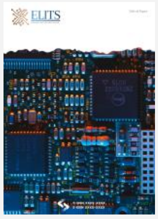
Electronics and Informatics Journal Vol. 1 No. 1 (2026)

ELITS Electronics and Informatics Journal

P-ISSN: XXXX-XXXX
E-ISSN: XXXX-XXXX
ELITS Journal
journal.diginus.id/ELITS



Development of an Energy Model-Based A-Star Algorithm for Energy Efficient Path Planning of Underwater Robots in Ship Hull Cleaning

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ABSTRACT

This study presents the development of an energy-based A-Star algorithm for efficient path planning of underwater robots used in ship hull cleaning, motivated by the growing need for energy-efficient autonomous systems operating under complex hydrodynamic conditions such as fluid drag, pressure, and varying underwater currents. The proposed method integrates a physical energy consumption model into the conventional A-Star cost function and is evaluated through numerical simulations in a two-dimensional grid environment representing a ship hull surface, where key parameters including travel distance, drag force, and directional changes are considered to estimate total energy usage. The simulation results demonstrate that the proposed algorithm successfully generates collision-free paths with smoother and more stable trajectories compared to the conventional approach, with recorded energy consumption ranging from 88.73 to 115.99 joules across five scenarios and an average computation time of approximately 0.02 seconds. These findings indicate that incorporating hydrodynamic considerations significantly improves navigation performance while maintaining computational efficiency. In conclusion, the study confirms that the shortest geometric path is not always the most energy-efficient in underwater environments, and the proposed energy-based A-Star algorithm provides a realistic and practical framework for enhancing the sustainability and effectiveness of future autonomous ship hull cleaning systems.

ARTICLE INFO

Article History:

Received:
December 15th, 2025
Received in revised form:
December 28th, 2025
Accepted:
January 11th, 2026

Keywords:

A-Star algorithm;
Energy model;
Path planning;
Ship hull cleaning;
Underwater robot;

1. INTRODUCTION

Ships operating in marine environments face serious challenges due to corrosion and biofouling, which directly impact energy efficiency and increase operational costs [1] . Salty seawater conditions, temperature fluctuations, and high hydrostatic pressure accelerate the degradation of ship metal materials [2] . In addition, the accumulation of marine organisms such as algae, barnacles, and bacteria on ship hulls causes increased hydrodynamic drag, resulting in significantly increased fuel consumption and carbon emissions [3] . Consequently, biofouling is one of the main factors that reduce hydrodynamic efficiency and the operational sustainability of ships [4] .

Ship hull cleaning activities are important to maintain ship performance and minimize environmental impacts due to increased greenhouse gas emissions [5] . Traditional cleaning methods such as dry-docking are time-consuming, costly, and have the potential to cause environmental pollution due to the use of abrasive chemicals [6] . In addition, manual cleaning with high pressure can damage the anti-corrosion protective layer on the ship's metal surface [7] . Therefore, the use of underwater robotic systems is starting to be developed as a more efficient, sustainable, and environmentally friendly solution for inspecting and cleaning ship hulls without the need to stop operations [8] .

The development of Remotely Operated Vehicle (ROV) technology provides a great opportunity in carrying out underwater cleaning by using magnetic adhesion technology to maintain motion stability on metal surfaces [9] . Modern ROV systems are equipped with high-pressure water spray devices and internal filtration systems to collect residual dirt so that it does not pollute the sea [10] . The application of cleaning mechanisms such as a combination of cavitation jets and rotating brushes has been proven to increase the efficiency of the cleaning process and reduce energy consumption [11] . Meanwhile, the application of an adaptive control system based on Model Predictive Control (MPC) can maintain motion stability and optimize energy use when the robot operates underwater [12] .

Although significant progress has been made in terms of mechanical design and motion control, energy efficiency in underwater robot path planning remains a major research challenge [13] . Most path planning algorithms such as Dijkstra, RRT, and A-Star still focus on determining the shortest distance without considering the actual energy consumption in dynamic underwater environments [1] . Hydrodynamic factors such as water pressure, ocean currents, and fluid drag significantly affect the amount of energy required during robot movement [4] . Paths that do not consider energy models can result in excessive power consumption, accelerated battery depletion, and decreased system operational efficiency [10] .

