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# An adaptive Probabilistic and deterministic path selection for cognitive radios

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## Abstract

Because it makes use of unused radio spectrum, cognitive radio (CR) has the potential to benefit alleviate wireless spectrum shortages. Environmental sensing is used to detect and adjust transmission characteristics in CR, a kind of wireless communication. This paper proposes the adaptive PDPS Protocol for CR networks, which uses probabilistic and deterministic route detection. If you want the best possible route between any source and any destination, PDPS can help. By completing extensive simulation scenarios and tests utilising a Java-based simulator, the suggested protocol is tested. According on the simulation findings, the suggested route selection method outperforms already used protocols. A number of performance indicators are used to make comparisons, including throughput, stability, and end-to-end latency.

**Keywords:** APDPS, CRs, deterministic path selection, Cognitive radio.

## Introduction

The most significant resource in wireless technology is the accessible radio frequencies. The rapid expansion of wireless services has exacerbated the problem of a lack of frequencies. The frequency spectrum is regulated and allocated only in the United States by the Federal Communications Commission (FCC). At the moment, the spectrum is too congested to accommodate the influx of new wireless services. A surprising number of investigations have shown that the bulk of the present spectrum allocation is being underutilised. For example, only around 5.2 percent of the spectrum below 3GHz is really in use on an average basis. New wireless services and the proliferation of "spectrum holes" have sparked the DAPRA to launch the XG initiative in order to explore the laws and regulations that allow the spectrum holes to be exploited more effectively by other users, a.k.a. secondary user. Opportunistic spectrum access (OSA) or dynamic spectrum access (DSA) is the name given to the new system. Cognitive radios are presented as a technique to maximise spectrum use by dynamically sensing the frequency spectrum and adjusting operating frequency. SDR-based "cognitive" radios are capable of detecting current spectrum, spotting gaps, and making adjustments to the parameters, such power and transmission rate. This allows for more efficient and cost-effective use of the available spectrum. Cognitive radios may take use of underutilised analogue TV broadcasts, for example, according to an IEEE 802.22 standard that allows them to do so. An important component of our research was made possible thanks to funding from the National Science Foundation, namely grants DBI-0529012 and CNS-0626881. When the major user, i.e., the TV broadcast signal, is missing, they are permitted to operate in the TV broadcast band. It is also possible for cognitive radios to dynamically swap frequencies in response to the unexpected returns of principal users if there are many primary users (i.e., numerous frequency opportunities).

MAC protocols for cognitive radio networks have been developed in the literature, which serve as guides for switching channels in response to environmental changes. The expense of changing frequencies in present wireless devices is not taken into consideration by many of these proposals. – The increased latency and worsened packet loss ratio caused by channel switching are becoming more well-known in the industry. As an example, a recent experimental research found that channel switching alone may result in a packet loss ratio of up to 3 percent. Cognitive radio networks make things much more difficult. Frequency-agility MAC protocols need the secondary user to alter the operating frequency consistently and adaptively due to the random features of main users. As a result, the overall throughput and quality of service (QoS) would suffer in the long run owing to the high cost of channel switching. As a result, from the perspective of the secondary user, it may be preferable to adopt a channel selection technique that relocates to transfer channels whenever possible. Another important consideration is that channel adaptations are carried out in order to reduce conflicts with the major users. That's why it's better for a secondary user to stick with the statistically optimum channel, rather than adapting to changes in main users' unexpected and random behaviour.

However, finding the best possible channel is not an easy task. To address the issue, it is sufficient to have previous knowledge about the distributions of return time and operation length for the principal users (figure 1), but this information is not readily available for usage in actual CRN. New stochastic channel selection technique based on learning automata (LA) is proposed in this study that dynamically modifies the probability of picking one channel on the fly and asymptotically converges to the best channel, in the sense of maximising transmission success.

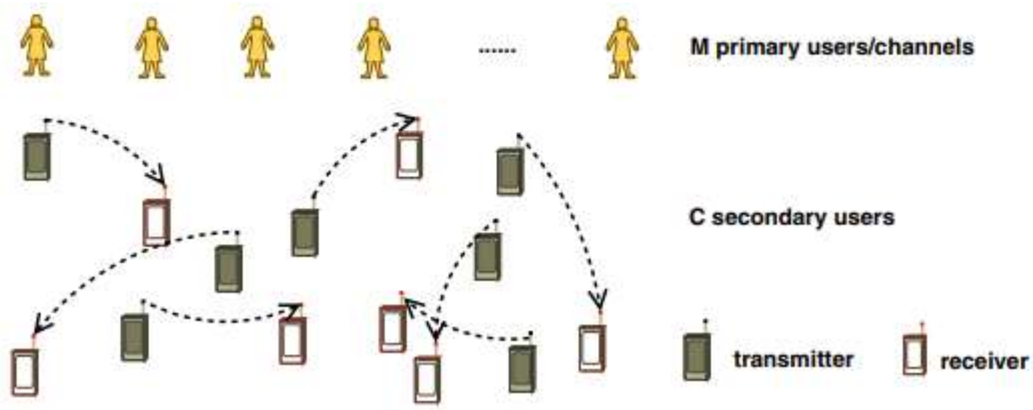


**Figure 1:** Topology cognitive network

What follows is a breakdown of the remainder of the document: Section II provides a short review of the paper's history and motivation. Section III introduces a new approach for channel selection that is based on stochastic processes. Section IV provides an example of the algorithm. Finally, Section V wraps up this article.

**Related work**

Darabkh, K. A., El-Yabroudi, M. Z., & El-Mousa, A. H. (2019) Sensor technology advancements have made it possible to create compact, low-cost, and low-power sensors that be linked by wireless media to form what are known as Wireless Sensor Networks (WSNs). Military target tracking and surveillance are only two of the many uses of wireless sensor networks (WSNs). Sensors, on the other hand, have limited power resources, thus researchers have been looking at ways to make better use of them. Using a Power-Aware and Balancing Aspects Clusters and Routing Protocol is the focus of this research (BPA-CRP). Network architecture is used in this batch-based method to divide the sensor field into layers and clusters of comparable size. Using this method, you may do a large number of clustering rounds (a batch) with no additional setup expenditures. BPA-CRP gives each sensor four broadcast ranges. There's also a "Forwarder" role in the routing algorithm that BPA-CRP introduces; this node may pass along information it collects at its location and at distant forwarders back to the base station. As soon as one or more of the forwarders loses energy, BPA-CRP recommends that a batch be stopped. BPA-"Only CRP's Normal" mode prevents tired nodes from serving as cluster chiefs or forwarders. To put it another way, they're more than simply environmentally friendly; they also help to distribute the weight of the system evenly. Finally, we put in place suitable node death-handling protocols so that each node dies without causing any data loss or network disturbance. The simulations findings showed that BPA-CRP had exceptional networking longevity and energy usage when compared to other similar research. In addition, the BPA-capacity CRP's for load balancing has been tested and proven effective [1].

Darabkh, K. A., Wala'a, S., Hawa, M., & Saifan, R. (2018) Threshold-based Low Energy Adaptive Clustering Hierarchy (T-LEACH) states that cluster leaders don't have to flip over every round but rather per batch of rounds. As long as a node's energy is over a certain level, it will continue to serve as a cluster head. The T-LEACH protocol's significant flaws are highlighted in this article, and a new MT-CHR approach is proposed. It has been suggested in the MT-CHR protocol that a new probability of becoming a cluster head has been provided for each node in any round that fits rather well with the assumptions presented in the LEACH protocol. The suggested revised threshold energy expression takes into account delays in the first node's demise and data loss. Based on live nodes, network lifespan, and network usage indicators, MT-performance CHR's is assessed. The MT-CHR protocol's contributions to the LEACH and T-LEACH procedures are further compared, and the findings are striking. The MT-CHR protocol is very relevant and very effective when it comes to real-world sensor networks, since long-term networks have been shown [2].

Darabkh, K. A., Al-Rawashdeh, W. A. S., Al-Zubi, R. T., & Alnabelsi, S. H. (2017) Low-cost and compact wireless sensors may now be produced because to new developments in electrical and electromagnetics technology. A large number of sensors equipped with radio frequency capabilities make up wireless sensor networks (WSNs). Data routing techniques in WSNs may be divided into flat, direct, and hierarchal types depending on the network architecture. An individual node in a hierarchical (clustering) protocol is assigned the role of a cluster head, while all other nodes are considered members. In addition, the system design should take into consideration the sensor nodes' processing, storage, bandwidth, and energy capabilities As a result, several scientists are working on developing a clustering process that uses less energy. In terms of energy efficiency, 'LEACH and T-LEACH procedures as well as MT-CHR and modified threshold-based cluster head replacement (MT-CHR) protocols stand out. Two clustering methods (namely, C-DTB-CHR and C-DTB-CHR-ADD) are proposed that aim to minimise the number of reclustering operations, prevent cluster heads nodes from premature death, deactivate so that so that so that so that so that so that so that so that By putting nodes in dense clusters into sleep mode based on an active probability, the C-DTB-CHR protocol increases the longevity of the network by reducing communication with the cluster leaders. In addition, the base station is accountable for generating the appropriate clusters and alerting sensor nodes of their active probability.. The C-DTB-CHR-ADD protocol's adaptive data distribution, which allows for direct and multi-hoping connections, enables for higher energy optimization. Interestingly, our simulated findings outperform the literature in terms of network lifespan, consumption, and network performance deterioration time [3].

