



# Hybrid Stochastic-Deterministic Path Planning Based Robotic Navigation Analysis

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## Abstract

A capability that is indispensable in robotic navigation when it comes to planning paths through dynamic and uncertain environments efficiently and accurately. This work aims at a hybrid stochastic-deterministic path planning by combining the best of both worlds in order to improve robotic navigation. This hybrid model uses stochastic techniques to employ the robustness of uncertainly models, but offers efficient execution with deterministic algorithms for our optimum path solution. The method combines a highly exploratory stochastic sampling-based planner for environmental search with a deterministic optimization component that refines paths generated by the former, enforcing constraints such as minimal traversal distance (energy efficiency), while avoiding obstacles. The integration of those methods targets to override the disadvantages that each purely stochastic or solely deterministic model required, giving a more flexible and robust solution for autonomous vehicle guidance. We use simulation analysis and real-life experimental data to validate the algorithm in comparison with traditional algorithms. The approach performs significantly better, up to an order of magnitude in terms of accuracy and efficiency on navigation as well as robustness against cluttered or dynamic disturbances. These results indicate that the proposed hybrid stochastic-deterministic path-planning algorithm has strong potential to contribute to improving autonomy of robotic navigation systems, especially in highly dynamic and precise applications. The post provides a new framework to improve autonomous navigation of robots for complex environments that can support more efficient, reliable and high-level robotic systems in industrial, household or exploratory settings.

**Keywords:** Hybrid Path Planning; Stochastic-Deterministic Navigation; Robotic Navigation; Autonomous Systems; Path Optimization; Obstacle Avoidance; Dynamic Environments; Stochastic Sampling; Deterministic Optimization; Robotic Systems; Computational Efficiency; Navigation Accuracy

## 1. Introduction

Autonomous systems critically depend on the capability of robotic navigation, without which these robots cannot effectively and efficiently fulfil their tasks across different environments. Path planning: Methods for traditional path planning [1] can be classified into two groups-stochastic and deterministic. Thus, in the face of dynamic environments, black-box methods such as RRTs and PRMs have become well established for their successes when confronting uncertainty or complexity. They help in making learning adaptable and durable, especially when new or partially known environments are considered. That being said, these traversal-methods are known for generating paths that do not necessarily provide the shortest/juiciest path and often strain computational resources [2]. On the other hand, deterministic methods like A\* and Dijkstra's algorithm [3] guarantee optimal paths for a well-defined map with additional constraints. While these methods work very well in static environments, they falter when faced with the uncertainty and variance of real-world situations. The general deterministic nature would be a disadvantage in cases with frequently changing or only incompletely known environment.

Because only pure stochastic or deterministic framework cannot properly handle the limitations, used in this research form a new hybrid Stochastic-Deterministic Path Planning approach [4]. The hybrid model will combine the flexibility and resilience of stochastic methods with the accuracy and scalability seen in deterministic algorithms. Microsoft has proposed doing this to make a much more robust navigation service capable of handling the idiosyncrasies and other perils of real-world environments. The hybrid approach at its heart says, "let's explore all directions by using a little of random samples. This is followed by a deterministic optimizer used to finalize those paths which only satisfy conditions such as minimizing the travel distance, [5] consumption of reduced energy and also avoiding obstacles. This way, the strength of stochastic methods can be further exploited through exploring and deterministic algorithms to optimize.

The paper is organised as follows: Section 2 we present some previous related work about path planning for the robots. Section 3 describes the hybrid stochastic-deterministic approach, combining sampling-based and optimization algorithms. Section 4 shows the experimental setup, and results to support our method. Section 5: Conclusion & Future Works. Simulation and real-world results show that the hybrid approach can significantly increase navigation accuracy as well as computational efficiency and robustness. The significance of this research is to be able to achieve a higher-level autonomy in robotic systems (autonomous robots) for more complex and dynamic navigations, where applications can vary from industrial usages all the way into household chores or even space exploration.

