation the EQURI-SE protocol introduces UVs as intelligent relays between CHs. To optimize UV selection the developed method that combines GA-based NN models with MCDM evaluating candidates based on depth, energy, distance and signal quality. A dynamic cooldown mechanism further ensures fair usage and prevents overuse of any single UV thereby extending their operational lifetime and maintaining high relay availability.

By extensive simulations conducted over 30 independent runs the results shows the superiority of both proposed protocols. The performance analysis show that EQURI-SE achieves an approximately 48% reduction in energy consumption compared to ABCQL-EASE and up to 80% energy savings when compared to baseline methods. With only 6 dead

UNs on average after 5000 rounds EQURI-SE significantly extends network lifetime while maintaining high throughput and achieving a highest network efficiency of 95%.

As conclusion the thesis provides several key contributions to the field of IoUT networking.

- The development of ABCQL-EASE provides self-adaptive CH management approach combining swarm intelligence and RL approach. It's optimized the following process.
  - CH management by ABC
  - Inter-cluster communication routing decision by QL approach.
  - QoS driven energy efficiency by using MCDM.
- The development of EQURI-SE use UV as relay between CHs in ABCQL-EASE by the following.
  - Integrates GA-optimized NN and MCDM for intelligent UVs relay selection.
  - Dynamic cooldown mechanism to ensure fairness and sustainability in UV utilization.

The proposed protocols are theoretically and practically applicable for deployment in mission-critical applications such as ocean monitoring, disaster prevention, and defense surveillance. It's expected to provide well performance with the extension to large-scale multi-layered architectures.

5.2 Limitations and Recommendations

Despite the significant performance achieved by the proposed ABCQL-EASE and EQURI-SE protocols several limitations observed to the current design and simulation framework must be acknowledged. Frist, the mobility model for UVs assumes ideal navigation and coordination without accounting for realistic hydrodynamic constraints such as ocean currents or mechanical failures. Second, while the dynamic cooldown mechanism prevents overuse of individual UVs it does not fully capture the energy cost related to physical movement through water which could impact overall system efficiency in real-world deployments.

Another limitation is the scalability of the GA-based NN and MCDM relay selection process. Although the proposed approaches are effective with small to medium networks for example with 120 UNs and 3 to 5 UVs, the computational overhead of multi-objective optimization increases significantly with large network sizes. Also, the integration of QL within the ABC framework enhances adaptability but introduces convergence variability due to the stochastic nature of exploration-exploitation trade-offs. This can lead to inconsistent clustering results across simulations especially during early epochs when the Q table is still being populated.

The recommendation in future work is to focus on enhancing the robustness of the proposed protocol in several key directions. First, integrating the hydrodynamic mobility model for UVs to reflecting fluid dynamics, propulsion energy and obstacle avoidance which will improve the energy consumption estimates and path planning. Second, use deep reinforcement learning (DRL) can replace the current QL module enabling faster convergence and better handling of high-dimensional state spaces. Third, extending the architecture to support multi-layered hierarchical clustering and inter-UVs cooperation to enhance scalability and fault tolerance in large-scale IoUT deployments. Finally the transition from simulation-based verification to platform-based testing using underwater sensor platforms will provide empirical evidence of performance under real environmental conditions.

List of Publications

1. Elmustafa Sayed Ali, Rashid A. Saeed, Ibrahim Khider Eltahir, Othman O. Khalifa, A systematic review on energy efficiency in the internet of underwater things (IoUT): Recent approaches and research gaps, Journal of Network and Computer Applications, Volume 213, 2023, https://doi.org/10.1016/j.jnca.2023.103594.

2. Sayed Ali E, Saeed RA, Eltahir IK, Abdelhaq M, Alsaqour R, Mokhtar RA. Energy Efficient CH Selection Scheme Based on ABC and Q-Learning Approaches for IoUT Applications. Systems. 2023; 11(11):529. https://doi.org/10.3390/systems11110529

3. Elmustafa Sayed Ali, Rashid A. Saeed, Ibrahim Khider Eltahir, Depth based stable election routing protocol for heterogeneous internet of underwater things (IoUT) energy efficiency, Computers and Electrical Engineering, Volume 119, Part A, 2024, https://doi.org/10.1016/j.compeleceng.2024.109507.

4. Ali, E.S., Saeed, R.A. & Eltahir, I.K. Theoretical modelling for optimised energy efficiency in IoUT networks using hybrid QL-based meta-heuristic and MCDM approaches. Discov Internet Things 5, 133 (2025). https://doi.org/10.1007/s43926-025-00228-z

5. E. S. Ali, R. A. Saeed, I. K. Eltahir and O. O. Khalifa, "A Stable Energy Balancing Based Clustering Routing Protocol for IoUT using Meta-heuristic Technique," 2024 IEEE 4th International Maghreb Meeting of the Conference on Sciences and Techniques of Automatic Control and Computer Engineering (MI-STA), Tripoli, Libya, 2024, pp. 433-439. doi: 10.1109/MI-STA61267.2024.10599658.

6. E. S. Ali, R. A. Saeed, I. K. Eltahir, O. O. Khalifa, M. S. Elbasheir and M. M. Saeed, "Hybrid Optimization of Developed DEEC Protocol for Enhanced Energy Efficiency in IoUT," 2024 9th International Conference on Mechatronics Engineering (ICOM), Kuala Lumpur, Malaysia, 2024, pp. 245-250. doi: 10.1109/ICOM61675.2024.10652349.

7. E. S. Ali, R. A. Saeed, I. K. Eltahir, M. Saeed and M. Barakat, "Theoretical Framework for Efficient UV-Relay Selection in IoUT Using Hybrid NN-GA Model with MCDM Approach," 2025 5th International Conference on Emerging Smart Technologies and Applications (eSmarTA), Ibb, Yemen, 2025, pp. 1-8. doi: 10.1109/eSmarTA66764.2025.11132151.

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