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Darabkh, K. A., Alfawares, M. G., & Althunibat, S. (2019) In the last decade, there has been a growing interest in using Unmanned Aerial Vehicles (UAVs) for a variety of services and purposes. For complicated activities that need to be completed in a short period of time, UAVs (also known as drones) have shown to be successful when connected together, creating the Flying Ad-hoc Network (FANET). FANETs, with their unique characteristics including high mobility, rapid topology changes, and frequent link failures, exacerbate the issues already present in these networks. It's little wonder that developing an efficient FANET routing protocol has drawn the attention of so many modern scholars. In this study, we describe a Multi Data Rate Mobility Aware (MDRMA) protocol that features novel routing and power management techniques. As a result of this extension, MDRMA is known as Mobility Aware Dual Phase Ad Hoc on-Demand Distance Vector with adaptive Hello Messages (MDRMA-DPAODV-AHM). The formation of routes in the MDRMA-Routing algorithm, in particular, is not done randomly, but rather is predicated on the fulfilment of specific conditions that may be deduced from the affirmative responses to the questions that follow. There are a number of factors to consider while selecting an intermediate UAV. A plausible explanation might be a dispersal of the UAVs involved in transmission and reception. The intermediate UAV's speed isn't beyond a certain threshold. The MDRM-Routing algorithm guarantees that dependable routes with fast wireless connections are established based on successful management of prior difficulties. Additionally, the MDRMA-Power controlled algorithm makes changes to the 802.11b standard, specifically the RTS/CTS collision avoidance technique, in order to keep the minimum transmission power required by a transmitting UAV for successful packet reception at the target UAV and at a desired data transmission rate, taking into account receiver sensitivity and signal-to-interference noise ratio threshold, ensuring fast data forwarding. End-to-end delay, control overhead, and packet delivery ratio were evaluated using the NS3 simulator which conducted enormous simulations on the basis of UAV density, packet rate and constant bit rate connections. According to simulated tests, MDRMA does a good job of controlling network instability by providing quick and reliable pathways and lowering connection failure. This is the second time that MDRMA has shown to be better than the MA-DP-AODV-AHM procedure [4].

Hawa, M., Darabkh, K. A., Al-Zubi, R., & Al-Sukkar, G. (2016) CRN Sensor Networks (CRSNs) are an intriguing idea because they enable a distributed group of low-powered sensor nodes to access spectrum bands that are underused by their licenced owners (referred to as main users (PUs)). CRN sensor networks It is also possible to use energy harvesting mode while the PUs are broadcasting in their respective bands, so that sensor nodes may reach virtually eternal life. CRSN sensor networks can simultaneously collect and transfer data, while smartly addressing the disproportionally large distinction between both the maximum voltage needed to transmit packets and a small amount of electricity it can collect wirelessly from the atmosphere, which is acknowledged in this work by a novel and highly decentralized MAC protocol called S-LEARN. Network performance and energy harvesting are both improved by the proposed MAC protocol, which is tolerant to network configuration changes. It's also possible to keep the cost of S-LEARN low and avoid the drawbacks of centralised systems [5].

Hawa, M., Darabkh, K. A., Khalaf, L. D., & Rahhal, J. S. (2015) The spectrum shortage problem may be solved by using cognitive radio, an upcoming wireless technology. There are plans in place to provide cognitive wireless users (unlicensed) an opportunistic access to unoccupied channels in order to better use the spectrum. A low-complexity and high-efficiency dynamic spectrum access strategy for cognitive radio networks is presented in this research. No central controllers or pre-established and maintained common control channels are needed for this spectrum assignment process. The throughput and fairness levels it can achieve are comparable to those of centralised systems, though. When new cognitive users join the network or when main users activate the cognitive radio network, the suggested approach responds very effectively to the disruptions. Furthermore, in this work, we give an analytical model that can be utilised to quickly forecast the performance of our approach [6].

Darabkh, K. A., Amro, O. M., Salameh, H. B., & Al-Zubi, R. T. (2019) The ever-increasing need for wireless communications has garnered considerable attention in recent decades. Spectrum efficiency is the primary objective of all wireless network designers. To combat this, a slew of new approaches have been developed. Cognitive Radio Technology (CRT) is one of these methods, which enables unlicensed users to make use of unused airwaves alongside licenced ones. Additionally, wireless devices may now interact in the same frequency band concurrently thanks to the invention of the In-Band Full-Duplex (IBFD) technology. For the last several years, experts have been intrigued by the possibility of combining these two cutting-edge technologies. IBFD–CRNs are examined from the standpoint of each layer, namely the physical (PHY), medium access control (MAC) and network levels. Researchers may use this work to help them get a better understanding of cognitive radios and other recent advances in IBFD communications, including many Self Interference Cancelation techniques, before moving on to basic IBFD–CRN concepts and potential future research directions [7].

Naeem, M., Anpalagan, A., Jaseemuddin, M., & Lee, D. C. (2013) To maximise radio resources in the recent decade, cognitive radio and cooperative communication solutions have been proposed in the literature Cognitive radio, a new technology being developed to make better use of the radio spectrum, is currently under development. Cooperative communication systems employing the same total power and bandwidth as historical wireless communication systems may boost the data throughput of future wireless communication systems. Future wireless networks may benefit from the use of cognitive radio and cooperative communication. Cooperative cognitive radio networks will be necessary for future wireless networks to efficiently allocate resources (CRN). This article examines the distribution of cooperative CRN resources. Taxonomy of purposes and techniques is used in the study on cooperative CRN resource allocation. It also examines the use of power management, collaboration, network designs and decision-making in CRNs. - Control of Power Finally, the future of research is considered in the concluding paragraphs. [8].

Darabkh, K. A., Judeh, M. S., Salameh, H. B., & Althunibat, S. (2018) Stable route establishment in highly mobile networks is a difficult problem, which has attracted the interest of many academics in the present day. Ad-hoc On-Demand Distance Vector (AODV) and Mobility and Direction-Aware AODV (MDA-AODV) are two earlier routing methods that are regarded to be key extensions of this new reactive routing technology. Ad hoc On-demand Distance Vector with Adaptive Hello Messages is its full name (MA-DP-AODV-AHM). For the most part, it focuses on constructing routes that take into account the speeds and directions of the moving vehicles in relation to their origins, which results in more stable routes with fewer route breakages. Control overhead and network problems may be reduced significantly by using adaptive control packet announcement, which is connected to periodic welcome messages and vehicle speeds. The new protocol, which comprises the MA-DP-AODV-AHM and AODV protocols, is proposed to ternate-workinge between two stages in order to guarantee timely construction of efficient routes. It was necessary to conduct extensive simulations using the QualNet simulator version 7.1 in order to verify the robustness of our protocol. According to the findings of the simulations, MA-DP-AODV-AHM is an effective tool for minimising network instability by developing stable routes and decreasing link failures.. AODV and MDA-AODV have been shown to be inferior to it [9].

Darabkh, K. A., & Alsukour, O. A. (2015) As one of the most widely used multicast routing protocols in ad hoc mobile networks, On-Demand Multicast Routing Protocol (ODMRP) stands out due to its ease of use, efficiency, and mobility resistance (MANETs). It is, however, worth noting that ODMRP's resilience comes at a considerable cost to the network. Based on input from the network on actual disconnections experienced by multicast network users, the Enhanced ODMRP (EODMRP) recommended a dynamic refresh interval for the multicast network's mesh. With its low packet delivery ratio, EODMRP did indeed reduce network management overhead, but at the expense of a higher packet loss rate when the network is highly mobile. As an upgrade to ODMRP and EODMRP, the refresh interval is tuned to source movement speed and the number of disconnections reported by multicast members in this work, which proposes two new methods The additional setup and failure methods we suggested to include in both protocols, as well as the outstanding local recovery we presented, all help significantly to improve the performance of our proposed protocols. The key contribution of this study is to reduce the amount of control information that is sent between nodes (i.e., decreasing the control overhead above that of ODMRP) while yet retaining a better packet delivery ratio than EODMRP [10].

Darabkh, K. A., & Judeh, M. S. (2018, June) Ad-hoc On-Demand Distance Vector (AODV) routing system has been extended to include Mobility Aware and Dual Phase Ad-hoc On-Demand Distance Vector with Adaptive Hello Messages, a new reactive routing protocol. Its primary focus is on constructing routes that take into account the speeds and directions of motion of nodes in relation to their source nodes, resulting in more stable routes and fewer route breakage instances. The periodic welcome messages strategy, which is directly linked to the adaptive control packet announcement mechanism, with nodes' speeds, yields a large decrease in control overhead and network congestion. End-to-end latency and energy usage are some of the metrics used to assess our approach [11].

Saifan, R., Msaeed, A. M., Darabkh, K. A., & Ala'F, K. (2019, March) Environmental sensing is used by wireless devices to detect and alter transmission characteristics in cognitive radio (CR). For cognitive radio networks, we present the PDPS Protocol, which is a probabilistic and deterministic path detection scheme. If you want the best possible route between any source and any destination, PDPS can help. Using a Java-based simulator, extensive simulation scenarios and tests are conducted to test the proposed protocol's performance. Simulated findings show that the suggested route selection approach outperforms one of the most widely used protocols currently available [12].