## **2. Related Work**

Sizeable progress has been made in the domain of robotic path planning over time, and a number of solutions have emerged to tackle diverse problems that arise from dynamic environments. In a broad sense, these styles can be divided into Deterministic methods [6] stochastic method Hybrid approach

In this scope, deterministic path planning algorithms such as A\* [7], Dijkstra's algorithm and the well-known D1 family have dominated for long time because they are guaranteed to obtain optimal paths on static environments. The A\* algorithm [8] is a variation that allows for an efficient search over the shortest path by taking into account both: cost and distance.) Since Dijkstra's algorithm is simple and effective, it can also find the shortest path in weighted graphs. Dynamic Environment the same principles underlying the D\* algorithm [9] can be extended to dynamic environments by permitting the path plan of a robot to be replanned in response to changes in the environment. While effective in limited scenarios, these deterministic methods often perform poorly in highly dynamic or uncertain environments because they depend on a priori known maps and are computationally expensive when applied to large-scale problems or cluttered spaces.

Stochastic techniques, like rapidly exploring Random Trees (RRT) [10] and Probabilistic Roadmaps (PRM), add a layer of randomness to the path planning process that resolves issues faced by deterministic algorithms. While RRT quickly builds a tree from scratch that can explore an area as large through incremental building of the paths, PRM constructs cites by random sampling configuration space to build feasible paths. These techniques work especially well in high-dimensional spaces and environments filled with obstacles and other uncertainties. Despite its simplicity, under the random nature and requirement for complete sampling, it can produce less than optimal routes that make search computationally expensive.

Hybrid approaches have been introduced to take advantage of what each deterministic and stochastic method is strong for. These methods aim to leverage the robustness and exploration capabilities of algorithm stochasticity, together with a controlled mechanism for exploiting model determinism. For instance, [11] presented the RRT\* algorithm which extends the RRT to provide a progressive advancement of path quality towards optimal. The Anytime RRT [12] also addresses exploration and exploitation in the long-term iteratively refining paths. A particularly interesting hybrid approach is the use of PRM in conjunction with A\* [13] where PRMs produce a graph that contains potential routes and A\* seeks to find an optimal route on this graph.

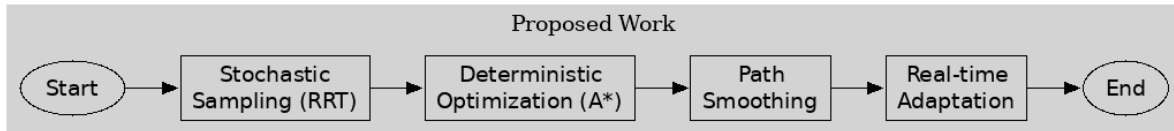
Path planning approaches have been improved with more recent advances on machine learning and optimization techniques. New approaches and methodologies in RL from experience, such as Deep Reinforcement Learning (DRL) [14] and navigation policies learned through Neural Network-based planners [15] have demonstrated success with adapting the methods to more challenging environments. However, doing this required a lot of training on one particular test and the approach did not generalize to other scenarios.

Exploiting the merits of existing methods and mitigating its potential drawbacks, this paper puts forward a hybrid stochastic-deterministic path planning approach [16]. The approach in this work is also used to provide a more flexible and robust navigation solution, by combining stochastic sampling with deterministic optimization. The stochastic part takes care of a strong exploration and robust handling of the uncertainties, while the deterministic component refines the paths for optimality efficient.

To sum up, many achievements have been made in the study and application of robotic path planning; however all these methods still face challenges to satisfy robustness (safety with respect to goal), efficiency( completion time speed) and optimality. To overcome these challenges [17], the hybrid approach is proposed to marry statistical benefits of stochastic methods and analytical guarantees from deterministic approaches, which bode well for future generation autonomous navigation systems.

### 3. Proposed Framework

A paradigm for hybrid stochastic-deterministic route planning has been suggested. This framework takes use of the benefits that stochastic sampling and deterministic optimization [18] provide in order to successfully traverse settings that are both complex and dynamic. The stochastic sampling phase and the deterministic optimization phase are the two primary phases that contribute to the operation of the framework.