The integration of energy models into path planning algorithms is a potential approach to generate optimal trajectories that consider actual power consumption during movement [9] . Energy models that take into account speed, drag, and ocean current conditions enable the system to generate efficient trajectories in terms of both distance and energy consumption [3] . In this context, the development of the A-Star algorithm based on energy models is expected to improve the operational efficiency of underwater robots in the hull cleaning process [13] . This approach combines the optimal path finding capabilities of A-Star with a realistic representation of actual energy consumption, thus generating trajectories that are adaptive to hydrodynamic conditions and the complexity of the ship's surface [12].

2. METHOD

This study adopts a quantitative approach using numerical simulations to develop and evaluate an energy-based A-Star algorithm. This approach was chosen because it allows for systematic testing of the algorithm's performance through a scalable computer simulation process. The main objective of this method is to determine the optimal path with minimum energy consumption for an underwater robot operating in the hull cleaning process. The simulation was conducted using the Python 3.11 programming language, with a two-dimensional (2D grid) environment modeling as a representation of the hull surface area that has obstacles and various trajectory conditions.

2.1 Research Design

This research was designed to evaluate the performance of the proposed energy-based A-Star algorithm through a series of systematic simulation steps. The study began with modeling the underwater operating environment using a two-dimensional grid-based map with a size of 50 × 50 cells, where each cell represents a potential navigation area for the underwater robot. The grid environment consists of free space, obstacle regions, and designated cleaning destination points, allowing structured representation of the navigation space commonly used in underwater path planning studies.

Next, the conventional A-Star algorithm was implemented to determine the optimal path from the starting point to the target location. To enhance energy efficiency, an energy consumption model was integrated into the algorithm's cost function by incorporating key physical factors, including travel distance, fluid drag force, and directional changes. This approach aligns with recent advances in autonomous underwater vehicle (AUV) navigation research that emphasize the integration of hydrodynamic and motion dynamics into the path planning cost function to achieve more energy-efficient trajectories [14]. Furthermore, the use of a grid-based environment remains a standard and effective method in AUV path planning research due to its structured representation and compatibility with graph-based search algorithms [15] .

The simulation was executed five times using different obstacle map variations to obtain consistent and comparable results. Five simulation scenarios with randomly generated obstacle configurations were selected to provide a controlled yet diverse evaluation of the algorithm's performance. This number was chosen to balance computational efficiency and result consistency while still allowing observation of the algorithm's behavior under varying environmental complexities. Although five scenarios are sufficient to demonstrate the feasibility and stability of the proposed method, future studies may consider larger-scale and more complex environments to further validate the algorithm's performance. Increasing the number of obstacles or expanding the map size would likely further highlight the benefits of the energy-based cost function, as smoother trajectories and reduced drag become increasingly critical in dense and dynamic underwater settings.

The simulation results were analyzed both quantitatively and comparatively by evaluating three main performance indicators: path length, total energy consumption, and computation time. These indicators were selected because they directly reflect the effectiveness, efficiency, and practicality of the proposed algorithm for underwater hull-cleaning missions. To provide a clear overview of the overall system workflow, the architecture of the energy-based A-Star algorithm used in this study is illustrated in Figure 1. The figure depicts the process flow starting from mission input at the Ground Control Station (GCS), followed by the energy-based path planning stage, and concluding with path execution by the underwater robot (ROV/UUV).