Mallat, Y., Ayari, A., Ayadi, M., & Tabaane, S. (2015, September) A slew of Cognitive Radio (CR) routing algorithms have recently been suggested to increase spectrum use efficiency. The Cognitive Ad hoc On demand Distance Vector might be used as an example (CAODV). On the basis of AODV, this protocol employs an on-demand technique to locate routes to which the principles of geographic activity avoidance of the Primary User (PU) have been added throughout the packet transfer process. Quality of Service (QoS) methods are not supported by this protocol as a key shortcoming. An adaptable QoS mechanism will be included into a cognitive on-demand routing system proposed in this work. QoS-CAODV is a novel protocol that combines QoS-AODV with CAODV. Numerical simulations have assessed the QoS-CAODV protocol's performance (OPNET 14.5). From the statistics we've seen, it seems that the QoS-CAODV protocol offers the best throughput and end-to-end latency, as well as the lowest amount of missed packets [13].

Singh, K., & Moh, S. (2016) Since it makes it possible to take advantage of the frequency spectrum, a limited resource in the communications industry, cognitive radio has gained attention as a potential new technology. CRAHNs, which combine cognitive radio technology with aspects of ad hoc networks, make efficient, opportunistic, and dynamic use of spectrum possible. CRAHNs, on the other hand, must contend with a number of difficult difficulties, including a dynamic topology, uncertain primary user behaviour, and a wide range of spectral variance. In addition, CRAHNs have a severe difficulty with their limited power supply. Existing research suggests a number of methods for increasing the energy's utility and conserving it. We can see that routing uses a significant amount of power. Routing in CRAHNs, on the other hand, requires a meticulous attention to detail. This study focuses on the numerous routing methods that have been published to far for extending the network's life span and boosting system performance and reliability.." As a result, it offers insight on the challenges of creating and implementing routing protocols in CRAHNs [14].

Moon, M. S., & Gulhane, V. (2016) To address the issue of radio spectrum scarcity, the wireless technology known as "cognitive radio" was developed. Primary channel sensing is critical here, as is the selection of a suitable unoccupied channel for secondary users to exploit. In this study, a number of main channel selection methods have been examined. Using a structure termed the Preferable Channel List (PCL), this work proposes a contention-based channel selection method in which the receiver plays a dominant role. In order to transmit data, the method will prevent collisions and use RTS-CTS contention [15].

Amin, T. (2016) The radio frequency (RF) scarcity issue is being fuelled by a constant rise in wireless subscribers and a static distribution of wireless frequency bands to main users (PUs). Because it makes efficient use of the limited RF resources, the cognitive radio network (CRN) is being touted as a solution to this conundrum. It is possible for SUs in CRN to take use of open frequency bands without interfering with primary users (PUs) in any way. Through the use of spectrum sensing, CRN's SUs may detect the presence of PUs and then use dynamic spectrum access to get access to any available free band space. In the literature, spectrum sensing methods do not take into account mobility. A major goal of this thesis is to include SU mobility into spectrum sensing. Because of CRN's unique physical properties, which allow unauthorised wireless devices to dynamically access licenced RF channels, security is becoming an increasingly pressing issue. CRN's physical layer security vulnerabilities are also addressed in this thesis. For spectrum sensing, the percentage of false alarms and misdetection and the estimated overlap duration are used to assess performance. SUs in a hostile environment are evaluated based on their ability to maintain secrecy rates [16].

## Methodology

After originally appearing in [10] as NP-hard, it was subsequently revealed to be APX-hard in [2.] If you'd want more information on the OP, please go to [11] and [23] for further details. The OP can be solved perfectly up to 500 vertices using integer programming techniques, but for bigger issues, these approaches expand exponentially in calculation time, making them ineffective. An exhaustive search of the literature yielded the best approximation technique, [8], which provides a (2+) approximation with no(1) where n is the number of vertices in the problem. Because of this, domain-specific heuristic approaches provide the optimum compromise between computing time and reward collecting (without guarantees). [17, 19], and 20] are examples of recent efforts that may handle very large OP cases (50,000 vertices) exceptionally rapidly by utilising the specific structure of networks encountered in our particular application. The SOP is often considered to be less well-known than the OP. Edge traversal and vertex service costs are explored in [5], however non-deterministic rewards are another way to look at the problem. A precise solution is presented in [5] for issues confined to extremely specific sorts of graphs, as well as more generalised heuristics. Nonadaptive O(log log B) approximation approach and an adaptive (policy driven) O(log log B) approximation are provided in [12].B is the cumulative cost budget for edge traversal and vertex servicing, respectively. [3] shows a lower limit on the worst-case ratio between the optimum rewards for adaptive and non-adaptive plans (called the adaptivity ap)off $\Omega(\sqrt{\ }\log\log B)$ in the associated literature. [3] They simply focus on maximising anticipated return

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without taking into account the danger of not meeting budget limits, which is what we're looking at in this study. In this paper, we propose a new WiFi offloading scheme based on Q-learning approach in order to select the appropriate target base station depending on what the user has learned from the environment and on the network condition.

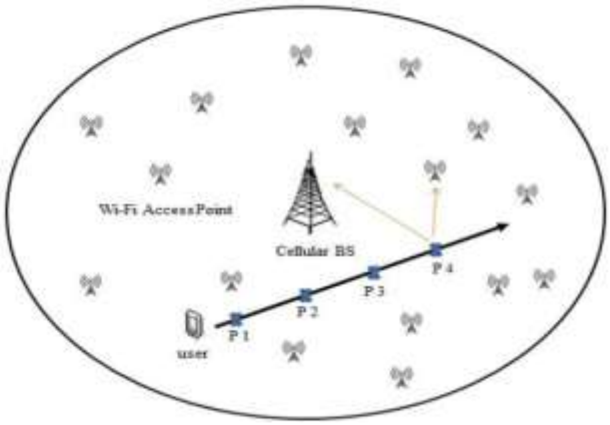


**Figure 2:** system model

Chance constraints are widely utilised in the context of stochasticity because they may limit hazardous behaviour in order to provide resilient solutions. Probability restrictions in the orienteering domain have been examined in a few publications, such as [14], which looked at how to maximise reward while making sure at least one agent survived with a certain probability. Using a mixed integer linear programme formulation and an open-loop solution, [24] examines risk sensitivity in the SOP formulation using stochastic weights and chance constraints. This, however, does not give a policy enabling an agent to dynamically modify its direction in light of current budget spending. A strategy that takes into account incurred travel expenses after each edge traversal is provided in our earlier work [18] and not here. There are several instances of this kind of issue being solved with the help of CMDPs, which are also known as the Constrained Partially Observable MDPs (CPOMDPs).

SOP and other important core ideas were presented in [18] to get us started. There is no longer a distinction between the terms "cost" and the term "time," which are used interchangeably from here on out.

**The Deterministic Orienteering Problem:** With an edge cost function of c: E R+ representing the time it takes to traverse an edge, G(V, E) has an undirected fully connected graph G(V, E). The vertex reward function is r: V R+. Additional edges with costs equal to the shortest path between two vertices may be added to G to make it totally connected. To calculate R(P) R(P) R(P) R(P), add up the rewards earned on each of the unique vertices that have been visited, but keep in mind that the total cost C(P) incurred each time an edge is travelled cannot exceed B. (P). A tour is determined if vs and vg are both equal. While it is not necessary to provide the start and target vertices for the OP in general, there are situations in which it is. Vs is required in certain cases, and this kind of difficulty is known as the "rooted" OP. Regardless of whether one or both vertices are defined, the OP is NP-hard.

**Path Policy:** a path If (vi, vi+1) is equivalent to E for all numbers from 1 to the power of I, then P on G is an ordered collection of I n+1) points. Whenever vi is in P, S(vi) = vi+1, vi+2,...,vn is the collection of vertices following vi. According to this definition, S(vn) is equal to To select which vertices to visit next, each vertex-time pairing (vj/t) is assigned a route policy over P, which is a function that assigns

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each vertex-time pairing to an action (the next vertex to visit) (vj ). This example formalises the practise of taking a shortcut via P (see Figure 1), which is useful in meeting a budget constraint in the context of randomised travel durations. By planning forward utilising current time and position of current vertex, an agent may achieve vn = vg before the deadline B ends, which is conceivable.

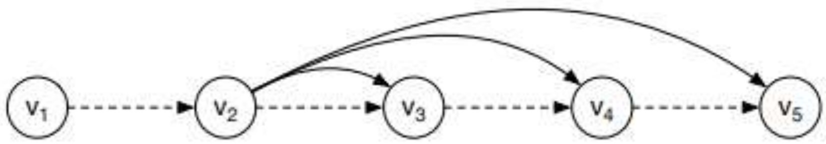


Fig. 3: For a hypothetical path of 5 vertices,

To skip one or more of the five vertex positions on a hypothetical route, may be used. Path policies determine which vertex an agent should go to next based on the temporal parameter t, in particular from v2. Even if skipping a few points in P reduces the projected total cost of getting to the last vertex, the overall reward is reduced as a result.

