

## A stochastic approximation approach to spatio-temporal anchorage planning with multiple objectives

Madadi, Bahman; Aksakalli, Vural

**DOI**

[10.1016/j.eswa.2019.113170](https://doi.org/10.1016/j.eswa.2019.113170)

**Publication date**

2020

**Document Version**

Accepted author manuscript

**Published in**

Expert Systems with Applications

**Citation (APA)**

Madadi, B., & Aksakalli, V. (2020). A stochastic approximation approach to spatio-temporal anchorage planning with multiple objectives. *Expert Systems with Applications*, 146, Article 113170. <https://doi.org/10.1016/j.eswa.2019.113170>

**Important note**

To cite this publication, please use the final published version (if applicable).  
Please check the document version above.

**Copyright**

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

**Takedown policy**

Please contact us and provide details if you believe this document breaches copyrights.  
We will remove access to the work immediately and investigate your claim.

# A Stochastic Approximation Approach to Spatio-Temporal Anchorage Planning with Multiple Objectives

Bahman Madadi<sup>1</sup> and Vural Aksakalli\*<sup>2</sup>

<sup>1</sup>Faculty of Civil Engineering and Geosciences, TU Delft, Mekelweg 5, 2628 CD Delft, Netherlands, E-mail: b.madadi@tudelft.nl

<sup>2</sup>School of Science, Royal Melbourne Institute of Technology, 124 La Trobe St, Melbourne, VIC 3000, Australia, E-mail: vural.aksakalli@rmit.edu.au

## Abstract

Globalization and subsequent increase in seaborne trade have necessitated efficient planning and management of world's anchorage areas. These areas serve as a temporary stay area for commercial vessels for various reasons such as waiting for passage or port, fuel services, and bad weather conditions. The research question we consider in this study is how to place these vessels inside a polygon-shaped anchorage area in a dynamic fashion as they arrive and depart, which seems to be the first of its kind in the literature. We specifically take into account the objectives of (1) anchorage area utilization, (2) risk of vessel collisions, and (3) fuel consumption performance. These three objectives define our objective function in a weighted sum scheme. We present a spatio-temporal methodology for this multi-objective anchorage planning problem where we use Monte Carlo simulations to measure the effect of any particular combination of planning metrics (measured in real time for an incoming vessel) on the objective function (measured in steady state). We resort to the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm for identifying the linear combination of the planning metrics that optimizes the objective function. We present computational experiments on a major Istanbul Strait anchorage, which is one of the busiest in the world, as well as synthetic anchorages. Our results indicate that our methodology significantly outperforms comparable algorithms in the literature for daily anchorage planning. For the Istanbul Strait anchorage, for instance, reduction in risk was 42% whereas reduction in fuel costs was 45% when compared the best of the current

---

\*Phone: +61-39925-2277 (Corresponding Author)

state-of-the-art methods. Our methodology can be utilized within a planning expert system that intelligently places incoming vessels inside the anchorage so as to optimize multiple strategic goals. Given the flexibility of our approach in terms of the planning objectives, it can easily be adapted to more general variants of multi-objective spatio-temporal planning problems where certain objects need to be dynamically placed inside two or even-three dimensional spaces in an intelligent manner.

**Keywords**— Anchorage planning; spatio-temporal planning; planning expert system; stochastic approximation; multi-objective optimization

## 1 Introduction

With ever-advancing globalization and burgeoning international trade, seaborne shipping has become an economical and environmentally friendly means of transportation, comprising 90% of the world’s commerce. Despite its advantages, expanding seaborne transportation brings about its own specific set of issues. In particular, escalating sea traffic congestion is as serious a problem in maritime traffic as it is on land. One of the efficient measures in dealing with maritime traffic is making use of anchorages, which tremendously contribute to alleviating traffic congestion just as parking lots do for land. Furthermore, anchorages provide vital services to vessels such as serving as a shelter from extreme weather conditions and loading/unloading of cargo. Anchorages also facilitate land services including fueling, legal issues, and repair (Oz et al., 2015). Taking into account the significance of anchorages along with the widespread popularity of maritime transportation, effective management of the anchorage areas has come to be a pressing concern.

In light of the fact that management and planning of anchorages with different characteristics may call for different considerations, it is appropriate to closely examine a challenging case in order to gain some insight into the issues that may be encountered when dealing with anchorages. One of the busiest and most congested waterways around the world is the Istanbul Strait, which requires constant and careful attention. Among the anchorages on this sea route, the Ahırkapı Anchorage located at the southern entrance of the Strait is a major geopolitical and critical anchorage area that can potentially effect world shipping in case of a serious accident and a subsequent shutdown.

As an inevitable consequence of heavy maritime traffic, high ship density in anchorages has recently raised significant safety concerns among maritime authorities. For instance, statistics indicate that more than half of maritime accidents in the City of Istanbul take place inside the Ahırkapı

anchorage alone (Aydogdu et al., 2012). Such accidents do not only cause physical damage to vessels and result in human casualties, but they also make some parts of the anchorage inaccessible for a period of time, which severely impedes maritime traffic. Furthermore, collusion of vessels inside anchorages can result in massive damage to the environment via spilling of oil and other environmentally dangerous cargo in extreme quantities.

An essential part of anchorage planning is determining the optimal berth location of vessels inside the anchorage. So far, the main focus in academic research has been on maximizing utilization, i.e., accommodating the maximum number of vessels inside the anchorage. Yet, risk, a critical issue in maritime traffic, has not received proper attention in the literature. Specifically, packing ships as dense as possible for the purpose of maximizing utilization can potentially increase the risk of accidents. Thus, risk and utilization need to be considered simultaneously when determining the optimal arrangement of vessels inside anchorage areas. Moreover, minimizing carbon emissions as well as the vessels' detrimental environmental impact on the anchorage ecology should also be incorporated into the anchorage planning problem, which has the additional benefit of reducing fuel costs.

Previous research on anchorage planning has traditionally approached the problem as a static disk packing problem without accounting for the time dimension. Such approaches typically start with an empty anchorage and terminate once the anchorage becomes full. Ignoring temporal aspects of the problem, however, is clearly not realistic due to the fact that vessels arrive and depart on a regular basis inside any given anchorage. In addition, the starting point is not an empty anchorage area and the problem is quite not solved when the anchorage area becomes full.

Our goal in this study is to transform the hitherto static problem of anchorage planning into a dynamic one by incorporating the time dimension. In particular, our study takes into account both vessel arrivals and departures in real time and our treatment of the problem does not end even if the anchorage reaches its full capacity. An appropriate approach for modeling the anchorage planning problem needs to entail a steady-state analysis and the optimal course of action should be defined only after observing the events in real time. Therefore, we conduct a steady-state analysis to identify an appropriate warm-up period and a reasonable simulation duration. We resort to Monte Carlo simulations for assessing relative performance of anchorage planning strategies where vessel arrival and anchorage duration times are sampled from probability distributions derived from empirical data. For an incoming vessel, we assume that its length as well as its anchor duration

are known at the time of the arrival for planning purposes. At least for the Ahırkapı Anchorage, anchoring is a service provided free-of-charge by the Strait authorities, so we do not consider any cost or revenue aspects in anchorage planning in this study.

In this work, we consider a multi-objective optimization model with three objectives: maximizing area utilization, minimizing risk of accidents and, distance traveled by the vessels, which is in lieu of environmental impact and fuel consumption. In order to measure these three objectives, we introduce four performance metrics that are measured in steady-state of a Monte Carlo simulation: (1) dynamic area utilization, (2) average distance traveled by the vessels, (3) average arrival intersection length (AIL), and (4) average departure intersection length (DIL). The first metric measures anchorage area utilization, the second metric measures vessels' fuel consumption, and the average of the last two metrics is intended to measure how safe vessels anchor over time. The objective function in our model is a linear combination of these performance metrics in a weighted sum scheme and it is constructed to define a minimization problem. Weight of each metric is assumed to reflect the relative priorities of anchorage planning authorities for each one of the three objectives.

Regarding potential berth locations for an incoming vessel, we consider a finite number of possibilities among the so-called corner points. In order to evaluate relative efficiency of a corner point for an incoming vessel, we introduce static as well as time-sensitive planning metrics that are computed in real time. In total, we consider three static and four dynamic planning metrics, which are described in detail in subsequent sections. For an incoming vessel, these metrics are computed in real time for each possible corner point. The corner point for which a linear combination of these seven planning metrics is the smallest is declared to be the berth location of this incoming vessel. The decision variables in our anchorage planning problem are precisely the seven real-valued coefficients corresponding to each one of these seven planning metrics.