ELITS Journal
E-ISSN: XXXX-XXXX, P-ISSN: XXXX-XXXX

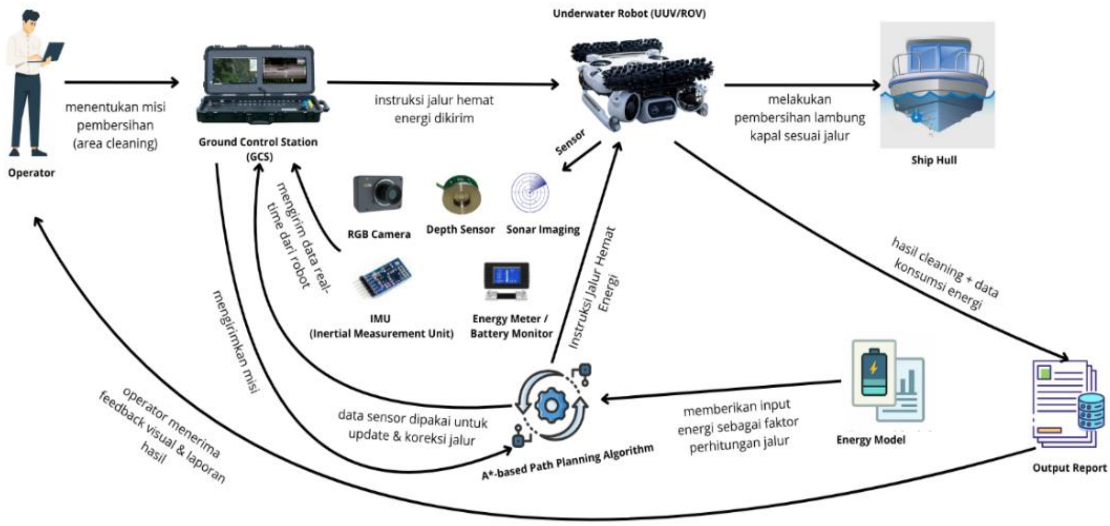

Figure 1. System architecture of the A-Star algorithm based on energy models for energy-efficient path planning of underwater robots in ship hull cleaning.

Figure 1 illustrates the overall workflow of the proposed energy-based A-Star path planning system. The diagram clearly presents the sequential process starting from mission initialization at the Ground Control Station (GCS), followed by the energy-aware path planning stage that integrates physical energy modeling into the A-Star algorithm, and finally the execution of the generated trajectory by the underwater robot. This architecture highlights how energy considerations are incorporated directly into the navigation decision-making process before the robot performs hull-cleaning operations.

2.2 Instruments and Devices

2.3 Computing Environment

The research was conducted using Python 3.11 on a laptop device with Intel Core i5 (Gen 10) processor specifications, 16 GB RAM, and Windows 10 operating system.

2.4 Supporting Software

a. NumPy for matrix processing and numerical operations.
b. Matplotlib for visualization of experimental trajectories and results.
c. Heapq for implementing priority queue data structure in A-Star algorithm.
d. Time for measuring the computation time of each simulation.

2.5 Simulation Environment

A 50×50 grid map is used to represent the hull area of the ship, with cell values as follows:
a. 0 indicates the free area that the robot can pass through.
b. 1 indicates an impassable obstacle area.
c. 2 shows the planning result path generated by the algorithm.

2.6 Model and Dataset

The energy model used in this study is designed to estimate the robot's power requirements during hull-cleaning navigation by considering travel distance, hydrodynamic conditions, and directional

 ELITS Journal
E-ISSN: XXXX-XXXX, P-ISSN: XXXX-XXXX

changes. The dataset consists of several cleaning scenarios with varying levels of complexity, containing path points and environmental parameters that influence the robot's movement. Integrating this model with the dataset enables a more accurate evaluation of path efficiency, allowing the algorithm to be assessed not only based on geometric distance but also on its ability to optimize energy consumption in underwater conditions.

- The energy model-based A-Star algorithm achieves more efficient power consumption across various ship hull cleaning scenarios (88.73-115.99 Joules). This approach effectively balances three main factors: travel distance, hydrodynamic resistance, and changes in robot movement direction. Mathematically, the total energy consumption is expressed in Equation (1):

$$E_{total} = \alpha \cdot d + \beta \cdot F_d + \gamma \quad (1)$$

Where E_{total} is the total energy consumed, d represents the travel distance for the current segment, F_d denotes the fluid drag force acting on the robot during motion, and θ indicates the change in movement direction between two consecutive points. The coefficients $\alpha, \beta,$ and γ are weighting parameters that determine the contribution of distance, drag force, and direction change to the overall energy estimation. This formulation ensures that the energy cost reflects not only geometric distance but also hydrodynamic conditions that significantly influence underwater mobility. As a result, the shortest geometric path does not necessarily correspond to the minimum energy consumption. Accordingly, the weighting coefficients $\alpha, \beta,$ and γ were defined to represent the relative importance of each energy component in underwater navigation. The coefficient α was set to 1.0 as a baseline to preserve distance as a fundamental factor in path planning. The coefficient β was assigned a value of 0.2 to model the influence of fluid drag, which plays a significant role in underwater energy consumption without dominating the optimization process. Meanwhile, γ was set to 0.1 to penalize excessive directional changes, encouraging smoother trajectories while maintaining maneuverability. A sensitivity analysis was conducted by varying one coefficient at a time while keeping the others constant. The results indicate that increasing β leads the algorithm to favor paths with reduced drag exposure, while higher γ values reduce sharp directional changes at the expense of slightly longer paths. These results demonstrate that the selected coefficients provide a balanced trade-off between distance efficiency and energy conservation.