**The Stochastic Orienteering Problem:** All edges of E must have a probability density function (pdf) that has a positive support and a finite expectation. This random variable (ci,j) has a cost per edge traversal (pdf) of vi,vj. Starting at time t0 = 0 and vertex v1, an agent follows the path policy to follow route P. At vertex vi and time ti, a random variable with pdf f is assigned, and the agent moves to the next vertex at time vj = (vi,ti)/ci,j + ti (vi,vj ). There is no end to this trail after you get to vn, therefore you have to keep going. All the costs and rewards accrued along the route P following path policy are also random variables in this example. Only the vertices in P are accessible according to, hence E[RP,] R(P) is always true. A path and policy are then requested that maximise the anticipated total of rewards E[RP,] for a given Pf by determining which path and policy maximise the expected total of rewards E[RP,]. The final vertex's likelihood of being attained after the budget B has been exceeded owing to this chance constraint may be gauged by looking at Pf. The SOP is likewise NP-hard since it generalises the OP.

**Defining an MDP:** In G, let's assume that P = vn in G is an example of what we're searching for. For each vertex in P and time, vj = (vi, ti) has to be established as a route policy. vj S. (vi). The transition time from Vi to vj is unpredictable and is represented by the edge's pdf. For this, a Markov Decision Process (MDP) for a well-augmented state space makes sense. An in-depth explanation of MDPs may be found in [4]. There are just four components needed to create an MDP: states S, actions A, transition kernel Pr, and reward function r(s S, an A).

- P has a set of vertices V and a time discretization T, resulting in N=dBe consecutive time steps of length tk between B and [k,(k + 1)] for the interval tk.
- Assume that an agent arrives at vertex vi at some point in time tk, and then use this composite state to describe that arrival.
- Set of vertex following vi, Avi = S, is each state's action set (vi). Any state's action set is unaffected by the time interval in which it occurs. A =Sni=1 Avi is the last action set.
- As a result of an action in state (vi, tk), the chance of landing in the successor state (vj,tl) is defined as Pr((vi, tk), (a, (tl)). Due to the action's deterministic selection of the next vertex, the transition probability for all states, even those with vertices other than equal to, is zero. Because the agent is unable to go back in time, the transition probability is also 0 for all successor states in which l k. F((tk+1)d)]d is the cumulative function of the pdf associated with edge transition probabilities for the remaining states (vi, vj ).

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- Each state/action pair's reward function, r, has a value of r((vi, tk), a), which represents the reward for vi in G. To be clear, it doesn't matter whether tk or an is used to denote the difference; the two are comparable.

In an MDP, the cumulative reward function that is utilised to create the policy is what defines the policy. A non-discounted reward and two distinct states, failure state sf and loop state sl, are selected since P is a singular episode. When tk > B, the failure condition is given as any vertex and time combination where the target vertex has not been reached before the deadline B. For any transitional activity that does not result in moving to or from sf at a desired vertex (vj), the budget is likely to be depleted, and there is no reward associated with doing so. The MDP definition has been completed and the traversal episode has come to a conclusion.

Vn and the failure condition sf have just one action al, which leads to sl with a chance of 1. A single action that leads directly to sl has a chance of one, and the payoff is zero. Once a loop has been entered, it cannot be left, and no more rewards may be obtained. Figure 2 depicts the MDP's composite state space, as well as some examples of transitions.

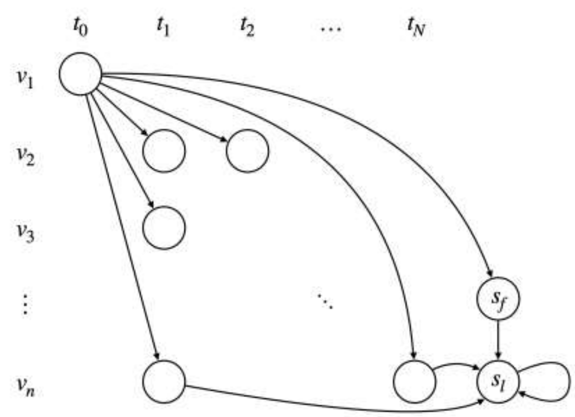


Fig. 4: The MDP states are displayed in grids having rows indicating vertex and columns indicating time periods.

The MDP displays states as a grid with rows denoting vertices and columns denoting time intervals between them. Some transitions with a non-zero probability have arrows shown. Any of the following vertices may be reached from state (v1, t0), and the time interval ti > t0 can determine the arrival time of the next vertice. sf is portrayed as the next step after B has been reached at the vertex. A deterministic transition from route vertex (vn) to loop vertex (sl) occurs when state reaches the latter.

This MDP structure is analogous to the studies [7], [9], and [15], which use failure and loop states to build control policies with finite failure probability. ' It's more likely that adopting a policy will result in failure than it is in success, therefore the final vertex along P won't be reached until B. It's possible to get to sl with all valid policies, but the start state is limited (v1, t0). This is why there is a reward function that does not discount.

$$\mathbb{E}[R_{\mathcal{P},\pi}] = R(\pi) = \mathbb{E}\left[\sum_{t=1}^{\infty} r(X_t, \pi(X_t))\right]$$

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where and Xi, a random variable for the state at time t, produce a probability distribution and the expectation is drawn from that distribution. There is an expectation, and it is limited since the chance of reaching sl is 1, and there are no loops before sl.

**Defining a CMDP:** Maximizing anticipated benefits while keeping the chance of entering sf under control is the purpose of the SOP described previously. An MDP isn't acceptable under this definition since it can only handle one specific goal function.

Because of this, we must redefine MDP to include a Constrained MDP (CMDP), a model that may maximise one objective function while maintaining expectations for other functions that are constrained [1]. A secondary cost is introduced for each state/action combination d: SA R+ that is 0 everywhere except for (sf, al) where it is 1. Only if an agent encounters a failure condition does this cost apply. Any policy has the same failure probability as the expected secondary cost E[D()], since an episode can only go through the failure state once.

It is common practise to use the linear programme (see [1], ch. 8) in order to solve the CMDP. The optimization variable is used to represent the occupation measure for each state/action pair, and the start state distribution (which is set to 1 for (v1, t0) but zero everywhere else) is used to represent the start state distribution.

$$\max_{\rho} \sum_{(x,a)\in S\times A} \rho(x,a) r(x,a) \tag{1}$$

$$\text{s.t.} \sum_{(x,a)\in S\times A} \rho(x,a) d(x,a) \leq P_f \tag{2}$$

$$\sum_{y\in S} \sum_{a\in S(y)} \rho(y,a)(\delta_x(y) - \Pr(y,a,x)) = \beta(x)$$

$$\forall x \in S \setminus \{l\} \tag{3}$$

$$\rho(x,a) \geq 0 \quad \forall (x,a) \in S \times A \tag{4}$$

In this formulation, Eq. (1) specifies an objective function that seeks to maximise reward across a collection of occupancy measurements. Failure state occupation costs must be less than or equal to Pf, according to Constraint (2). It is impossible to visit the failure state more than once, which limits the failure probability.

Constraint (4) requires a non-negative occupancy measure for all state/action pairings. The collection of valid occupancy measurements is defined by the flow preservation constraint in constraint (3). Both the initial distribution and the probability of state transitions (see [1], ch. 8 for more information) are connected to this concept. When x equals y, the function x(y) has a value of 1, otherwise it has a value of 0.

Linear programming is possible only if the cost constraint is satisfied by a stationary, randomised strategy that is defined by as follows:

$$\pi(x,a) = \frac{\rho(x,a)}{\sum_{a\in S(x)} \rho(x,a)} \qquad \forall (x,a) \in S \times A \tag{5}$$

Where x, an is the probability of action an in state x, as defined by (x, a)

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When a state's denominator for E.q. 5 has a 0 in it, the policy for (x, a) may be established in any way. You may find out more about this method by reading the following passages: ([6,7,9,15]). To demonstrate that the above linear programme satisfies the failure probability constraint Pf, we established the following theorem in [18].

**Theorem 1**. If the linear program permits an answer, then the policy fails to reach the vertex vn inside budget B with a probability of at most Pf.

The following method for resolving an instance of the SOP is generated by using the CMDP formulation:

1) Create a deterministic OP instance that assigns the predicted trip cost E[c] to each edge e.

2) Use any deterministic technique to solve the deterministic OP using vs, vg, and B and return P as the route found.

3) Use P to create and solve the CMDP stated above and return, as indicated before.

The method employed in step 2 to solve the deterministic OP has an impact on the quality of the solution provided by this new algorithm. An precise answer may be obtained by solving the OP using the conventional mixed integer programme [11] for minor issue instances. A heuristic or estimated technique may be employed when employing mixed integer programming becomes computationally infeasible for big issues or repeated executions of the algorithm.

**AN ADAPTIVE PDPS:**

When computing solutions for the SOP, we employed the Section IV technique outlined in [18], where we demonstrated the feasibility of using a deterministic route to begin path policies that maximise rewards while still reaching a target vertex within a defined failure limit. Because this technique generates a policy that can only visit vertices in P, the greatest possible reward is limited to R(P), and there is minimal possibility for reward growth. In this paper, we provide a novel strategy that does not depend exclusively on the initial deterministic route, but rather provides policy options where reward collection rises in anticipation.

Building on the prior strategy, this new one allows the policy to diverge from its beginning point. This is accomplished by generating new pathways from a subset of the intermediate vertices on the path. Deviating from the original deterministic route might be helpful in situations such as arriving at a vertex vi sooner or later than planned. A deviation from the predicted average behaviour may necessitate calculating a different route based on the present location and remaining money, in these instances.

When a new route P new and policy new based on vi can be found in the budget, it may be worth it to explore a different subset of V, since the predicted reward is bigger than if the original path and policy were followed. The new route P new and the new path policy new can be calculated online, but this calculation is costly and difficult to do on the fly, limiting the adaptability advantages that can be achieved.