It is critical to note the distinction between the three performance metrics (risk, utilization, and distance traveled) and the seven planning metrics. The performance metrics are measured in steady-state for the entire anchorage within a simulation environment whereas the planning metrics are computed in real-time for each candidate corner point for each incoming vessel. In addition, the weights of the performance metrics reflect relative priorities of anchorage planners whereas the coefficients of the planning metrics are the decision variables whose values need to be optimized. Furthermore, the performance metric weights are nonnegative real numbers whereas the planning

metric coefficients are real numbers with no sign restrictions.

Clearly, there is a need for a methodology to determine the optimal coefficients of each planning metric (for picking the best corner point for an incoming vessel) that minimizes the objective function, i.e., the weighted sum of the performance metrics. On the other hand, the impact of a particular planning metric on the objective function is not explicitly known. In addition, the objectives of risk, utilization, and environmental impact are conflicting in nature, which is further complicated by incorporation of the time dimension. For instance, berthing a vessel at the entrance of the anchorage might be a good choice from an environmental impact point of view. If the vessel’s anchorage duration is short, this would probably not pose a safety issue, but if the anchorage duration is long, this choice might pose significant safety risks and it might be a better choice to berth this vessel further away from the entrance. Moreover, implications of these decisions from a utilization point of view can only be assessed at the end of the simulation. Thus, identification of the best corner point, hence the best planning metric coefficients, is a rather challenging problem.

Since the performance metrics are measured via (noisy) Monte Carlo simulations, an explicit mathematical form for the objective function is not available, suggesting traditional optimization methods are not readily applicable. Therefore, we turn to stochastic optimization techniques that do not require explicit objective function nor gradient information. The specific method we resort to is the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm. SPSA is a stochastic pseudo-gradient descent algorithm that approximates the gradient from noisy objective function measurements. In SPSA, there is no need for explicit modeling information between the objective function and the decision variables and, the noise in function measurements is formally accounted for. Under mild conditions, SPSA converges to a locally optimal solution almost surely (Spall, 1992). Thus, it is critical to observe that SPSA is a stochastic pseudo-gradient descent algorithm and not a heuristic method in the traditional sense. Nonetheless, solutions obtained by SPSA are not guaranteed to be globally optimal in general.

To our knowledge, there are currently no studies in the open literature treating the anchorage planning problem as a dynamic one with a time dimension. In particular, explicitly accounting for vessel departures as well as new arrivals in a dynamic fashion fundamentally changes the problem structure—thereby calling for utilization of a stochastic optimization algorithm for optimal vessel placement in real-time—and places it far away from the traditional disk packing problem. We remark that incorporation of a time dimension and utilization of an appropriate stochastic

optimization method for identification of the most appropriate berth locations in a multi-objective setting are the first of their kind in the anchorage planning literature, which we believe to be major contributions to this field. Given the flexibility of our methodology in terms of the planning objectives, we believe that our work is also a major contribution to spatio-temporal planning in general where certain objects need to be placed inside two- or even-three dimensional spaces in a dynamic fashion in the presence of multiple planning objectives.

We now provide a brief review of our work from an expert systems' point of view. Expert systems are computer programs that exhibit high levels of intelligent performance as human experts. These systems solve difficult problems of the real world by utilizing inference processes on explicitly stated knowledge (Schmalhofer, 2001). A planning expert system, on the other hand, intelligently solves real-world planning problems via expert knowledge supported by optimization and/ or artificial intelligence. In the case of a multi-objective spatio-temporal planning problem such as the one considered in this work, our novel optimization-based methodology provides the much needed machinery to tackle these challenging problems where expert knowledge alone would not always be sufficient due to the dynamic and multi-objective nature of the problem. In regards to our theoretical contribution to the planning expert systems literature, we show in this work (1) how long-term performance metrics can be measured by the help of proxy planning metrics that can be calculated in real-time and, (2) how these long-term metrics can be optimized via Monte Carlo simulations and state-of-the-art stochastic optimization methods.

Subsequent sections of this article are as follows: Section 2 presents the problem environment and discusses relevant previous work. Section 3 introduces the performance metrics designated to measure the objectives of risk, utilization, and environmental impact. Sections 4, 5, and 6 respectively describe the planning metrics, the SPSA algorithm, and the simulation system developed for benchmarking our strategy. Section 7 presents computational results and comparisons against the current state-of-the-art approaches. Section 8 presents a summary and our conclusions.

## 2 Problem Environment and Previous Work

Anchorage operate year around with vessels arriving and departing around the clock. From a modeling stand point, they can be considered as polygon-shaped sea spaces next to land. There are open sea edges in anchorages from which vessels enter, called the *entry side* of the anchorage. As mandated by Istanbul Straight authorities, for instance, while entering and leaving anchorages,

vessels are obligated to cross the entry side from the nearest point to their berth locations perpendicularly, and they are just allowed to move around inside the anchorage only for mandatory reasons such as avoiding collisions with other vessels.

Despite the fact that a vessel's anchor is dropped at a particular location, the precise position of the vessel during its stay is dictated by natural conditions such as winds, waves, and currents. Based on the anchor position, a safe anchor circle can be considered as the zone the vessel shall reside, which is demonstrated in Figure 1. Excluding extreme environmental conditions resulting in anchor displacement, the vessel is guaranteed to be inside the associated anchor circle throughout its stay.

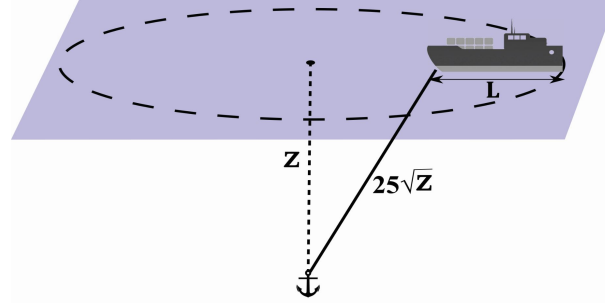


Figure 1: Illustration of anchor circle associated with an anchored vessel.

The size of the safe anchor circle depends on the length of the vessel and its anchor chain as well as the sea depth at the anchor position. Danton (1996) suggests an appropriate length for the anchor chain is  $25\sqrt{Z}$  where  $Z$  is the sea depth. Per the Pythagorean theorem, the anchor circle radius can be calculated as below where  $\ell$  is the vessel length:

$$r = \ell + \sqrt{(25\sqrt{Z})^2 - Z^2}. \quad (1)$$

A formal definition of the dynamic anchorage planning problem is given in Section 4.3 subsequent to definitions of the performance metrics and corner points.

Anchor circles of different vessels should not overlap due to safety reasons. Therefore, previous research on anchorage planning has traditionally approached the problem as variations of the disk packing problem. Of particular interest is the intractable circular open dimension problem (CODP) wherein the goal is to minimize the area of a rectangular region that contains a given number of disks with known diameters (Akeb and Hifi, 2008). It appears that the first study of its kind on practical anchorage planning and management was conducted by Huang et al. (2011). In this study,



the authors introduced two different algorithms for anchorage planning based on disk packing and they proposed an anchorage simulation tool in order to assess empirical performance their anchorage planning algorithms. This simulation tool was later used in a real-world vessel traffic simulation system (Huang et al., 2013).

We now discuss previous studies in the maritime transportation literature that pertains to our work. A river terminal system for bulk cargo operations was considered by Bugaric and Petrovic (2007) wherein the anchorage region was modeled as a first-in first-out queue with a fixed capacity. Fan and Cao (2000) modeled sea space as a directional network and presented capacity models for berthing and anchorage areas as well as fairways and their intersections. The authors also developed a corresponding software system that has been deployed in Singapore. A simulation-based approach was presented by Shyshou et al. (2010) where, in the presence of weather and equipment-related constraints, the goal was to determine the optimal number of anchor handling tug vessels needed to relocate an oil rig. The problem of anchorage capacity planning in non-uniform depth anchorages was investigated by Malekipirbazari et al. (2015) whereas the problem of network capacity estimation of vessel traffic for port planning was addressed by Olba et al. (2017).