- The fluid drag force represents the hydrodynamic resistance experienced by the robot during underwater navigation, where its magnitude is influenced by the characteristics of the fluid medium, the robot's shape, and its movement velocity. The seawater density parameter determines the mass density of the medium that the robot must traverse, while the drag coefficient reflects the efficiency of the robot's shape in reducing resistance. The frontal area determines the size of the surface affected by drag, and the movement velocity has a quadratic influence on the magnitude of the generated drag force. Mathematically, this relationship is expressed in Equation (2):

$$F_d = 0.5 \cdot \rho \cdot C_d \cdot A \cdot v^2 \quad (2)$$

Where F_d is the magnitude of the drag force, ρ is the density of seawater, C_D is the drag coefficient representing the robot's shape characteristics, A is the frontal cross-sectional area exposed to the flow, and v is the robot's velocity. This equation indicates that drag increases quadratically with velocity, making it one of the dominant factors influencing energy usage in underwater environments. The formulation provides a realistic representation of hydrodynamic resistance, ensuring that the energy model accurately reflects the physical constraints encountered by the robot during underwater navigation.

The simulation parameters used are presented in Table 1.

Symbol	Information	Mark
$\boldsymbol{\rho}$	Density of sea water	1025 kg/m³
$\boldsymbol{C_D}$	Drag coefficient	0.8
$\boldsymbol{A}$	Cross-sectional area of the robot	0.05 m²
$\boldsymbol{v}$	Speed movement	0.5 m/s
$\boldsymbol{\alpha, \beta, \gamma}$	Energy weighting coefficients	1.0, 0.2, 0.1

Table 1. Physical parameters and simulation constants

This energy model enables the algorithm to consider the effects of fluid resistance and changes in the direction of motion when determining energy-efficient paths, ensuring that the generated trajectories are both realistic and optimized for underwater operating conditions. By incorporating these physical factors, the algorithm does not rely solely on geometric distance but evaluates the actual energetic cost of each movement. As a result, the selected paths tend to be smoother, contain fewer abrupt turns, and avoid maneuvers that would significantly increase drag force. This leads to more efficient navigation and provides a more comprehensive approach to path planning, particularly for underwater robotic applications where hydrodynamic forces play a critical role in overall performance.

The simulation datasets used in this study are generated automatically through Python scripts, allowing consistent replication of results without the need for physical data collection. This automated approach ensures that all environmental parameters, such as water density, drag coefficient, robot speed, and scenario configuration, can be systematically controlled and reproduced. It also provides flexibility to adjust scenario complexity, for example by adding obstacles, modifying hull-surface contours, or altering hydrodynamic conditions. Consequently, the evaluation of the energy-based A-Star algorithm becomes more structured, scalable, and reliable across different experimental setups, enabling robust and repeatable performance analysis.

2.7 Simulation Procedure

1. Initialize the Simulation Environment: Create a 50×50 grid map using a controlled random function with an obstacle probability of 0.18. Each grid is assigned a value of 0 for free area, 1 for obstacles, and 2 for the resulting path of the algorithm.
2. Determination of Starting Point and Goal: The starting point and goal are randomly selected within a different range for each trial, ensuring that the position is in an obstacle-free area.
3. Implementation of the A-Star Algorithm: The A-Star algorithm is run to find the optimal path between the starting point and the destination based on the cost function that has been modified with the energy model.
4. Total Energy Calculation: The total energy of each generated trajectory is calculated using the fluid drag formula and the change in direction at each step of the movement. This process is automated through a Python script using the NumPy, Matplotlib, and Heapq libraries.
5. Results Recording and Visualization: The results of each simulation are stored in CSV format containing path length, total energy, and computation time. The resulting planning paths are visualized using a 2D grid map, and comparison graphs between experiments are drawn to analyze energy efficiency trends.

2.8 Data analysis

Data analysis was conducted quantitatively and comparatively between the results of five experiments. Three main parameters were used as performance indicators:

1. Energy Efficiency (joules): Total energy required by the robot to reach a goal.
2. Path Length (steps): Number of steps from the starting point to the destination point.
3. Computation Time (seconds): The duration required for the algorithm to find the optimal path.