This may be done at any time and retrieved at any place. Directed path trees (PTs) with branching show both the initial deterministic route as well as any deviations from that path. From (v1, t=0), it travels down P until (vi, tj), at which point it may either continue down P or take a different branch depending on the time at which the current policy arrives. Using shortcuts to future vertices along P new is authorised only from (vi, tj) onward, according to the policy. It is possible to find a single route from vi

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to vg with budget Btj that maximises the awards that have yet to be collected by using a deterministic orienteering solution with rewards set to 0. Vi may create an unlimited number of new pathways, but only one can be used for each conceivable arrival time. Multiple branches may be added to PT since there may be several states when a new route is desirable. A directed route tree prevents branches from merging. A route must contain an ordered collection of vertices in order to build new branches, and each vertex along a branch automatically encodes information about previously visited vertices. The merging of two branches might result in inconsistent information about which vertices have been previously visited. In other words, recombination of branches would eliminate vertices that an agent may not have visited, since branches are intended to explore separate subsets of V. Figure 3 shows PT in action.

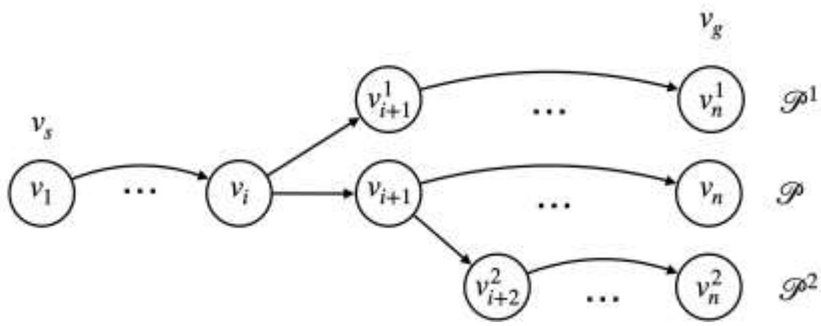


Fig. 5. Vi and vi+1 are two extra branches added to a route in order to build a path tree

In Fig. 3 Vi and vi+1 are two extra branches added to a route in order to build a path tree, as seen in Figure 3. V1 may access every vertex in P1j>i and P1j>i+1, as well as any vertex in P2j>i+1. However, the only vertices farther along in P and any vertex in P2j>i+1 may be accessed by shortcuts from vi+1, but v1i+1 can only access vertices in P1.

Superscript notation is used to denote pathways that follow various PT branches, whereas subscript notation is used to denote a path vertex. v1 is the starting point and vn is the ending point of all pathways that are viable (equivalently Pk1 or vs). In the case of PT policies, shortcuts from certain vi to vertices farther down the route and any future connecting branches may be considered, but not to any branches that linked before to vi. To solve an instance of the SOP, a novel adaptive path method is developed by replacing the singular deterministic route P with a path tree PT.

1) Create a deterministic OP instance that assigns the predicted trip cost E[c] to each edge e.
2) A deterministic approach may be used to solve this problem and return the route PT.
3) Section IV describes a CMDP to be built and solved using PT to yield.
4) Set of states (vi, ti) where Sjump induces an action that results in a shortcut to a future vertex vj where j > I + 1 is found.
5) Add a new path branch with budget B ti to the path tree PT for each state in Sjump using any deterministic orienteering approach.
6) As explained previously, create and solve the CMDP using PT.

For the purposes of determining where branches should be located (step 4) before adding further PT branches (step 5) and starting from scratch to create a new policy, the steps 1–3 of IV are represented in Figure 4. This is the last step (step 6). A new branch at vi may begin with the same P vertices as in Vi+1 through Vj, therefore the branch may be chopped down and start at Vj instead of Vi+1 through Vj in Step 5. It is also possible to remove all branches that are the same. Final output from policy new prescribes activities to be taken at various times to maximise expected reward and minimise the probability of failing to Pf.

It is possible that the projected reward E[RPT,new] will be greater than R, given that the route tree is dynamic (P). Recursive execution of steps 4–6 may be used in order to create additional route branches originating from the previously added branches, but this greatly increases the amount of compute required to discover new even when employing heuristics, and we do not use it here.

**Branch Heuristics:** The computing difficulty of a CMDP linear programming solution is directly proportional to the number of state-action pairings |S A|. With vast state spaces, the deterministic route technique described in section IV expands super-linearly, and computation time becomes intractable. To put it another way,

$$|\mathbb{T}| \cdot \left(\frac{n(n-1)}{2} + 1\right) + 2 = \mathcal{O}(|\mathbb{T}| \cdot n^2)$$

When there are as many vertices in P as there are time intervals, the answer to this question is (n-T). With a greater anticipated reward, the adaptive route algorithm can generate policies with more state space and computation time than the traditional deterministic path approach, but this comes at a price.Shortcuts are taken in the original policy, and new branches are introduced where they exist. However, there may be several states where shortcuts are made. There are significantly more state/action pairings in PT because of this, and the number of vertices may be several times bigger than in P.

$$|\mathbb{T}| \cdot \sum_{\mathcal{P}^b \in \mathcal{PT}} \left(\frac{|\mathcal{P}^b|(|\mathcal{P}^b| - 1)}{2} + 1\right) + 2 = \mathcal{O}\left(|\mathbb{T}| \cdot |\mathcal{PT}|^2\right)$$

which has a total number of vertices of |PT| plus the number of vertices in branch |Pb|.

This means that the route lengths of any new branch added to PT are random and cannot be controlled manually since they are estimated using a stochastic navigational approach instead.

It is possible, however, to regulate the number of branches and to reduce this number using heuristics is a simple way. Adding just those branches that are most likely to be used by the policy is a simple but effective strategy to follow. is equal to the likelihood that a state/action pair is performed by the policy since non-loop states in the CMDP can only be visited once. That way, only kb shortcut actions with the greatest values will be used to augment Sjump's state as part of the adaptive route method. According to this new version of the formula:

1) The adaptive route algorithm calls for you to do steps one through four.
2) Sort Sjump by in decreasing order
3) If you're using Sjump, you'll first need to determine which route from vi to vg has a budget of Bti and then add that path to the path tree.
4) As previously mentioned, construct and solve the CMDP using PT to get a new.

Instead of n|T| branches, this adaptive path heuristic restricts PT to kb branches. You should be aware that this technique generates the same policy as deterministic path if kb = 0.

## Results and Discussions

For the purpose of evaluating the general efficacy of our proposed adaptive route algorithm for solving the SOP, we performed simulations of the techniques on randomised synthetic issues. Edges e E were inserted between every vertex in order to produce vertices v V for G by sampling the unit square uniformly. Vertex r(v) received a random sample from a uniform distribution in the range [0, 1] for its reward. Travel times along the edge (vi, vj) were measured using a stochastic model.

$$\alpha d_{i,j} + \mathcal{E}\left(\frac{1}{(1-\alpha)d_{i,j}}\right)$$

Sample E() is drawn from the exponential distribution with parameter E(), which is defined as the correlation between expected cost of edge (di,j) and variance ((1)di,j) in terms of the parameter E(). 2 The edges' costs are always positive in this formulation.

To solve both techniques, we employed the S-algorithm heuristic from [22] because of its speed and robustness. The adaptive route technique, which uses the orienteering solver several times, would be inefficient if an exact solver based on mixed-integer linear programming were employed. This is because solving the CMDP with such a solver would take too long. Initial route P with estimated cost less than or equal to B is the result of using the deterministic orienteering solver. For the sake of a fair comparison between the two methods, this route and the graph it travels through were fixed for each trial simulation. As E[RP, ] R, each algorithm's predicted reward to P's total reward is divided by P's total reward (P). Adaptive Path may depart from P, allowing this ratio to be more than one. Both approaches were performed on 10 separate occasions, each with a distinct G and P. Averaging the data from each of the ten tests yielded the final findings.

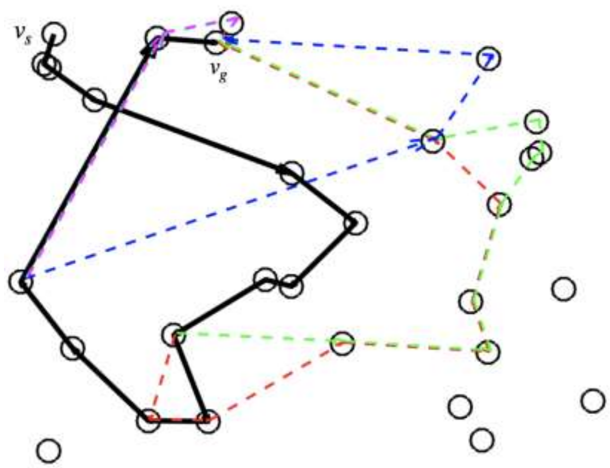


Figure 6. an example of a problem's calculated route tree. Different coloured pathways branch from the original path.