Disser et al. (2015) considered the problem of scheduling bidirectional traffic along a path composed of multiple segments. Zhang et al. (2016) studied the vessel transportation scheduling optimization problem based on coordination of channels and berth. In this work, the authors formulated a mathematical model for minimizing total wait time by taking into account travel direction and distance of the berth and they utilized simulated annealing together with multiple population genetic algorithm for solution of the model. Lalla-Ruiz et al. (2018), on the other hand, studied the waterway ship scheduling problem wherein the goal was to schedule incoming and outgoing vessels via restricted waterways for entering or leaving the port so that the vessels' waiting time is minimized. The authors proposed mathematical models and heuristics for the problem and presented a case study involving the Yangtze Delta in Shanghai, China. Jajac et al. (2018) analyzed applications of multi-criteria decision making methods for spatial planning in anchorages that take into account various aspects of the problem including sociological, cultural heritage, economic, technical, and environmental issues and presented a case study for the Island of Solta in Croatia. Li et al. (2019) investigated the ship routing and scheduling problem for a steel plants cluster wherein they took into account the multi-layer structure of the shipping network, raw material prices, transportation costs, and market demand over multiple periods.

In a closely related study, Oz et al. (2015) proposed a dual-objective optimization strategy with safety and utilization considerations and achieved improvement in safety while maintaining similar utilization levels as competing methods. Both in Huang et al. (2011) and Oz et al. (2015), the simulations start with an empty anchorage and terminate as soon as the anchorage reaches its full capacity with no vessels departing the anchorage during the simulation. If one were to establish a practical analogy for comparing anchorage capacity planning as in Oz et al. (2015) and Huang et al. (2011) versus dynamic anchorage planning as in this study, an appropriate one would perhaps be as follows: Consider an unmarked vehicle parking lot with a certain topology. Capacity planning would be determining the maximum number of cars, trucks, and other land vehicles that can be safely parked inside the parking lot. The planners might post this number at the entrance of the parking lot as the maximum capacity. Daily planning, on the other hand, would be telling the drivers of these vehicles the exact location to park in real-time as they arrive and other vehicles leave, where it is also assumed that the arriving vehicle’s park duration is known in advance. Clearly, these two problems are fundamentally different problems that call for different solution approaches. Incidentally, the three objectives of maximizing utilization and minimizing accident risk as well as carbon emissions would also be applicable in this analogy. In practice, dynamic anchorage planning would be even more challenging than the hypothetical dynamic parking lot planning, because once parked, vehicles stay put inside parking lots whereas vessels tend to move constantly inside the anchorage due to winds, currents, and waves. In addition, navigation dynamics of vessels, some of which can be longer than 250 meters and weigh more than 100,000 tonnes, are much more sophisticated compared to land vehicles.

In this study, we investigate the three-objective dynamic anchorage planning problem and present computational experiments that compare our strategy against the algorithms introduced by Oz et al. (2015) and Huang et al. (2011), which we consider to be state-of-the-art to date in anchorage planning, static or otherwise. While our approach is more suitable for daily anchorage planning tasks, we believe both Oz et al. (2015) and Huang et al. (2011) have their place in the literature for *anchorage capacity planning* where the goal is to assess maximum safe capacity of an anchorage and a static approach is more appropriate than a dynamic one.

### 3 Performance Metrics

In this section, we present the performance metrics intended to measure the objectives of risk, utilization, and distance traveled (in lieu of environmental impact). The first performance metric, *dynamic area utilization*, is aimed at assessing utilization from the start of steady-state until the end of the simulation. The next metric, *distance to entry*, relates to distance and the last two metrics of *arrival intersection length* and *departure intersection length* are intended to assess risk. Performance metrics and other related parameters are described below and listed in Table 1.

Table 1: Performance metrics and related parameters

Performance Metric/ Parameter	Unit	Notation
Risk	meters	$R$
Dynamic area utilization	%	$U$
Average distance traveled	meters	$D$
Total number of arrivals	#	$N$
Total number of departures	#	$E$
Total anchorage area	meters squared	$A$
Total simulation time	days	$T$
Sea depth	meters	$Z$
Length of vessel $i$	meters	$\ell_i$
Anchor duration for vessel $i$	hours	$t_i$
Distance to entry for vessel $i$	meters	$d_i$
Anchor circle area for vessel $i$	meters squared	$c_i$
Anchor circle radius for vessel $i$	meters	$r_i$
Average intersection length (AIL) for vessel $i$	meters	$\alpha_i$
Average departure length (DIL) for vessel $i$	meters	$\beta_i$

#### 3.1 Dynamic Area Utilization

The *dynamic area utilization* performance metric  $U$  aims to measure anchorage area utilization efficiency throughout the simulation. This metric is defined as the ratio of summation of anchorage circle areas weighted by the corresponding anchor duration to the total anchorage area weighted by the total simulation time:

$$U := \frac{\sum_{i=1}^N c_i t_i}{AT} \quad (2)$$

where  $N$  denotes the total number of arrivals in the simulation,  $c_i$  is the area of the  $i$ -th anchor circle associated with the  $i$ -th vessel,  $t_i$  is the anchor duration (i.e., dwell time) of the  $i$ -th vessel

and,  $A$  and  $T$  denote the anchorage area and total simulation time respectively.

In case the anchorage becomes full at any point in the sense that the length of an incoming vessel is too long to place it safely inside the anchorage due to currently anchored vessels, such incoming vessels are put in a queue. The queued vessels are allocated anchor circles with sufficiently large radii on a first-come first-serve basis as currently anchored vessels leave the anchorage.

### 3.2 Average Distance to Entry

The second performance metric, *average distance to entry*, measures the distance vessels travel inside the anchorage while arriving to and departing from their berth locations as a proxy for measuring distance traveled and impact on the environment. Distance to entry is defined as the distance between the entry point of the ship to anchorage area and its berth location, which is illustrated in Figure 2. In general, port authorities prohibit vessels from maneuvering inside anchorages due to safety reasons. That is, vessels are required to follow a direct path inside the anchorage upon arrival and departure, so two times distance to entry will yield the total distance traveled by each ship. Subsequently, *average distance traveled* is defined as the total distance traveled by all vessels divided by the total number of vessels. Distance to entry for the  $i$ -th vessel is denoted by  $d_i$  and average distance traveled is denoted by  $D$ . That is,

$$D := \frac{\sum_{i=1}^N 2d_i}{N}. \quad (3)$$

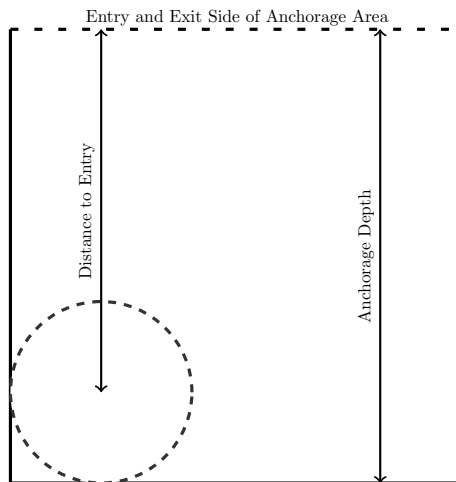


Figure 2: Distance to entry for an incoming vessel.

### 3.3 Arrival Intersection Length (AIL)

The next performance metric is devoted to assessing the safety risks for vessels upon their arrival. For each vessel, its *arrival intersection length (AIL)*, denoted by  $\alpha_i$ , is defined as the summation of distances it travels inside other vessels' anchor circles until it arrives at its berth location. Average anchorage AIL, denoted by  $\bar{\alpha}$ , is defined as the sum of arrival intersection lengths for all vessels divided by the total number of vessels in the simulation, i.e.,

$$\bar{\alpha} = \sum_{i=1}^N \alpha_i / N. \quad (4)$$

Although vessels can, in fact, navigate through other vessels' anchor circles, there is a certain level of risk associated with this passage, especially since the exact location of vessels inside the anchor circle is uncertain. Clearly, the danger the vessels incur is likely to be greater with longer intersections. In our interview with the Istanbul Vessel Traffic Services (VTS) Authority officials, the feedback provided to us was in favor of the argument that the distance traveled inside other vessels' anchor circles is a more plausible criterion compared to the number of intersecting circles on the arrival path. As an illustration, Figure 3 shows five different arrival paths indicated with dotted lines. Arrival intersection number for both path C and path D is 3, but it is fairly discernible that undertaking path D, which has a greater total intersection length, carries greater risk than undertaking the alternative path. Moreover, in comparing paths B and E, although path B has a greater intersection number, path E requires crossing a large vessel, thereby potentially more steering and more risk.