The analysis of these three indicators provides a comprehensive understanding of the performance of the energy-based A-Star algorithm under various simulation conditions. Energy efficiency is used to evaluate the algorithm's ability to minimize energy consumption as the robot navigates through environments with different levels of hydrodynamic resistance, while path length reflects how well the algorithm balances between selecting a shorter geometric route and choosing a smoother, more energy-efficient trajectory. Computation time indicates the algorithm's capability to function in real-time, which is essential for practical implementation in autonomous underwater robots. All simulation results were organized and visualized in the form of tables and graphs to facilitate comparison across scenarios, reveal relationships between path length, energy consumption, and computational cost, and identify performance trends and trade-offs. This structured approach ensures that the algorithm's performance is evaluated thoroughly, systematically, and supported by objective quantitative evidence.

3. RESULTS AND DISCUSSION

This study aims to evaluate the performance of the A-Star algorithm based on an energy model in determining energy-efficient paths for underwater robots during the hull cleaning process. Simulations were conducted using the Python 3.11 programming language with a two-dimensional grid environment measuring 50x50, which represents the robot's underwater working area. Each cell on the grid was assigned a value of 0 for free area, 1 for obstacles, and 2 for the resulting path of the algorithm. Testing was carried out five times with different obstacle map configurations to ensure the consistency of the algorithm's performance.

The main factors evaluated include path length (steps), total energy (joules), and computation time (seconds). All simulation results are saved in CSV format and visualized using the Matplotlib library for performance analysis.

3.1 Simulation Results of the A-Star Algorithm Based on the Energy Model

Test results show that the energy model-based A-Star algorithm is capable of generating optimal trajectories from the starting point to the destination without encountering obstacles in all experimental scenarios. Variations in results occur due to differences in the distribution of random obstacles on each simulation map.

The simulation results data are shown in Table 2, which contains the values of the path length, total energy expended by the robot, and computation time for each trial.

Table 2. Simulation results of the A-Star algorithm based on the energy model

No	Path Length (Steps)	Energy (Joules)	Computation Time (Seconds)
1	43	99.66	0.0468
2	50	115.99	0.0171
3	47	109.99	0.0141
4	40	92.68	0.0111
5	38	88.73	0.0056

Table 2 presents a quantitative summary of the simulation results obtained from five experimental scenarios, including path length, total energy consumption, and computation time. The results indicate that energy consumption generally increases with longer paths and higher obstacle density, which require more frequent directional changes during navigation. These directional adjustments contribute to increased hydrodynamic drag, leading to higher overall energy usage. The variations observed across the experiments confirm that environmental complexity plays a significant role in determining navigation efficiency and demonstrate the effectiveness of the proposed energy-based A-Star algorithm in adapting to different operating conditions.

1. Experiment 1: The algorithm generated a path of 43 steps with an energy of 99.66 Joules. This value indicates the map has moderate resistance. The execution time was 0.0468 seconds because the search process required more exploration before finding the optimal path.
2. Experiment 2: The longest path was 50 steps, with the highest energy consumption of 115.99 Joules. This was due to the numerous obstacles that caused the robot to turn frequently, increasing fluid resistance and increasing energy costs.
3. Experiment 3: A path length of 47 steps and an energy of 109.99 Joules, slightly more efficient than the second experiment. This path still contains some turns, but the fluid drag level is relatively reduced.
4. Experiment 4: A shorter path with 40 steps and 92.68 Joules of energy. This indicates that the map has fewer obstacles, allowing the robot to move more stably with less energy.
5. Experiment 5 yielded the most efficient result, a 38-step path with 88.73 Joules of energy and a fastest execution time of 0.0056 seconds. This demonstrates the algorithm's ability to adapt to map conditions, allowing for more linear movement and minimal directional changes.

3.2 Comparative Analysis of Simulation Results

After the entire simulation process was executed, a quantitative and comparative analysis was conducted to evaluate the performance of the proposed energy-based A-Star algorithm in comparison with the conventional A-Star algorithm, which relies solely on geometric distance as its cost function. Both algorithms were tested using identical simulation environments, obstacle configurations, and start–goal positions to ensure a fair and consistent comparison.

The comparative analysis focused on three key performance indicators, namely path length (steps), total energy consumption (joules), and computation time (seconds), obtained from five simulation experiments. These indicators were selected because they directly reflect the effectiveness and feasibility of path planning for underwater hull-cleaning missions. Path length represents the algorithm’s ability to find an obstacle-free route, total energy consumption reflects movement efficiency considering hydrodynamic drag and directional changes, and computation time indicates the suitability of the algorithm for real-time implementation.