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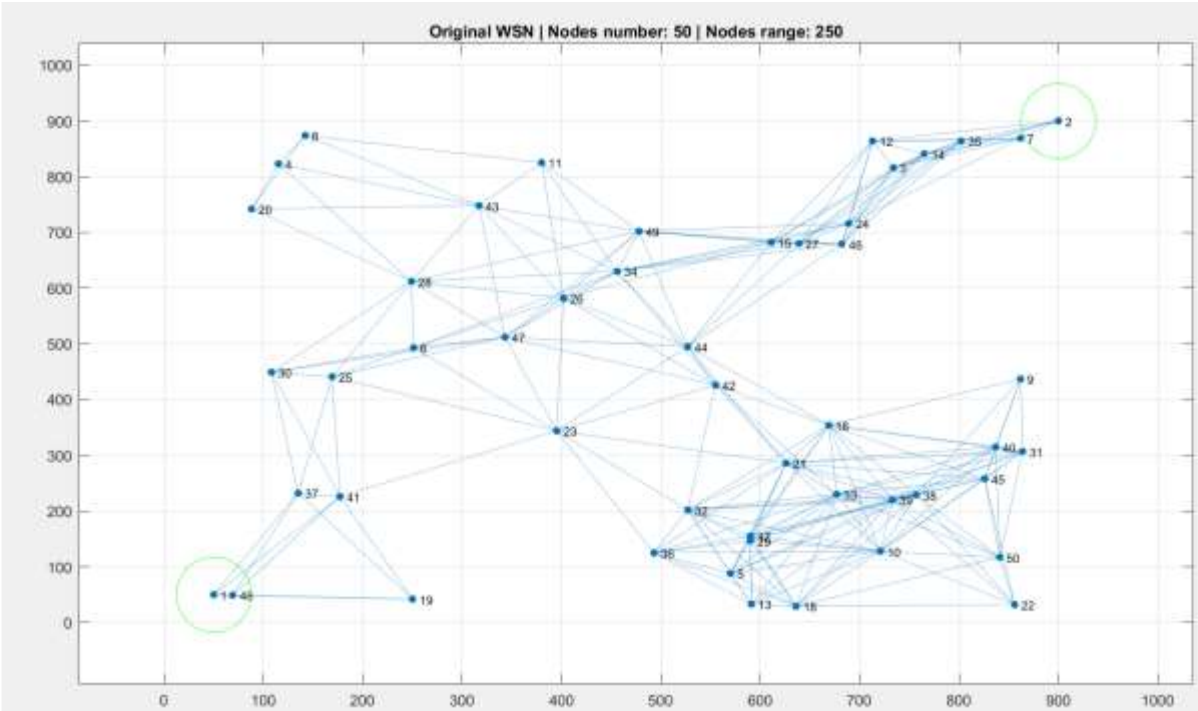


Figure 7: Representation of Original WSN with Node Number 50 & Node range 250

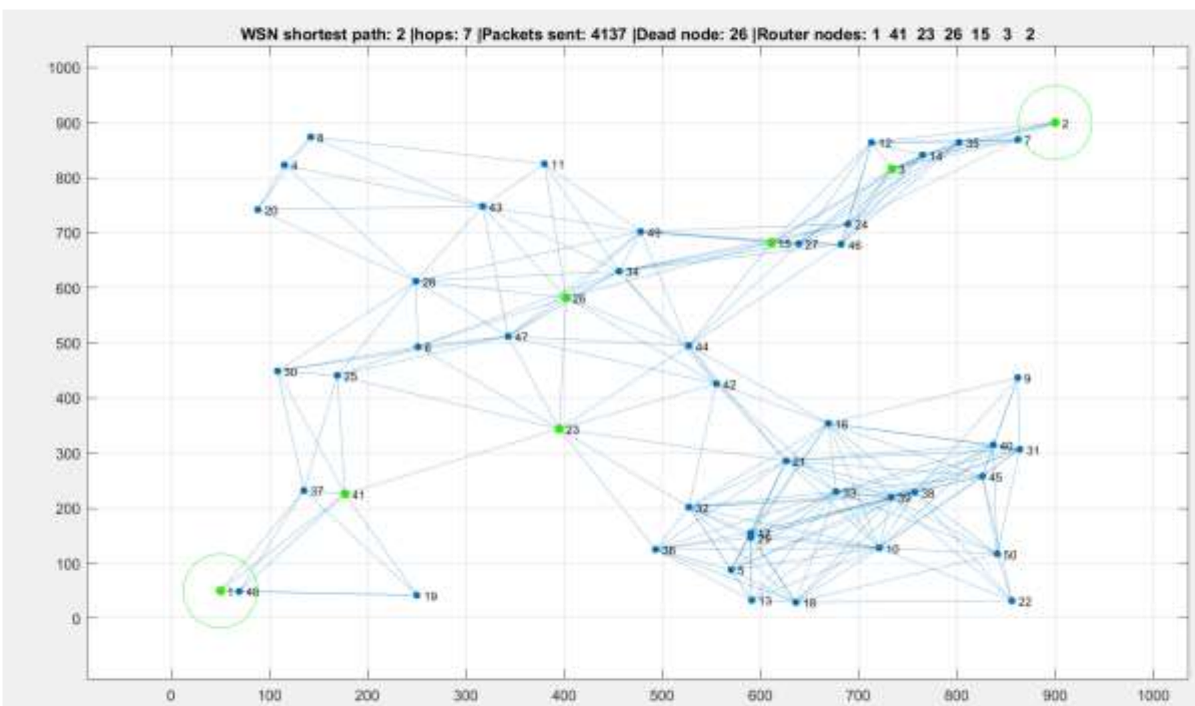


Figure 8: Representation of WSN shortest path 2

Using a constant number of vertices and varying the number of time steps, we were able to get the results shown in Figures. Using the same number of time steps but varying the number of P vertices, we ran the second set of simulations and obtained the same findings as the first. It is important to note that for both sets of simulations, average predicted reward and average total computation time are shown. CMDP linear algorithms were solved using Matlab and CPLEX on an Intel 6700k CPU with 32GB of RAM for all simulations.

Figures 5 and 6 demonstrate strong patterns in the average anticipated reward and the average calculation time. All time steps (5 in Figure 5), P vertex counts, and Pf values (a measure of anticipated rewards) show that the expected reward for the route with no branching is much lower than that for the path with branching. As state space develops, the average difference between the two is 6.07 percent, which rises as the vertices in the state space increase in number (up to 10.5 percent in these instances). Because kb = 5 stays close to or below the same average anticipated reward as kb =, this demonstrates that the branching heuristic works well in selecting just the most valuable branches to include in a route tree. On average, the adaptive route approach with kb = 5 is slower than the deterministic path method in terms of calculation time, demonstrating that solution quality must be sacrificed to save time.

The number of branches grows linearly with the number of time steps or vertices in P if the kb value is set lower. A tiny branching factor increases the anticipated reward by just 56.5 percent, and this value decreases as the state space expands in size, suggesting that a small branching factor pays a minor price for boosting the expected reward.