### 3.4 Departure Intersection Length (DIL)

Vessels undertake fairly identical paths upon arrival and departure. However, this does not necessarily mean they are exposed to the same level of risk since the arrangement of vessels inside the anchorage is likely to change upon their departure. We define a vessel's *departure intersection length (DIL)*, denoted by  $\beta_i$ , analogous to its AIL. In our simulations, in some cases, the difference between AIL and DIL was so significant it could clearly reflect some algorithms' inability to provide a proper look-ahead approach. The following equation shows how departure intersection length is calculated where  $\bar{\beta}$  denotes average DIL and  $E$  denotes total number of departures in the simulation:

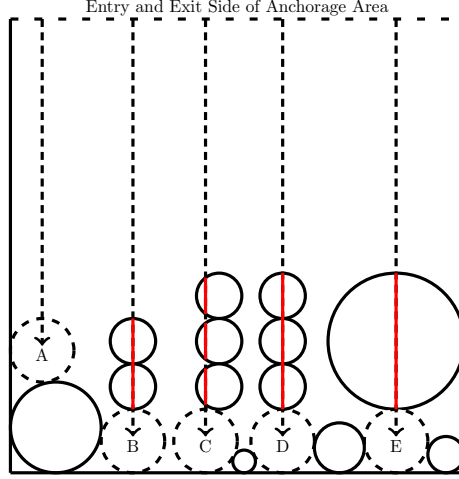


Figure 3: Different anchor paths with different arrival intersection values.

$$\bar{\beta} = \sum_{i=1}^N \beta_i / E. \quad (5)$$

### 3.5 The Multi-Objective Model

The performance metrics defined above are measured inside Monte Carlo simulations within a particular simulation time window. With respect to these metrics, the objective function to be minimized is defined as

$$L(\mathbf{W}) := W_R R + W_U (1 - U) + W_D D. \quad (6)$$

In this equation,  $R$  measures risk that we aim to minimize and it denotes the mean of average anchorage AIL and DIL, i.e.,  $R := (\bar{\alpha} + \bar{\beta})/2$ . Our model also attempts to minimize the average distance to entry  $D$  in lieu of minimizing distance traveled and environmental impact. As for utilization, we aim to maximize the dynamic area utilization rate  $U$ . Weights of the risk, utilization, and distance objectives are denoted by  $W_R$ ,  $W_U$ , and  $W_D$  respectively with  $0 \leq W_R, W_U, W_D$ . It is assumed that these weights are specified as seen appropriate by the anchorage planners per their priorities with respect to each objective. These three weights are denoted by the vector  $\mathbf{W} := (W_R, W_U, W_D)$ . While constructing the objective function, all three performance metrics are normalized to assume values between zero and one and, since we are minimizing  $R$  and  $D$ , the term  $1 - U$  is used to define a multi-objective minimization problem.

## 4 Berth Location

There are three steps involved in choosing an appropriate berth location for an incoming vessel: (1) identifying candidate berth locations, (2) scoring these candidates, and (3) finding the best berth location. In what follows, we explain these steps in detail and discuss the planning metrics used in the berth location process, which is illustrated in Figure 4. In this figure, it is assumed that optimal coefficients of the seven planning metrics have already been computed using SPSA.

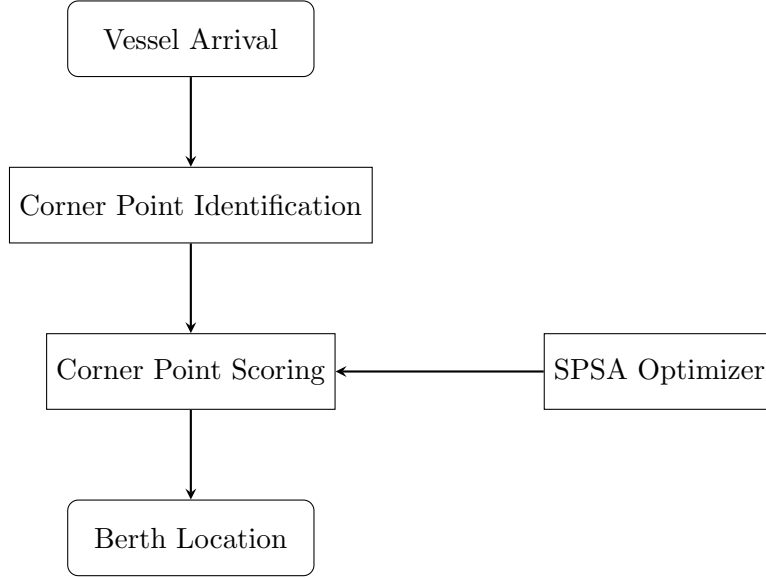


Figure 4: The berth location process.

### 4.1 Corner Point Identification

The anchorage planning problem is inherently a continuous space problem, yet, treating the problem as such makes it extremely challenging. Following previous work, for any given anchorage configuration, we consider a finite number of candidate berth locations called *corner points*. Specifically, for a given particular layout of anchor circles inside an anchorage, corner points are defined as the points where a circle centered at those points would be tangent to at least two items among the sides of the anchorage area and currently existing anchor circles (Huang et al., 2005). Corner points are classified into three types according to the items they are tangent to, which are explained below and depicted in Figure 5.

**Side-and-Side (SS):** These are the centers of the circles whose sides contact two sides of the

anchorage area.

**Side-and-Circle (SC):** These corner points are the centers of the circles contacting (but not overlapping) an existing anchor circle and a side of the anchorage area.

**Circle-and-Circle (CC):** These are the centers of the circles contacting exactly two anchor circles (without overlapping).

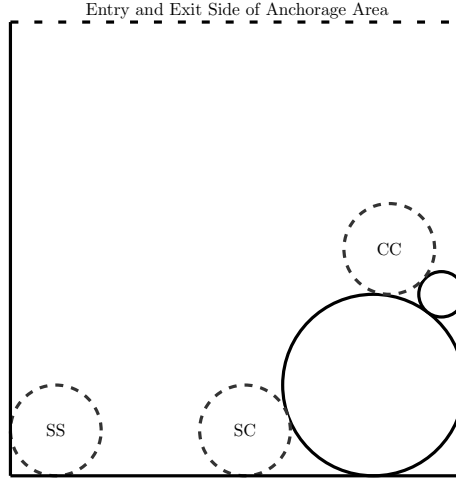


Figure 5: Three types of corner points in an anchorage.

Corner points perform the task of limiting the infinite number of possible anchor locations inside the anchorage to a finite set of candidate anchor points to place the center of new anchor circles. Specifically, for an incoming vessel, the first order business is to iterate over all sides of the anchorage and all existing anchor circles in order to identify all possible corner points for which an appropriately sized anchor circle can be fit in that is (1) fully inside the anchorage and, (2) does not overlap with any other anchor circles. In particular, the radius of the circle associated with a corner point is computed in real time using the incoming vessel's length and sea depth using Equation 1. For instance, for a 100-meter incoming vessel anchoring at a depth of 35 meters, the radius of the anchor circle would be  $100 + \sqrt{(25\sqrt{35})^2 - 35^2} = 244$  meters. Once all the feasible corner points are identified, the next task is to score these corner points and pick the one that optimizes the objective function at hand.

For an empty anchorage, only Side-and-Side corner points are calculated. For an incoming vessel in a non-empty anchorage, on the other hand, calculation of corner points only depends on the sides of the anchorage and currently anchored vessels. In other words, the corner point calculation process



is independent of the particular anchorage planning algorithm being used. However, different algorithms are likely to place incoming vessels at different corner points, resulting in different anchorage configurations, which in turn results in different corner points for future incoming vessels.

## 4.2 Corner Point Scoring

Previous work on anchorage planning typically defines planning metrics for scoring of corner points in such a way that they are closely related to each objective considered and minimizing or maximizing that metric will be the touchstone for berth location optimization. Huang et al. (2011) suggests *hole degree*, denoted by  $H$ , as the criterion for determining the optimal berth location (illustrated in Figure 6). For an anchor circle  $i$ , its hole degree is defined as

$$H_i := 1 - \frac{y_i}{r_i} \quad (7)$$

where  $r_i$  is the radius of the circle and  $y_i$  is the minimum distance from this circle to the closest item excluding the contacting items. The Maximum Hole-Degree (MHDF) Algorithm of Huang et al. (2011) starts with placing two circles at two corners of the anchorage and places each subsequent anchor circle by selecting the corner point with the highest hole degree. On the other hand, Oz et al. (2015) uses maximum *normalized distance to entry (NDE)* in order to choose the optimal berth location (please see Figure 2 for an illustration of the distance to entry concept). Normalization of this distance to entry happens via dividing it by the anchorage depth. Both algorithms start with an empty anchorage and terminate when the anchorage becomes full, yet they do not account for any departing vessels in the meantime. Simply put, the idea in Huang et al. (2011) is to pack circles as densely as possible whereas the idea in Oz et al. (2015) is to pack circles as further away from the entrance as possible. Oz et al. (2015) argues that while both algorithms achieve similar utilization levels, the latter results in safer anchorage planning. In comparison, our approach entails a much more sophisticated scheme that considers multiple planning metrics within a Monte Carlo simulation framework in order to determine the optimal berth locations of incoming vessels.