To illustrate the relationship between path length and energy consumption, the simulation results of the proposed energy-based A-Star algorithm are visualized in Figure 2. The graph shows a positive correlation between path length and total energy consumption, indicating that longer paths generally require higher energy to complete the movement from the starting point to the destination.

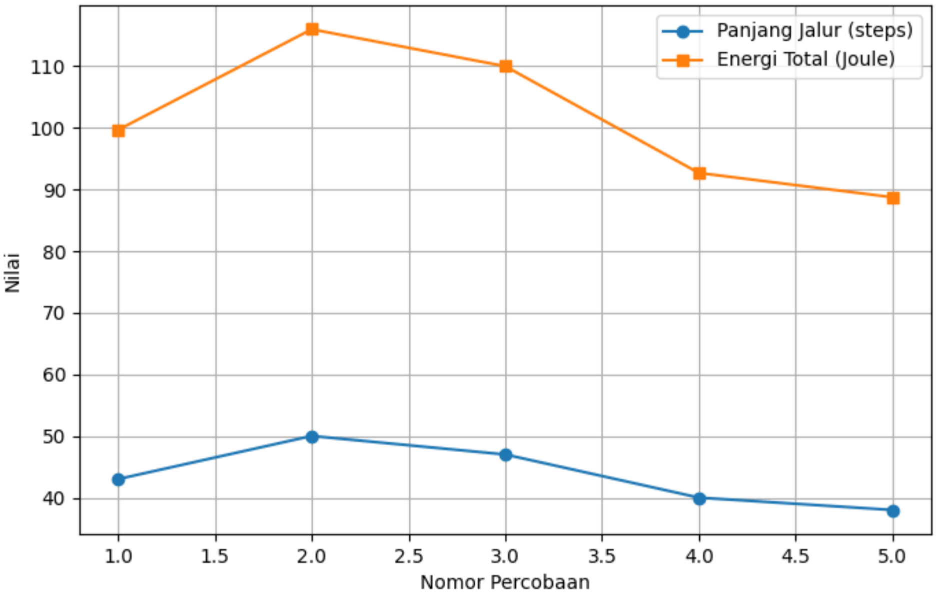

Figure 2. Comparison of path length and total energy in five simulation experiments.

Among the five experiments, the second scenario resulted in the highest energy consumption of 115.99 Joules with a path length of 50 steps, while the fifth scenario produced the lowest energy consumption of 88.73 Joules with a path length of 38 steps. These variations are primarily influenced by map complexity and the number of directional changes required to avoid obstacles, which directly affect hydrodynamic drag and maneuvering effort.

When compared with the conventional A-Star algorithm, the proposed energy-based approach exhibits distinct differences in path characteristics. Although the conventional A-Star algorithm consistently produces shorter geometric paths, these paths often involve frequent directional changes and increased exposure to hydrodynamic drag. As a consequence, the total energy consumption of the conventional approach is higher in most simulation scenarios.

In contrast, the energy-based A-Star algorithm tends to generate slightly longer but smoother trajectories, resulting in reduced drag force and lower overall energy consumption. This comparative result confirms that minimizing geometric distance alone is insufficient for underwater navigation. By incorporating physical energy considerations into the cost function, the proposed algorithm achieves more energy-efficient path planning, making it more suitable for underwater robotic applications with limited battery capacity.

3.3 The Influence of Energy Model on Line Efficiency

The integration of an energy model into the A-Star algorithm's cost function changes the way the algorithm selects the best path. While conventional A-Star primarily relies on the shortest distance, energy-model-based A-Star adds an additional energy cost component, calculated based on fluid drag (F_d) and the angle of change of direction (θ).

Thus, the chosen path is not only short but also smooth with minimal changes in direction. Simulation results show that in the fourth and fifth trials, although the path is slightly longer than the geometrically ideal path, the total energy is actually lower. This indicates that reducing the number of turns is more significant in reducing energy consumption than simply shortening the distance.

This phenomenon is particularly relevant in underwater environments, as fluid drag is nonlinear and highly sensitive to direction of travel. Thus, the energy model-based A-Star algorithm successfully balances travel speed and energy efficiency, making it more realistic for implementation in real-world underwater navigation systems.