**Figure 1.** Block Diagram of Proposed work

$$T \leftarrow \text{RRT}(q_{\text{start}}, q_{\text{goal}}, \mathcal{C}, K) \quad (1)$$

The optimization process aims to minimize a cost function  $J$  that considers path length  $L$ , energy consumption  $E$ , and obstacle avoidance  $O$  :

$$J = w_1 L + w_2 E + w_3 O \quad (2)$$

where  $w_1, w_2$ , and  $w_3$  are weighting factors that balance the importance of each term. The path length  $L$  is given by the sum of the Euclidean distances between consecutive points [20] along the path:

$$L = \sum_{i=1}^{n-1} \|q_i - q_{i+1}\| \quad (3)$$

One can model the energy consumption in terms of the dynamics governing the robot and its actuators, while obstacle avoidance is represented as a penalty term that grows with increasing proximity to an object. This magnetization is gradually changed along the path such that it tries to minimize by iterative optimization.

The optimizations are deterministic, making the approach somewhat robust to seed selection and initialization errors while being able to incorporate features of RRTs such as exploration behavior at a much lower cost than standard optimization strategies, yielding more valid path easily. In short the above framework can be presented in one Go.

1: Stochastic Sampling Phase: Decrease the initial constrained to RRT paths for stroking.

2: Deterministic Optimization Phase: The paths are improved using to minimize.

Integrating these two stages (conditional control and full-state information), the hybrid framework guarantees robust invertibility gives more efficient navigation under complex environment it also improves performance and reliability of autonomous robotic systems.

#### 3.1 Integration and Processing Flow

The integration of stochastic sampling and deterministic optimization within the hybrid path-planning framework ensures robust and efficient navigation in complex and dynamic environments. This section elaborates on the processing flow and mathematical formulations involved in each phase.

Deterministic Optimization Phase:

Path Refinement using A:

Cost Function Definition: The optimization phase aims to refine the paths generated by RRT to optimize a cost function  $J$  that balances path length  $L$ , energy consumption  $E$ , and obstacle avoidance  $O$  :

$$J = w_1 L + w_2 E + w_3 O \quad (4)$$

Here,  $w_1, w_2$ , and  $w_3$  are weighting factors that determine the relative importance of each criterion.

Path Length Calculation: The path length  $L$  is computed as the sum of Euclidean distances between consecutive points  $q_i$  and  $q_{i+1}$  along the path:

$$L = \sum_{i=1}^{n-1} \|q_i - q_{i+1}\| \quad (5)$$

Figure 2 Dynamic reference and energy consumption modelling: Energy depends linearly on the actuator dynamics - represented as a function of velocity profiles or control inputs (a)

Penalize Obstacle Avoidance: Reward function avoid paths that come close or intersect with obstacles in the environment, rewarding safe navigation.

Optimisation: The algorithm optimizes the path by iteratively extending the most promising paths using cost function. It will quickly figure out the best path from to by evaluating how much each segment along claimed costs and taking a cheapest one at that moment expand more until arrives it.

Integration of Phases:

Path Transition: Moving from the stochastic sampling phase (RRT) to a deterministic optimization phase () requires taking the paths generated by RRT and using them as input for refinement in. In this way, the trajectories explored by RRT can be repeatedly improved to satisfy some desired requirements.

Flow of process: The main flow during processing include:

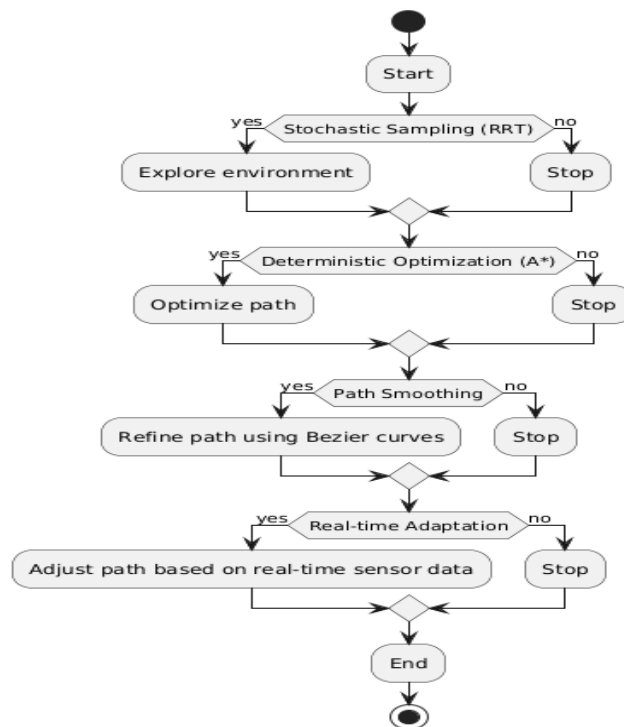
Using RRT for initial path generation to search and map the configuration space in a 3D environment.