## 4.3 The Dynamic Anchorage Planning Problem

This section formally defines the dynamic anchorage planning problem. As we attempt to simultaneously optimize the objectives of risk, utilization, and distance, we define a total of seven planning

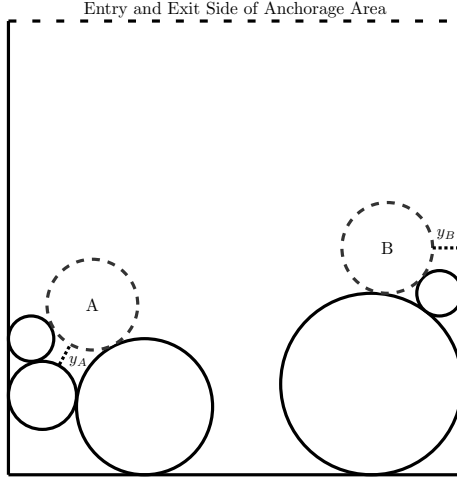


Figure 6: Illustration of two different cases for minimum hole degree.

metrics in order to score a given corner point  $j$  associated with incoming vessel  $i$ , which are denoted by  $m_{i,j}^p$  for  $p = 1, \dots, 7$ . Three of these metrics are static and the remaining ones are time-sensitive, all of which are intended to capture the characteristics of these three objectives from different perspectives. It is important to note that these metrics are computed in real time for each corner point once an incoming vessel's candidate corner points have been calculated. These planning metrics are described in detail in the next section.

The interactions between the seven planning metrics along with the fact that some metrics may have opposing effects on unintended objectives necessitate a weighting system for determining the appropriate contribution of each planning metric to the score of a candidate corner point. In this study, we work with a linear combination of the planning metrics for scoring of corner points that also includes certain interaction terms. In order to find the best coefficient for each term in this combination, we resort to the Simultaneous Perturbation Stochastic Approximation (SPSA) algorithm whose details are discussed in Section 5.

In our anchorage planning model, the decision variables to be optimized via SPSA are the coefficients of the seven planning metrics, which we denote by  $x_p$  for  $p = 1, \dots, 7$ . For a given  $\mathbf{x} := (x_1, \dots, x_7)$ , candidate corner points are identified for each incoming vessel  $i$  and each associated candidate corner point  $j$  is scored based on the following formula

$$s_{i,j} := \sum_{p=1}^7 x_p m_{i,j}^p. \quad (8)$$

The corner point with the lowest score with respect to the optimal coefficients obtained by SPSA is then declared to be the berth location for this incoming vessel. We note that we do not impose any sign restrictions on the components of the  $\mathbf{x}$  vector. Thus, contribution of some planning metrics to the score  $s$  could be positive whereas those of some other metrics could be negative. As mentioned earlier, the relationship of the individual objectives to the decision variables in the multi-objective function  $L$  is measured via Monte Carlo simulations, which can be stated as follows:

$$L(\mathbf{x}|\mathbf{W}) = W_R R(\mathbf{x}) + W_U(1 - U(\mathbf{x})) + W_D D(\mathbf{x}). \quad (9)$$

A typical instance of the dynamic anchorage planning problem consists of the following components:

- Sea depth and topology of the anchorage.
- Performance metrics weight vector  $\mathbf{W} = (W_R, W_U, W_D)$  as specified per the needs of the anchorage planners.
- The probability distribution for vessel inter-arrival times (in hours). This distribution specifies the frequency of vessel arrivals at the anchorage.
- The probability distribution for vessel dwell times (in hours). Dwell time for an incoming vessel is sampled from this distribution at the time of its arrival.
- The probability distribution for vessel lengths (in meters). Vessel lengths are used to determine the radius of the associated anchor circle.

The *dynamic anchorage planning problem* is then defined as finding the optimal planning metrics coefficient vector  $\mathbf{x}^*$  that minimizes the multi-objective function  $L$ :

$$\mathbf{x}^* := \arg \min_{\mathbf{x} \in \mathbb{R}^7} L(\mathbf{x}|\mathbf{W}) = \{\mathbf{x}^* \in \mathbb{R}^7 : L(\mathbf{x}^*) \leq L(\mathbf{x}) \quad \forall \mathbf{x} \in \mathbb{R}^7\}. \quad (10)$$

#### 4.4 Planning Metrics

This section describes the seven planning metrics used for scoring of candidate corner points for an incoming vessel.

#### 4.4.1 Realized AIL (RAIL)

The metric we present as *AIL* in Section 3 can perform the task of an effective planning metric as well. Since our measure for risk is the mean value of average AIL and average DIL, the AIL value for each arrival, which we call *realized AIL (RAIL)*, provides valuable information concerning the contribution of this particular arrival to overall risk. The mere difference is that in planning we calculate the RAIL score for each individual candidate corner point while the average AIL used in performance measuring is the total AIL for all vessels arrived divided by the number of arrivals.

#### 4.4.2 Expected DIL (EDIL)

Analogous to *RAIL* for arrivals, a *DIL* value can be measured for each departure, thereby allowing calculation of the contribution of each vessel departure to risk. In practice, future vessel arrivals and/ or their dwell times may not be fully known, though they can be predicted using historical data. On the other hand, in our Monte Carlo simulations, future vessel arrivals and their dwell times are readily available in the simulation’s event queue, which we make use of in order to compute an *expected DIL (EDIL)* for vessels that depart with the simulation window.

#### 4.4.3 Normalized Distance to Entry (NDE)

The concept of *distance to entry* was introduced in Section 3. *Normalized distance to entry (NDE)* is calculated by dividing *distance to entry* with the anchorage depth, which is the distance between the entry side of the anchorage and the land. We use NDE as another planning metric for scoring of candidate corner points.

#### 4.4.4 Dynamic NDE (DNDE)

The next four metrics include a time dimension. This notion is inspired by the simple fact that if a vessel is going to dwell for long, it seems appropriate to berth it closer to land in order to keep the anchorage’s entrance and middle space clear for passage. On the other hand, if the vessel’s dwell time is relatively short, berthing the vessel close to land would increase total distance traveled as well as the risk of accidents. Multiplying *NDE* by the dwell time culminates in a metric we call *Dynamic NDE (DNDE)*. This planning metric is a useful measure of risk that maintains a reasonable trade-off with distance.

#### 4.4.5 Dynamic RAIL, Dynamic EDIL and Dynamic Fused Risk

Following the same idea, we multiply RAIL, EDIL, and RAIL times EDIL by the dwell time to obtain three new metrics respectively called *Dynamic RAIL (DRAIL)*, *Dynamic EDIL (DEDIL)* and *Dynamic Fused Risk (DFR)*. Intuitively, for a relatively idle anchorage, vessel dwell time is less important for small values of RAIL and EDIL. On the other hand, for a busy anchorage with large values of RAIL and EDIL, the dwell time becomes a pressing matter. This impact is recognized by multiplying the dwell time by RAIL, EDIL, and *Fused Risk*, i.e., RAIL times EDIL. In short, when our risk metrics have large values, dwell time will be weighted by larger numbers leading to larger values for dynamic risk metrics and more contribution to corner points' score. Our experimental results provide more evidence for effectiveness of our time-sensitive metrics. The following equations show the calculation of the dynamic planning metrics:

$$m_{i,j}^4 = m_{i,j}^1 \times t_i \quad (11)$$

$$m_{i,j}^5 = m_{i,j}^2 \times t_i \quad (12)$$

$$m_{i,j}^6 = m_{i,j}^3 \times t_i \quad (13)$$

$$m_{i,j}^7 = m_{i,j}^1 \times m_{i,j}^2 \times t_i \quad (14)$$

where  $t_i$  is the dwell time for the  $i$ -th vessel and  $m_{i,j}^1$  through  $m_{i,j}^7$  respectively stand for RAIL, EDIL, NDE, DRAIL, DEDIL, DNDE, and DFR planning metrics as summarized in Table 2.