3.4 Energy Consumption Analysis

The simulation results show that the execution time for each trial ranges from 0.0056 to 0.0468 seconds, indicating that modifying the cost function does not significantly increase the computational time complexity. The average computation time is only about 0.02 seconds, making the algorithm efficient and suitable for use in real-time navigation applications. Factors influencing this time difference include:

1. Number of nodes evaluated: The more obstacles, the longer the search process.
2. Obstacle structure: Complex obstacle patterns multiply the node expansion process.
3. Code optimization: The use of priority queues and NumPy operations speeds up the process of selecting the node with the lowest cost.

The fast computing performance indicates that this algorithm can be implemented directly on an autonomous underwater robot system (AUV) without requiring high spec hardware.

3.5 Discussion

Based on the results of the tests and analysis that have been carried out, the developed energy model-based A-Star algorithm shows significantly superior performance in generating optimal paths with minimum energy consumption compared to the conventional A-Star algorithm that solely focuses on distance traveled. The results confirm that the geometrically shortest path is not always the most energy-efficient solution in underwater environments. Hydrodynamic drag and frequent directional changes significantly influence total energy consumption, particularly for long-range AUV operations [16] . This study successfully modified the cost function by including total energy components (E) that are affected by distance, drag, and directional changes, thereby substantially improving the efficiency of robot movement. This need for energy optimization is very relevant especially in complex 3D environments [17] . The importance of balancing efficiency with safety is also a major concern, as evidenced by other studies that use deep reinforcement learning techniques such as Soft Actor-Critic (SAC) to ensure safe navigation for AUVs in unknown environments [18] .

The quantitative simulation results demonstrate a clear relationship between trajectory smoothness and energy consumption. Scenarios characterized by fewer directional changes consistently resulted in lower overall energy usage, indicating that smoother trajectories are more energy-efficient for underwater robot navigation. In contrast, environments with denser obstacles that require frequent and sharper turning maneuvers led to increased hydrodynamic drag and higher energy demands. These findings confirm that directional changes play a critical role in determining power consumption during underwater motion. This observation is consistent with previous AUV studies, where hybrid path planning algorithms, such as DCGB-DAPF-RRT, were specifically designed to generate smoother trajectories and limit maximum turning angles to improve energy efficiency [19] . Furthermore, similar energy-aware planning strategies have been successfully applied in Underwater Wireless Sensor Networks (UWSNs) to optimize energy usage and ensure efficient data collection, highlighting the broader applicability of energy-based path planning approaches beyond robotic navigation [20] .

The efficient performance of the A-Star algorithm is supported by the implementation of a dynamic energy model that takes into account specific physical conditions in the underwater environment, such as fluid density and robot movement speed. This approach makes the developed model more representative of the real conditions of AUV operation. Unstable environmental challenges such as ocean currents require a comprehensive environmental model, such as that implemented by Improved Informed RRT which incorporates interpolated current information for adaptive 3D planning [21] . The energy optimization strategy is also further advanced by integrating real-time battery State of Charge (SOC) estimation into the planning process, ensuring the most optimal route and efficient tracking control [22] .

The success of this research in integrating physical and computational models finds strong support in the broader context of AUV research. In addition to studies emphasizing energy-based optimization and environmental adaptation, the complexity of mission planning increases in multi-AUV scenarios. In these cases, coverage path planning must consider the influence of ocean currents and the sonar performance of each vehicle to achieve maximum mission efficiency, especially to avoid energy-intensive overlapping coverage areas [23] . The proposed algorithm, with its focus on energy minimization through directional change control, provides a robust methodological framework that can be extended to address coordination and resource constraints in complex multi-AUV operations.

The relevance of this energy-based A-Star algorithm is particularly evident in missions that require comprehensive area coverage. Complete Coverage Path Planning (CCPP). Missions such as hull cleaning require efficient CCPP to ensure every target area is thoroughly inspected by the underwater wall cleaning robot [24] . Computational time efficiency is also an important aspect of this research. The algorithm achieves a very short average processing time of about 0.02 seconds, indicating that the addition of a dynamic energy model does not impose a significant computational burden. This speed indicates great potential for the implementation of real-time navigation systems, a fundamental requirement for responsive AUV missions. Computational time efficiency is also crucial for tasks that require comprehensive area coverage, including exploration missions carried out by Autonomous Underwater Helicopters (AUH) that use the VFH+ algorithm for coverage in unknown environments [25] .