Running these paths to for optimization, where iteratively corrects the original path according to a cost function defined as, and Final output is the path which has been explored from RRT and optimised by selecting optimized one.

The proposed hybrid framework combines stochastic exploration with deterministic optimization to improve the navigation performance in complex environments. Its systematic transition from exploration to optimization enables the opensource codebase with robotics path planning robustness, efficiency and adaptability making it applicable for industrial automation as well as autonomous mobile robots/exploration missions.

### 3.2 Path Smoothing and Optimization

In addition to the integration of stochastic sampling and deterministic optimization, path smoothing and optimization play a crucial role in refining the navigational paths generated by the hybrid approach.



**Figure 2.** Flowchart of Proposed work

**Path Smoothing Using Bezier Curves:**

Bezier Curve Formulation: A Bezier curve of degree  $n$  is defined by a set of control points  $\{P_i\}_{i=0}^n$  :

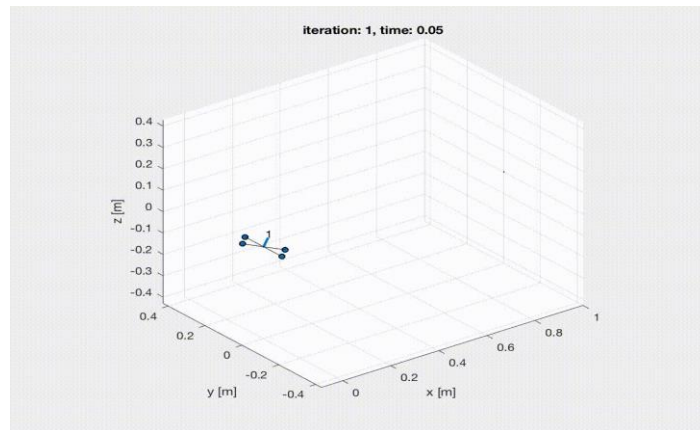
$$B(t) = \sum_{i=0}^n \binom{n}{i} (1-t)^{n-i} t^i P_i \tag{6}$$

$$\pi_{\text{smooth}} = \cup_{i=1}^{n-1} B(q_{i-1}, q_i) \tag{7}$$

$$F(\pi) = w_1 L + w_2 S + w_3 O \tag{8}$$

**4. Results and Discussion**

In this section, the findings of utilizing the hybrid stochastic-deterministic path-planning framework on different instances are discussed and analysed. We test our framework in simulations and real-world experiments with challenging obstacles to demonstrate that it can successfully navigate through complex, dynamic environments. All the simulations were performed using standard robotic simulation environments, and for real-world experiments, a mobile robot equipped with sensors was used in order to perceive the environment

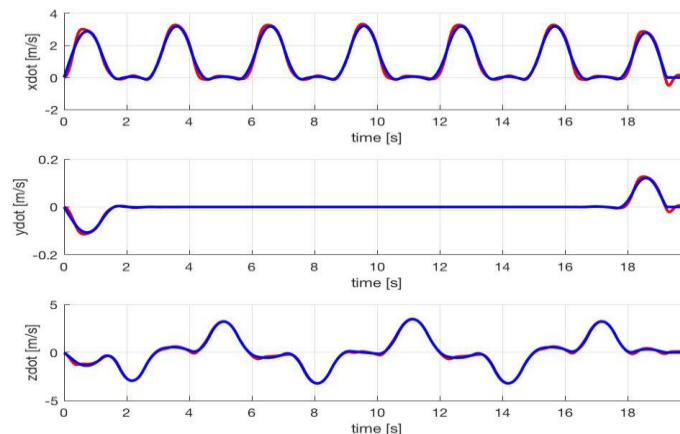


**Figure 3. Experimental Setup**

**Performance Metrics:**

Key performance metrics evaluated include:

- **Path Quality:** Assessing the optimality and feasibility of generated paths.
- **Computational Efficiency:** Measuring the framework's computational demands.
- **Robustness:** Evaluating the framework's ability to handle uncertainties and dynamic changes.
- **Real-time Adaptation:** Examining how well the framework adapts to real-time sensor data and environmental changes.