Table 2: Planning metrics used in scoring of candidate corner point  $j$  for an incoming vessel  $i$ .

Planning Metric	Abbreviation	Notation
Realized arrival intersection length	RAIL	$m_{i,j}^1$
Expected departure intersection length	EDIL	$m_{i,j}^2$
Normalized distance to entry	NDE	$m_{i,j}^3$
Dynamic realized arrival intersection length	DRAIL	$m_{i,j}^4$
Dynamic expected departure intersection length	DEDIL	$m_{i,j}^5$
Dynamic normalized distance to entry	DNDE	$m_{i,j}^6$
Dynamic fused risk	DFR	$m_{i,j}^7$

## 5 The SPSA Algorithm

This section describes how the planning metric coefficients in the dynamic anchorage planning problem can be optimized via the SPSA algorithm. For a given vector of planning metric coefficients  $\mathbf{x}$  and performance metric weights  $\mathbf{W}$ , the objective function  $L(\mathbf{x}|\mathbf{W})$  is a random variable with an unknown explicit form that can only be observed at the end of a noisy Monte Carlo simulation with a certain margin of error. The inputs to a Monte Carlo simulation are as follows:

- Sea depth and topology of the anchorage.
- Planning metrics coefficient vector  $\mathbf{x} = (x_1, \dots, x_7)$ .
- Performance metrics weight vector  $\mathbf{W} = (W_R, W_U, W_D)$ .
- The probability distributions for vessel inter-arrival times, dwell times, and vessel lengths.

The outputs of one simulation run are the risk, utilization, and distance performance metric values measured over a certain amount of time once the run reaches steady-state.

In order to find a local minimum of a real-valued deterministic function  $L : \mathbb{R}^p \rightarrow \mathbb{R}$ , a widespread practice is the gradient descent approach. In conventional gradient descent algorithms, it is presumed that the objective function (usually called loss function in minimization problems) and its derivatives are known. However, when the loss function assumes the form of a random variable and information regarding its realized values can only be observed through sampling, such an approach would be of no use. This is particularly pertinent to the cases when the information regarding the loss function is available only through simulations which are inherently noisy. In such cases, stochastic pseudo-gradient descent algorithms can be convenient choices since they estimate the loss function from noisy measurements that are simulation runs. Additionally, such algorithms formally account for noise and they do not require explicit information regarding the loss function nor its derivatives.

Let  $L(\mathbf{x}) : \mathbb{R}^p \rightarrow \mathbb{R}$  denote the loss function that is not explicitly known, yet we can make noisy measurements  $y(\mathbf{x}) := L(\mathbf{x}) + \epsilon(\mathbf{x})$  where  $\epsilon$  denotes noise. The gradient of  $L$  is defined as:

$$g(\mathbf{x}) := \frac{\partial L}{\partial \mathbf{x}}. \quad (15)$$

Similar to traditional gradient descent based algorithms, SPSA starts with an initial estimate

$\hat{\mathbf{x}}_0$  and iterates with respect to the recursion below in order to find a locally minimum vector  $\mathbf{x}^*$ :

$$\hat{\mathbf{x}}_{k+1} := \hat{\mathbf{x}}_k - a_k \hat{g}_k(\hat{\mathbf{x}}_k). \quad (16)$$

In the equation above,  $a_k$  is an iteration gain sequence and  $\hat{g}_k(\hat{\mathbf{x}}_k)$  stands for the approximate gradient at  $\hat{\mathbf{x}}_k$ . Since it is assumed that  $L$  is not known explicitly, the gradient  $g(\mathbf{x})$  is not readily available and thus it needs to be approximated. The perturbation amount is taken as  $c_k \Delta_k$  where  $\Delta_k$  is a  $p$ -dimensional simultaneous perturbation vector and  $c_k$  is a gradient gain sequence. Per regularity conditions (Spall, 1992), each component of  $\Delta_k$  needs to be independently sampled from a symmetric probability distribution with a zero mean, such as the symmetric Bernoulli distribution with  $+1$  or  $-1$  with equal probability. Simultaneous perturbations around the current solution vector  $\hat{\mathbf{x}}_k$  are defined as:

$$\hat{\mathbf{x}}_k^\pm := \hat{\mathbf{x}}_k \pm c_k \Delta_k. \quad (17)$$

In the rest of this manuscript, the terms decision variables, solution vector, and planning metrics coefficient vector shall be used interchangeably. Once  $y(\hat{\mathbf{x}}_k^+)$  and  $y(\hat{\mathbf{x}}_k^-)$  are computed, the estimate of gradient  $\hat{g}_k$  is calculated as:

$$\hat{g}_k(\hat{\mathbf{x}}_k) := \frac{y(\hat{\mathbf{x}}_k^+) - y(\hat{\mathbf{x}}_k^-)}{2c_k} \begin{bmatrix} \Delta_{k1}^{-1} \\ \Delta_{k2}^{-1} \\ \vdots \\ \Delta_{kp}^{-1} \end{bmatrix}. \quad (18)$$

SPSA requires three loss function measurements in each iteration:  $y(\hat{\mathbf{x}}_k^+)$ ,  $y(\hat{\mathbf{x}}_k^-)$ , and  $y(\hat{\mathbf{x}}_{k+1})$ . The first two are needed to approximate the gradient and the third is required for measuring the quality of the subsequent solution vector, i.e.,  $\hat{\mathbf{x}}_{k+1}$  (Aksakalli and Malekipirbazari, 2016).

The gradient gain sequence is defined as  $c_k := c/k^\gamma$  and the iteration gain sequence is defined as  $a_k := a/(A+k)^\alpha$  where  $A > 0$  is a stability constant. SPSA's pre-defined parameters are thus  $a, c, A, \alpha$ , and  $\gamma$ , whose careful fine-tuning is critical to ensure superior algorithm performance. A common stopping rule for SPSA is reaching a pre-defined number of iterations due to the fact that automatic stopping criteria do not exist for stochastic approximation algorithms in general.

Even though SPSA has been widely used in a variety of stochastic optimization problems, few studies exist on its parameter calibration. Spall (1998) provides certain guidelines for identifying

suitable values for the algorithm parameters. In particular, the asymptotically optimal values of  $\alpha$  and  $\gamma$  are 0.602 and 0.101 respectively. The parameter  $c$  is suggested to be set to the standard deviation of the measurement noise, the stability constant  $A$  to one-tenth of the number of intended iterations and,  $a$  to a small value close to 0.05. Moreover, a common choice for the elements of  $\Delta_k$  is independent  $\pm 1$ -valued Bernoulli-distributed random variables with a 0.5 probability. Nonetheless, optimal SPSA parameters are case-dependent in practice and can vary significantly under different circumstances. More details on our SPSA parameter fine-tuning process are provided in Section 7.

## 6 Anchorage Simulation System

Optimization of the planning metrics coefficients for a given problem instance as well as comparison of our approach against existing state-of-the-art algorithms necessitate Monte Carlo simulations, which in turn, call for an anchorage simulation system. This system facilitates empirical performance assessment of anchorage planning algorithms under a wide variety of conditions as detailed in Section 7. Our implementation of the simulation system is similar to that of Oz et al. (2015) whose logical flow is shown in Figure 7 and main components are described below.

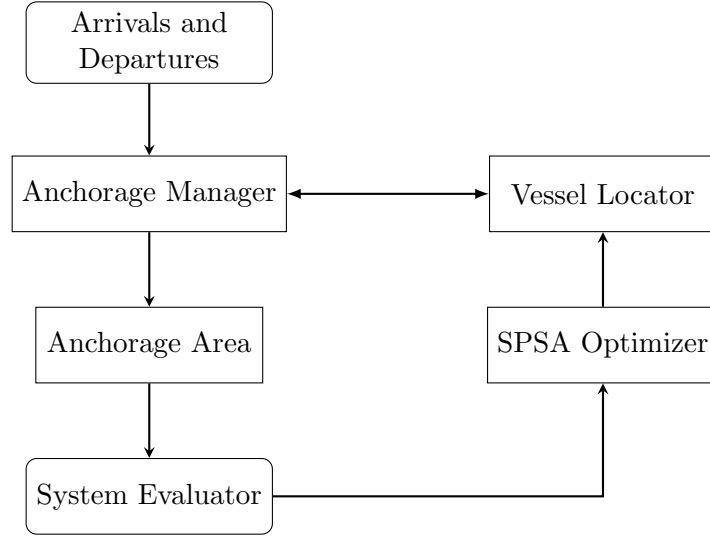


Figure 7: Flowchart of the anchorage simulation system.