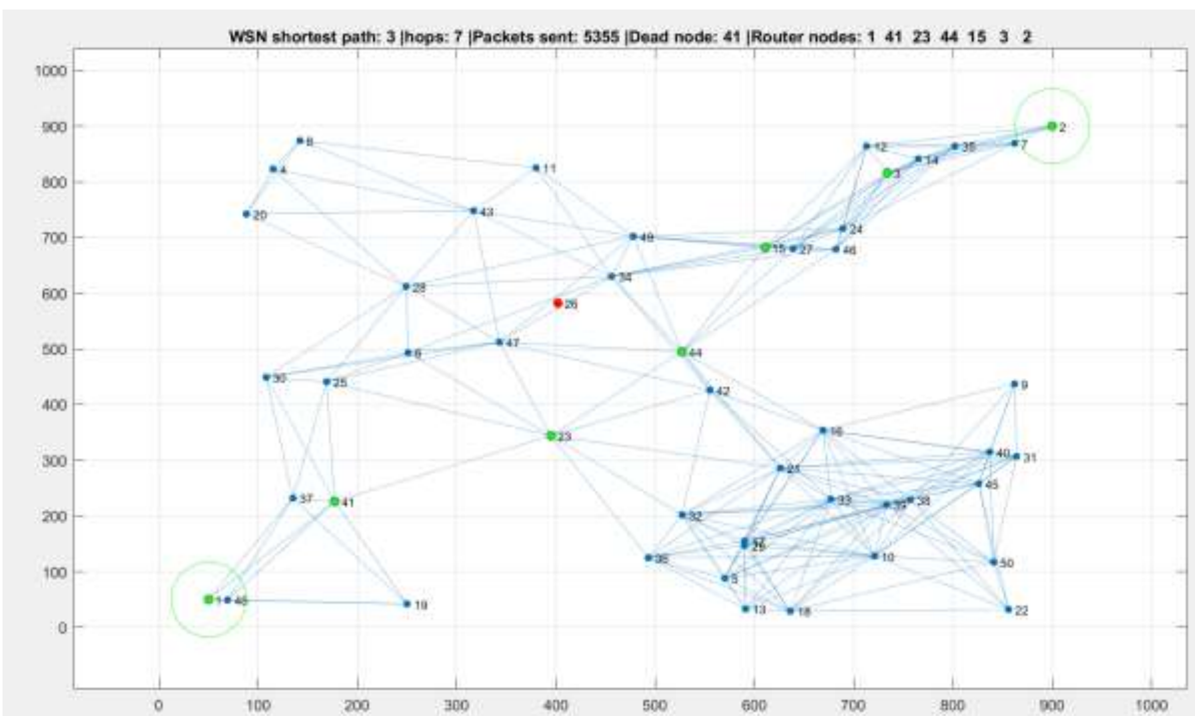


Figure 9. Representation of WSN shortest path 3

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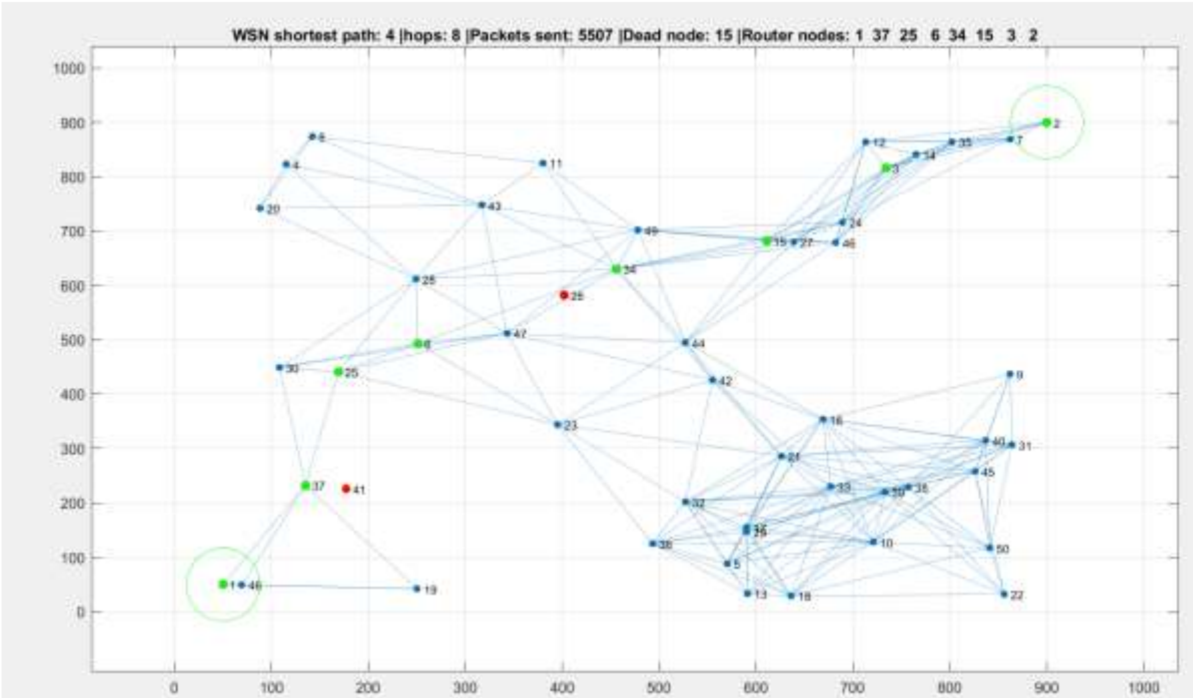


Figure 10. Representation of WSN shortest path 4

The method's scalability should also be investigated further. To this end, we ran final simulations to determine the largest network |V| for which the adaptive route method could solve the SOP. So we set the number of time steps to |V |/10, which is the number of vertices in G, and the values of kb and Pf were set to 0.75 and 5 respectively to achieve this goal. N = b|V |/2c, or half the number of vertices in G, was used to determine the length of the starting route. Figure 4.8 illustrates the findings for each issue size from 100 to 220 in 10 separate graphics. Additionally, the figure displays the number of non-zero transition probabilities, as they are related to the number of non-zero entries in Eq (3). It took us an average of 1, 191 seconds (less than 20 minutes) on graphs with a |V| = 220 (|n| = 110) size to discover a solution, using the identical computer configuration as for the findings in figures 5 and 6. No solutions could be found within 24 hours using the specified parameters on networks with more than 220 vertices because of the limits of the technology we use.

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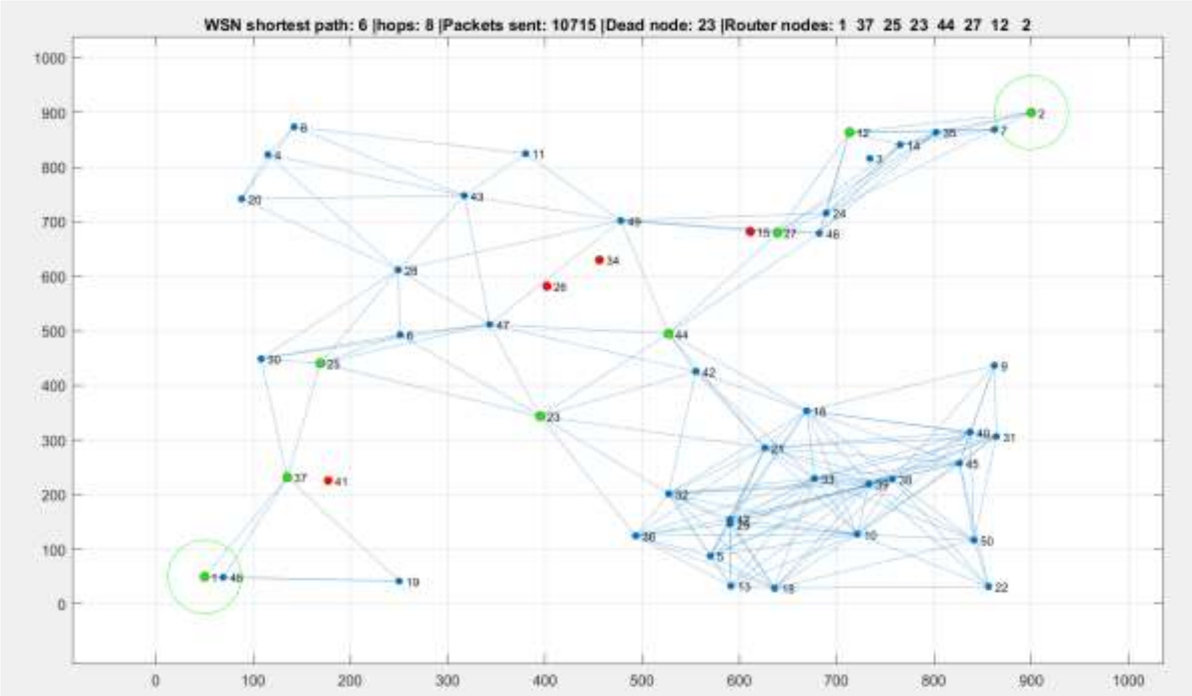


Figure 11. Representation of WSN shortest paths 6

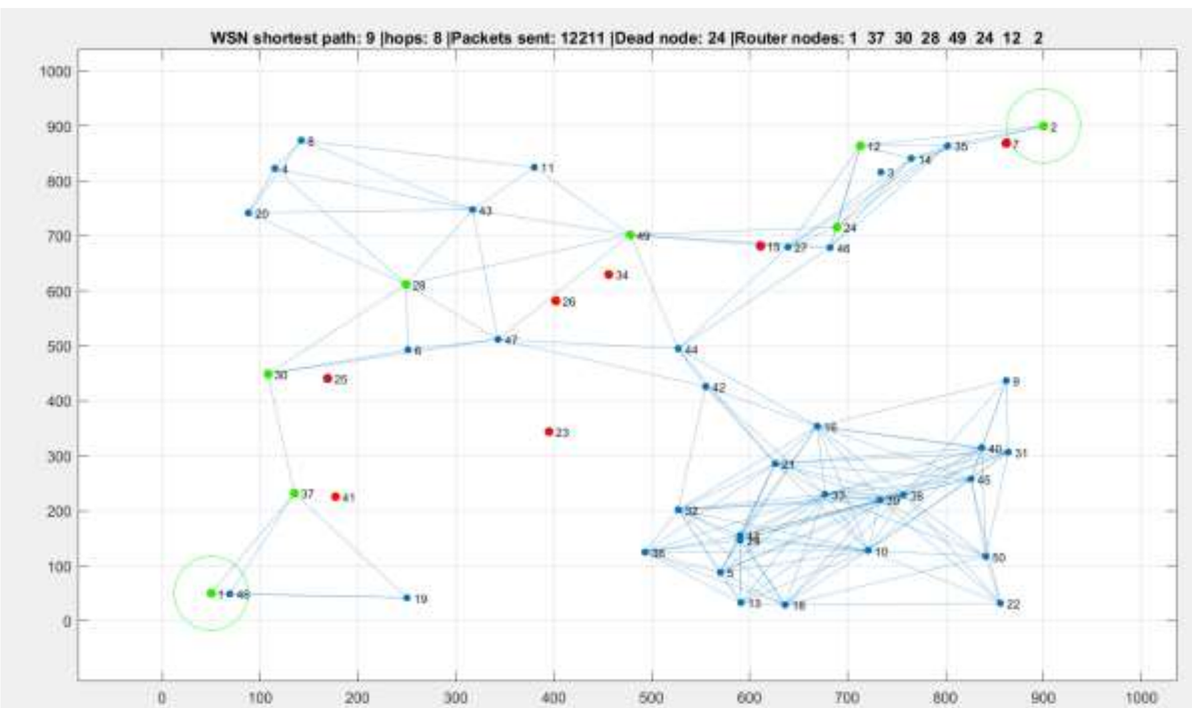


Figure 12. Representation of WSN shortest path 9

There are a few areas in which this strategy might be improved via more study. It's possible to cut computing time and increase anticipated reward by studying how to adaptively change temporal

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discretization. There is also the possibility of doing away with time discretization completely and resolving the issue in a time space that is continuous. We'll be focusing our attention on these issues in the future.