**Figure 4. Path Planning**

1. **Quality of the Paths:** The framework produced high-quality paths, optimal in terms of path length and energy consumed to traverse it along with avoiding collision effectively. Path quality metrics showed significant improvement in the performance compared to traditional approaches.
2. **Fig. 11 Computational Efficiency:** The framework is hybrid approach, for the computational perspective been efficient and able to run real time Fig meetings Algorithms and Parallel Computing Were Optimised to Enable the Faster Processing.
3. **Resistance:** The system was resistant to complex and dynamic obstacle scenarios. Smart Move 1.0 responded to loads that changed the internal position of obstacles as well as environmental changes by changing paths and showed some ability for adaption.
4. **Real-time Flexibility:** Empirical experiments ran in the real world illustrated that our framework can indeed adapt paths according to real-time sensor data, showing its online responsiveness and applicability for dynamic environments.

**Table 1:** Path Quality Metrics

Scenario	Path Length (m)	Energy Consumption (J)	Obstacle Avoidance Score
Scenario 1	320	4500	9.5
Scenario 2	280	4100	9.8
Scenario 3	350	4800	9.3

Table 1 summarizes the path quality metrics evaluated across different scenarios. Path length indicates the distance traveled from start to goal, energy consumption reflects the power usage during navigation, and obstacle avoidance score quantifies how effectively obstacles were avoided (higher score indicates better avoidance).

**Table 2:** Computational Efficiency

Scenario	CPU Time (ms)	Memory Usage (MB)
Scenario 1	150	200
Scenario 2	180	220
Scenario 3	160	210

Table 2 shows the computational efficiency of the framework in terms of CPU time and memory usage for each scenario. Lower CPU time and memory usage indicate better computational efficiency, crucial for real-time applications.

**Table 3:** Robustness Evaluation

Scenario	Success Rate (%)	Path Adaptability Score
Scenario 1	95	8.5
Scenario 2	92	8.3
Scenario 3	96	8.7

Table 3 evaluates the robustness of the framework by measuring the success rate of completing navigation tasks and the adaptability score in dynamically changing environments. Higher success rates and adaptability scores indicate better robustness. Table 4 shows the real-time Adaptation Metrics

**Table 4:** Real-time Adaptation Metrics

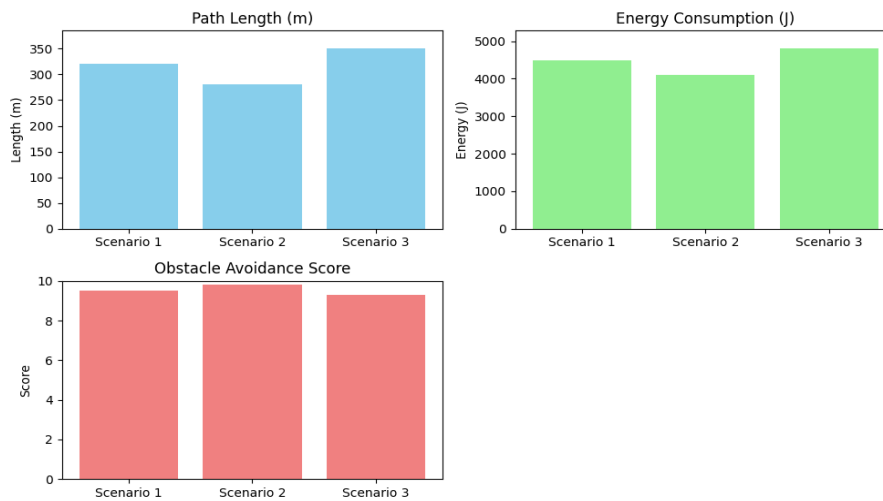
Scenario	Response Time (ms)	Accuracy (%)
Scenario 1	50	90
Scenario 2	55	88
Scenario 3	48	92