### 6.1 Anchorage Area

Following common practice, the anchorage area is modeled as a two-dimensional polygonal region containing anchor circles with various radii associated with anchored vessels. It is assumed that



(1) per regulations, vessel entry and exits occur through the entry side of the anchorage with the vessels following a straight path to their berth locations and, (2) the anchorage has uniform depth. The uniform depth assumption is not always realistic, yet relaxation of this assumption is relatively straightforward with the non-uniform depth corner point calculation algorithm discussed in Malekipirbazari et al. (2015).

## 6.2 Vessel Arrival and Departure Generator

The *Vessel Arrival and Departure Generator* component is in charge of generating vessel traffic with an associated arrival time, an anchor duration (i.e., dwell time), and a vessel length for calculating the vessels' anchor circle radii. These quantities are sampled from respective probability distributions as discussed in Section 7. This component also initiates a departure event at the end of the vessel's anchor duration.

## 6.3 Vessel Locator

The *Vessel Locator* component is responsible for calculating scoring the candidate berth locations and determining the berth location of incoming vessels with respect to these scores. The scoring is based on a linear combination of the planning metrics as described in Section 5 and coefficients of each planning metric as computed by the *SPSA Optimizer* component.

## 6.4 SPSA Optimizer

The *SPSA Optimizer* iteratively improves upon the coefficients of the planning metrics  $\mathbf{x}$  using the SPSA algorithm. The system starts with an arbitrary  $\mathbf{x}_0$ , forms a gradient estimate by averaging multiple Monte Carlo simulations (for loss function evaluation) in each iteration and computes the next solution vector  $\mathbf{x}$  until termination.

## 6.5 Anchorage Manager

The *Anchorage Manager* component oversees the entire simulation system and manages the connection between the system's components. When an event takes place in any component, this component receives a notification and determines the appropriate course of action, including sending the information to the component responsible for an appropriate action.

## 6.6 System Evaluator

The *System Evaluator* component is responsible for computing and maintaining all relevant statistics related to performance and planning metrics including averages and standard deviations.

## 7 Computational Experiments

This section presents computational experiments for empirical performance assessment of our SPSA-based optimization strategy. Our goal in this section is two-fold: (1) benchmark our strategy against the current state-of-the-art anchorage planning algorithms and, (2) briefly investigate the effect of different performance metric weight combinations on the individual objectives. Our experiments comprise of the following variations:

- Two different anchorage topologies: The Ahırkapı Anchorage in the southern entrance of the Istanbul Strait and a rectangular-shaped synthetic anchorage. The Ahırkapı Anchorage has a bounding box of 2.5 by 4 kilometers and the synthetic anchorage's dimensions are 2.5 by 4 kilometers. The depth of both anchorages is taken as 35 meters. Figure 8 shows Ahırkapı and the synthetic anchorage topology used in the simulations. To our knowledge, anchorage traffic data is not readily available for any other anchorage in the open literature, which consequently restricts our work to the Ahırkapı Anchorage for a real-world case study.
- For the synthetic anchorage, three different vessel inter-arrival distributions representing busy, average, and idle anchorage traffic respectively. Combined with the Ahırkapı Anchorage, this results in a total of four different anchorage settings.
- Five different performance metrics weight vectors for assessing impact of this vector on the respective objectives of risk, utilization, and distance. The weight vectors we consider are  $(1,0,0)$ ,  $(0,0,1)$ ,  $(1,0,1)$ ,  $(5,0,1)$ , and  $(1,0,5)$ .

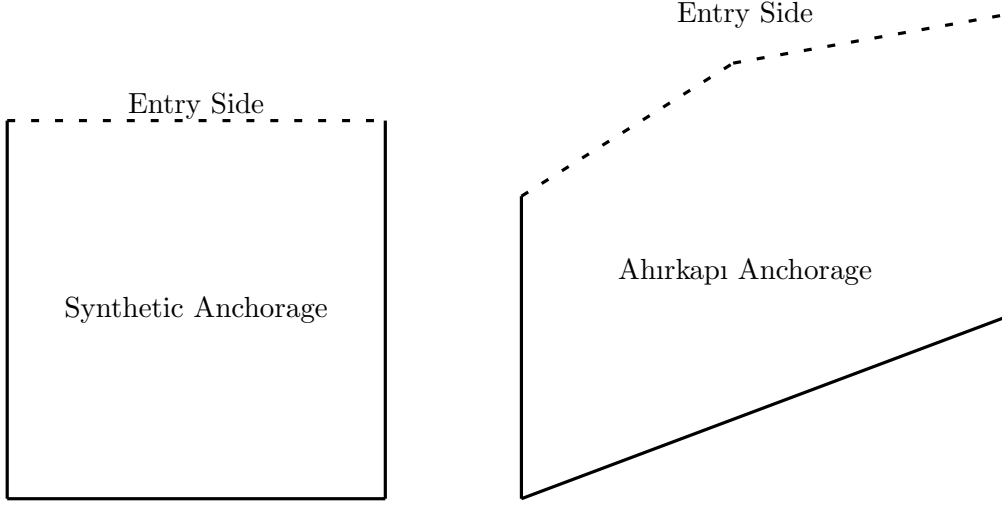


Figure 8: Anchorage topologies used in the computational experiments.

Our Monte Carlo simulations require probability distributions for sampling vessel inter-arrival time, dwell time, and vessel length quantities. For this purpose, we make use of Ahırkapı Anchorage historical data information for the month of July 2015. We determine the best fitting probability distribution for each one of these three quantities via Kolmogorov-Smirnov goodness of fit tests, which are then used for sampling in the simulations. The probability distributions fitted to the Ahırkapı historical data are as follows:

- Inter-arrival times (hours): Exponential( $\mu = 0.45$ )
- Dwell times (hours): Log-normal( $\mu = 2.4, \sigma = 1.3$ )
- Vessel lengths (scaled between 30 and 300 meters): Beta( $\alpha = 2.4, \beta = 2.4$ ).

It should be noted that our general methodology is not tied to any particular distribution and these probability distributions are merely used for illustration purposes. In order to simulate synthetic anchorage settings with busy and idle anchorage traffic, we use a multiplier  $k$  for dwell times to manipulate departure to arrival ratio. The multiplier values used in the four different anchorage settings are as follows:

- Ahırkapı anchorage:  $k = 1$ .
- Average synthetic anchorage:  $k = 1$ .
- Busy synthetic anchorage:  $k = 2.2$ .

- Idle synthetic anchorage:  $k = 0.5$ .

As an example, suppose sampling from the Log-normal(2.4, 1.3) distribution yields a dwell time of 2.5 hours. For the busy setting, the dwell time would be set to 5.5 hours whereas the dwell time for the idle setting would be set to 1.25 hours.

## 7.1 Steady State Analysis

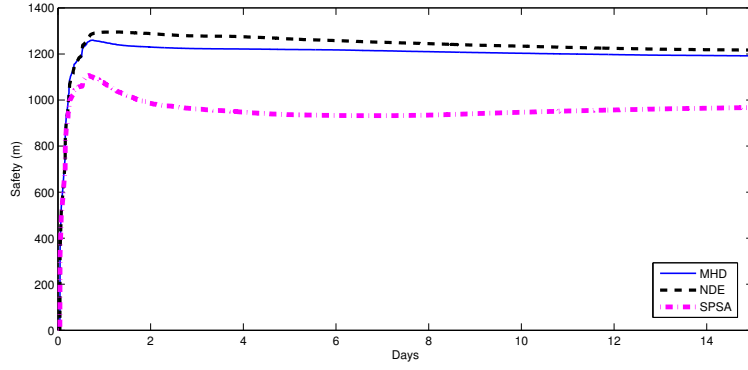
Transcending the static anchorage planning problem into a dynamic one with a time dimension necessitates rather significant changes in the simulation approach, one of which is a steady-state analysis. In planning stages of any Monte Carlo simulation, an important decision is whether to use terminating conditions or steady-state. Since anchorages serve around-the-clock, there is really no terminating condition for their operation. Also, it is hard to imagine an empty anchorage waiting for vessels to arrive. Thus, as we are interested in estimating a set of performance metrics in the long run, it is favorable to eliminate any improbable factors that would potentially cause a deviation in the trend of the parameters of interest such as initial and terminating conditions.