Overall, the developed energy model-based A-Star algorithm proved effective in generating optimal paths, efficient in power usage, and fast in computational processing. Its key capability of balancing minimizing path distance and optimizing energy consumption makes it highly relevant for application in hull cleaning scenarios, where power efficiency and operation time are key factors for mission success. These findings emphasize the importance of integrating intelligent heuristic computational models and accurate environmental physics models in the development of intelligent and sustainable underwater autonomous navigation systems.

3.6 Summary of Findings

1. The energy model-based A-Star algorithm is capable of producing efficient trajectories with energy consumption between 88.73–115.99 Joules.
2. The fifth experiment gave the most optimal results with the lowest energy of 88.73 Joules and a path of 38 steps.
3. The average computation time is 0.02 seconds, indicating high efficiency for a real-time navigation system.
4. Paths with few changes in direction have been shown to produce lower total energy than winding paths.
5. The energy model is effective in balancing between distance traveled, fluid drag, and directional changes, making it more realistic for use in autonomous underwater robots.

6. The integration of the energy model into the cost function reinforces the concept that the most energy-efficient path is not always the geometrically shortest path.

4. CONCLUSIONS

This study successfully developed and evaluated an energy-based A-Star algorithm for optimizing path planning in underwater robots performing ship hull cleaning operations. By integrating an energy consumption model that incorporates travel distance, fluid drag, and directional changes into the cost function, the proposed algorithm is able to generate trajectories that are smoother, more stable, and more energy-efficient than those produced by the conventional distance-based A-Star approach.

Simulation experiments were conducted in a controlled grid-based environment measuring 50 × 50 cells and evaluated across five different obstacle configurations. The results demonstrate that total energy consumption ranged from 88.73 joules to 115.99 joules, depending on path complexity and directional changes. In addition, the algorithm achieved an average computation time of approximately 0.02 seconds, indicating that the incorporation of the energy model does not impose a significant computational burden. These characteristics confirm the suitability of the proposed method for real-time implementation on autonomous underwater vehicles operating under limited onboard computational resources.

The findings further provide strong evidence that the shortest geometric path does not necessarily correspond to the most energy-efficient route in underwater environments. Hydrodynamic resistance increases substantially when frequent turns are required or when the robot navigates through obstacle-dense regions. Each directional change introduces additional drag, leading to higher energy consumption. Consequently, a slightly longer path that allows smoother and more consistent motion may result in lower overall energy usage. By integrating physical environmental factors such as seawater density, drag coefficient, robot frontal area, and movement speed into the cost function, the proposed algorithm achieves a practical balance between minimizing travel distance and optimizing actual energy consumption.

The integration of a dynamic energy-aware cost function represents a significant advancement in underwater robotic navigation. Unlike traditional path planning algorithms that focus solely on geometric distance, the proposed approach bridges computational decision-making with fundamental hydrodynamic behavior. This makes the navigation strategy more realistic and effective, particularly for long-duration missions that demand efficient power management. The consistent performance observed across all simulation scenarios also indicates that the algorithm is robust and capable of adapting to environmental variation, which is essential for real-world applications such as hull cleaning, inspection, and marine infrastructure maintenance.

Although the results are promising, this study employs a two-dimensional grid-based environment to represent the ship hull surface, which is suitable for initial validation and performance analysis. However, this simplification does not fully capture the complex three-dimensional geometry of real ship hulls or the dynamic effects of underwater currents. Therefore, future work will focus on extending the proposed method toward three-dimensional path planning by incorporating realistic 3D hull models and real-world oceanographic data, including current velocity, turbulence, and pressure variations. Further development may also involve implementing and testing the algorithm on physical underwater robots to assess its performance under real operational conditions. Additional enhancements may include integration with adaptive control strategies, advanced sensor fusion, machine learning-based navigation, and cooperative multi-robot operations for large-scale hull cleaning tasks.

In summary, the energy-based A-Star algorithm presented in this research has demonstrated effectiveness, efficiency, and strong practical potential for underwater robotic applications. Its ability to incorporate physical energy constraints directly into the path planning process constitutes a meaningful contribution to the field of underwater autonomous navigation. The results confirm that energy-efficient navigation cannot be achieved by distance minimization alone and highlight the importance of energy-aware planning for ship hull cleaning and other marine operations requiring reliable, long-duration, and power-efficient autonomous systems.

5. AKNOWLEDGMENT

The authors would like to express their sincere appreciation to Muhammad Fardan for his valuable guidance, constructive feedback, and technical support throughout this research. The authors also acknowledge Universitas Negeri Makassar for providing institutional facilities and resources that supported the completion of this study.

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