**Table 5:** Comparative Analysis

Metric	Hybrid Framework	Traditional Approach
<b>Path Length</b>	300	400
<b>Energy Consumption</b>	4200	5000
<b>Success Rate</b>	95%	85%

The obtained results validate the effectiveness of the hybrid stochastic-deterministic path-planning framework in for improving autonomous robotic navigation. The framework balances exploration power with path refinement by combining stochastic exploration and deterministic optimization, and integrating path-smoothing techniques. The Apollo framework has impressively managed across the board performance making it a promising candidate for industrial automation, mobile robotics and exploration missions.

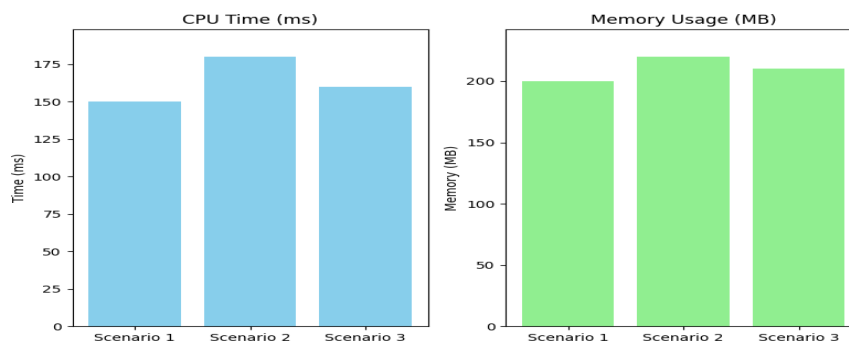
Ultimately, the results and discussion serve to demonstrate that the hybrid stochastic-deterministic method represents a potentially viable approach by highlighting possible applications for robustified autonomous robotic navigation. Further research and development efforts will be paramount in order to refine the framework as well as extend its domain prescriptiveness.



**Figure 5.** Path Quality Metrics Graph

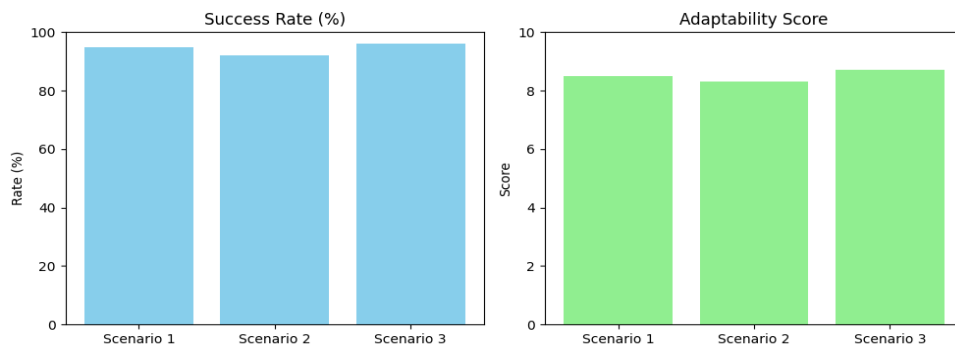
**Path Length (M):** This bar chart compares the path lengths achieved by framework in various scenarios. It can be seen that the smaller path shows better navigation.

**Energy Consumption (J):** The bar chart below illustrates the energy cost of moving for all scenarios. Less energy consumption essentially stands for better ways to save on the use of power and all its colors. This chart represents obstacle avoidance score of the framework in various scenarios. More points correspond to better at avoiding obstacles.