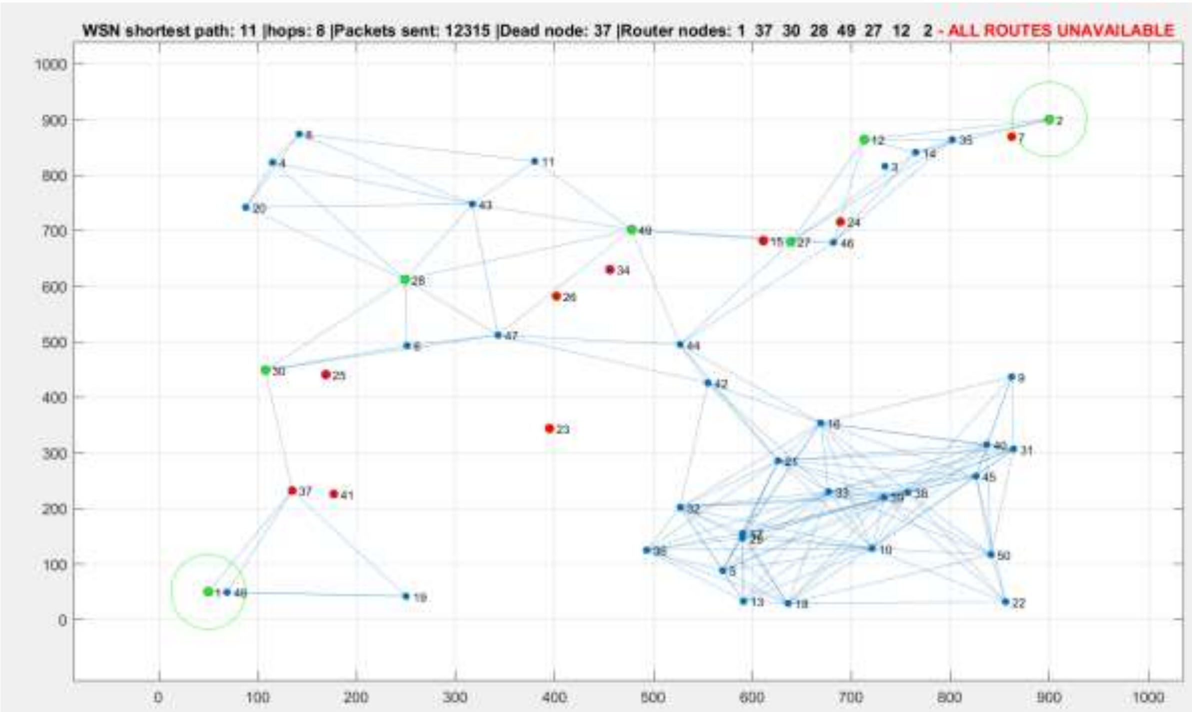


Figure 13. Representation of WSN shortest path 11

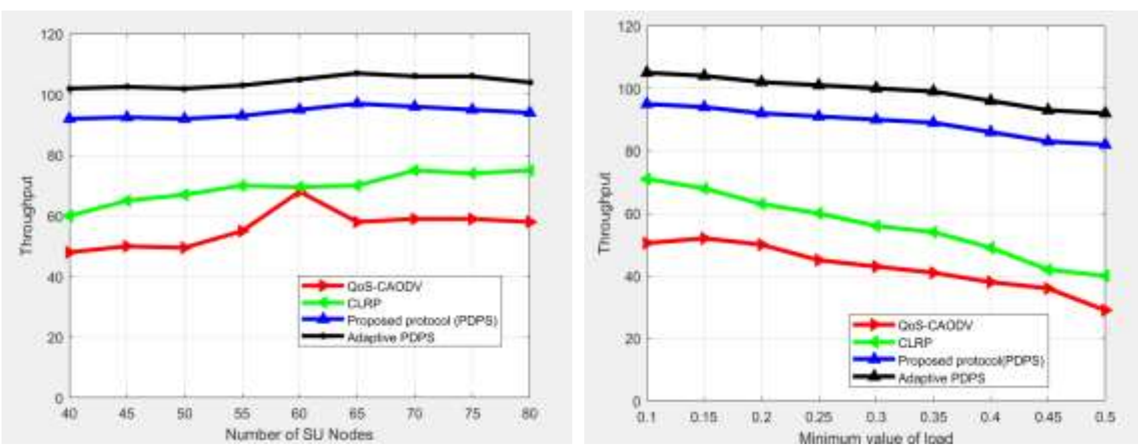


Figure 14. Graphical representation of various models with proposed model

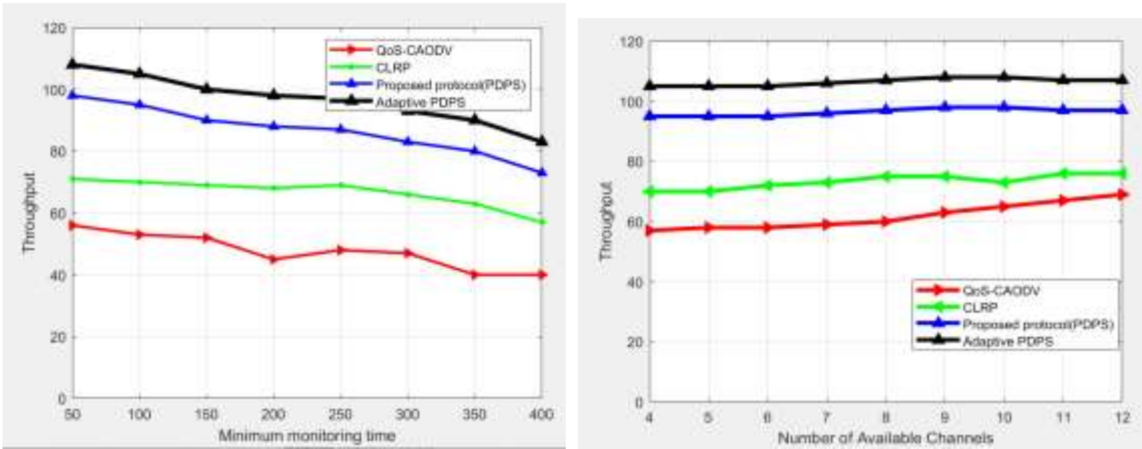


Figure 15. Graphical representations of various models with Min monitoring time & no. of available channels

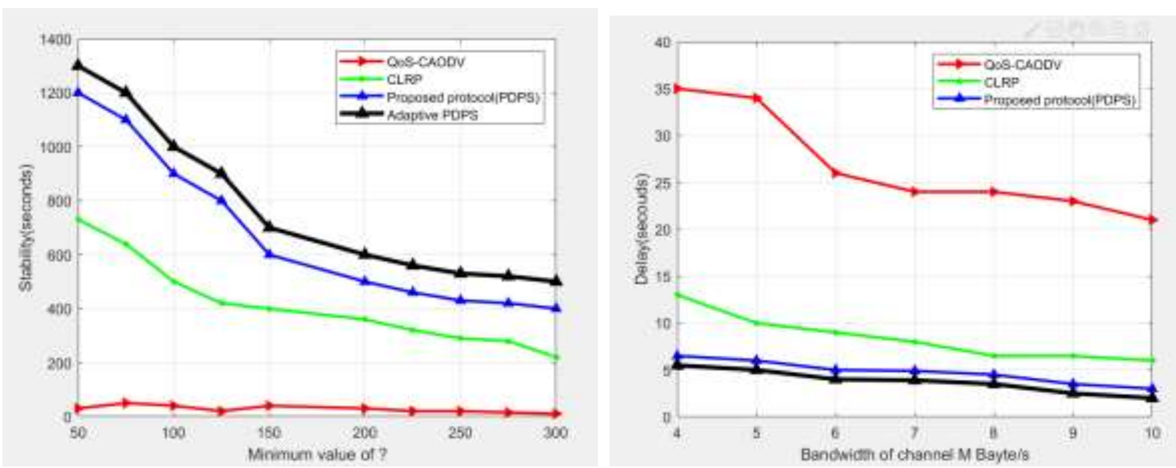


Figure 16. Graphical representations of various models with various models

## Conclusion

As a part of our research into the Stochastic Orienteering Problem (SOP), we looked at how unpredictable the trip durations between two vertices may be. With a given probability, the SOP seeks to find a policy that maximises the anticipated benefit of visiting each vertex in a graph within the constraints of a given budget. An orienteering problem solver is used to establish an initial route across the graph and to design a policy utilising CMDP architecture for taking shortcuts along that path to reach the destination vertex within the budget and provided probability. Our approach expands upon this strategy. It is no longer constrained to a single predetermined route in our new strategy. It is preferable, instead, to construct a path tree with several paths leading to the objective vertex, which the policy may then employ to maximise the predicted collected reward while minimising the failure chance. In addition, we devised a heuristic to keep our new method's adaptability while minimising its possible computing cost rises. Results from our tests suggest that the adaptive route technique increases the anticipated reward, while the branching heuristic is good for reducing the increase in computing time necessary for the adaptive method. There are a few areas in which this strategy might be improved via more study. It's possible to cut computing time and increase anticipated reward by studying how to adaptively change temporal discretization. There is also the possibility of doing away with time discretization completely and resolving the issue in a time space that is continuous. We'll be focusing our attention on these issues in the future.

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