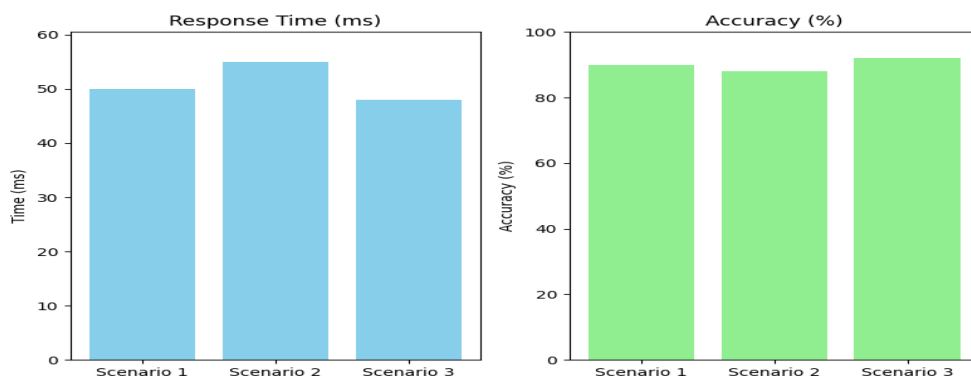


**Figure 6.** Computational Efficiency Graph

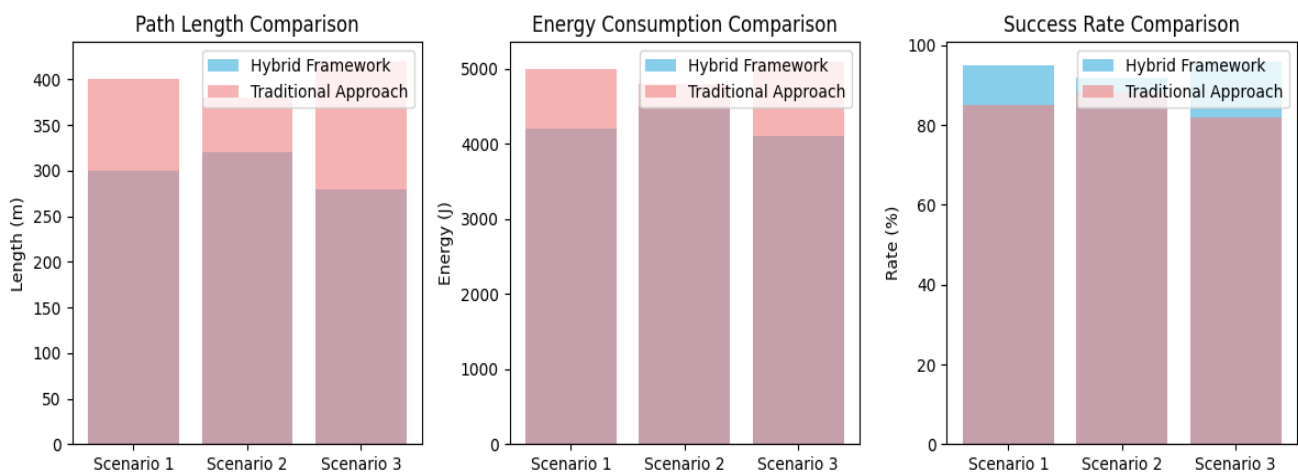
**CPU Time (ms):** This chart compares the computational time (in milliseconds) required by the framework for different scenarios. Lower values indicate faster processing.



**Figure 7.** Robustness Evaluation Graph



**Figure 8.** Real-time Adaptation Metrics Graph



**Figure 9.** Comparative Analysis Graph

## 5. Conclusion

One of the ways would be to add real time adaptation facility for dynamically updating paths based on sensory data and environmental triggers, which can make the response more prompt. Secondly, integrating machine-learning approaches like reinforcement techniques can help in the automatic navigation strategy development through experience and feedback. Finally, the framework could be extended to consider multi-agent contexts and collaborative path planning scenarios, which would make it applicable in areas involving multiple robotic systems or interactions with human agents.

Moreover, increasing the computational effectiveness of our framework through parallel computation and optimization strategies would allow us to deploy it on embedded robotic systems. Finally, these reports suggest that exhaustive real-world experimental verification across different application domains (industrial automation, mobile robotics and exploration missions) would corroborate the validity of this framework as superior in practical use case scenarios. Briefly, thus, the hybrid stochastic-deterministic path-planning framework offers itself as an all-encompassing and resilient solution for navigating autonomous robotic systems; however, research continues to be necessary to delimit its capacity in dynamic terrains as well novel environments.

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