Figure 9 shows the trend of our performance metrics throughout the first fifteen days of simulation for all the competing algorithms for the Ahırkapı Anchorage starting with an empty anchorage. This figure, as well as similar analyses we conducted with various simulation settings suggested there is no considerable increase or decrease due to initial settings after the seventh day and all metrics seem to stabilize by this point. Therefore, we regard the first seven days as the warm-up period and we consider the second seven days of simulation to be the window of study during which we monitor the system's behavior in order to compare the planning algorithms.

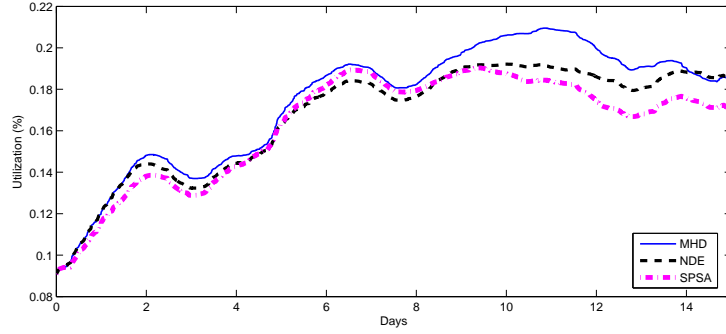
## 7.2 SPSA Implementation

As mentioned earlier, careful fine-tuning of SPSA parameter values is of utmost importance for convergence to a good solution. In our implementation, we use the symmetric Bernoulli distribution with  $\pm 1$  outcomes for the perturbation vector  $\Delta_k$ , which is a simple and commonly used distribution in the SPSA literature. Regarding  $\alpha$  and  $\gamma$ , we use the theoretically optimal values of 0.602 and 0.101 respectively. For the parameters of  $a$ ,  $c$ , and  $A$ , subsequent to a comprehensive fine-tuning process involving various simulation settings, we use the values of 0.17, 0.019 and 0, respectively.

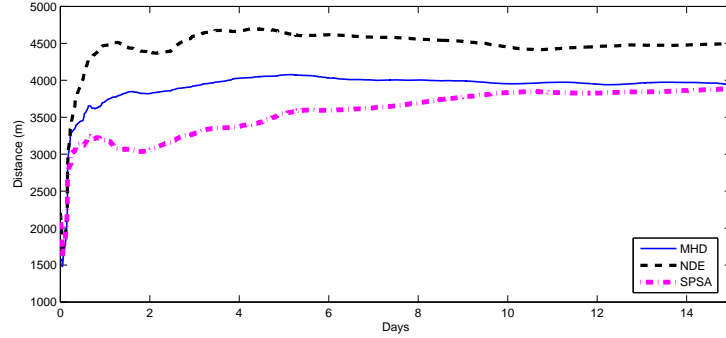
The number of SPSA iterations is taken as 500, which we observed to be sufficient for conver-



(a) Risk



(b) Utilization



(c) Distance

Figure 9: Performance metrics over time for the Ahirkapi Anchorage during fifteen days of simulation time.

gence in general. SPSA is inherently a probabilistic algorithm due to two factors: (1) the sampling process while generating the simultaneous perturbation vectors and, (2) noise in the loss function measurements. For this reason, its performance tends to vary slightly from one particular run to another. A common way of reducing the effect of noise as well as randomness in SPSA implementations is averaging simulation runs, see, e.g., Aksakalli and Malekipirbazari (2016). Thus, for each instance of the dynamic anchorage planning problem we consider in this study, the loss function measurement for SPSA is taken as the average of 10 independent Monte Carlo simulations with

a different sequence of symmetric Bernoulli samples. In particular, for each SPSA iteration, 10 independent simulations are performed for each one of the following loss function measurements:  $y(\hat{\mathbf{x}}_k^+)$ ,  $y(\hat{\mathbf{x}}_k^-)$ , and  $y(\hat{\mathbf{x}}_{k+1})$ . This results in a total of  $30 \times 500 = 15000$  simulations for each planning metrics coefficient vector optimization.

Consider, for instance, the case when  $W_R = 0$ ,  $W_U = 0$  and  $W_D = 1$ . Figure 10 shows the normalized values of objective function for this performance metrics weight vector over 500 iterations for Ahırkapı Anchorage. The solution vector with the lowest objective function value over the entire range of SPSA iterations is declared to be the optimal solution vector  $\mathbf{x}^*$ .

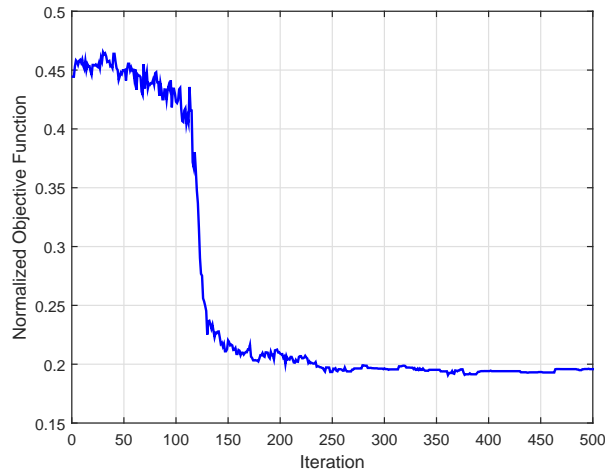


Figure 10: Normalized objective function value vs. iteration count for SPSA for the Ahırkapı Anchorage.

### 7.3 Performance Comparison of Algorithms

Once we identify the optimal coefficients vector for the planning metrics using SPSA, we are ready to benchmark our algorithm against the alternatives. For a fair comparison, we use the average over 100 simulation replications for each algorithm for each anchorage setting by using the method of common random numbers (CRN) to reduce variance. Each one of the 100 Monte Carlo simulation runs require sampling of the following three quantities from their respective probability distributions over a period of fourteen days: (1) vessel arrival times, (2) vessel departure times, and (3) vessel lengths. Per CRN, each planning algorithm is fed in the same sequence of vessel arrival and departures together with the same vessel lengths, thereby eliminating the variability in these three quantities between the algorithms in a particular Monte Carlo simulation. We remark

that, for a particular anchorage setting, these Monte Carlo simulations are conducted only after the optimal planning metrics coefficients have been found using SPSA.

Competing algorithms are the Normalized Distance to Entry (NDE) method of Oz et al. (2015) and the Maximum Hole Degree (MHD) method of Huang et al. (2011), which are named based on the metric they use for choosing the best candidate corner point for an incoming vessel. The idea in the NDE method is to place incoming vessels so as to maximize its distance to the entry line, whereas the idea in the MHD method is to place the vessel in the tightest available space in the current anchorage configuration. In addition to NDE and MHD, we consider random candidate corner point selection in order to provide a baseline for comparisons, which we call the *Random Method*.

For each one of the four anchorage settings, we use SPSA with five different sets of  $W_R$ ,  $W_U$  and  $W_D$  weights in order to demonstrate the performance of SPSA as a robust multi-objective optimizer with various anchorage planning priorities. Tables 3, 4, 5, and 6 show the comparison results for all four methods for each anchorage setting. The tables show the average for each performance metric over the 100 simulations along with the margin of errors for a 95% confidence interval. Optimal planning metric coefficients for the Ahırkapı Anchorage are shown in Table 7 to illustrate how these coefficients relate to each other for one particular anchorage setting.

Table 3: Comparison of algorithms for the Ahırkapı Anchorage averaged over 100 simulations. The plus/minus values denote the margins of error for a 95% confidence interval.

Algorithm	Risk (m)	Utilization (%)	Distance (m)
<b>MHD</b>	480.4±13.5	0.19±0.0079	4031.6±57.5
<b>NDE</b>	389.3±8.7	0.19±0.0079	4289.8±19.9
<b>RANDOM</b>	488.0±8.9	0.19±0.0079	4046.2±26.1
<b>SPSA: <math>W_R/W_U/W_D</math></b>			
1/0/0	223.7±6.3	0.19±0.0079	3620.4±43.2
5/0/1	231.7±7.4	0.19±0.0079	2395.1±20.3
1/0/1	244.2±7.4	0.19±0.0079	2313.8±23.5
1/0/5	245.9±7.8	0.19±0.0079	2288.7±22.1
0/0/1	315.6±8.8	0.19±0.0079	2199.1±21.4

Table 4: Comparison of algorithms for average synthetic anchorage.

Algorithm	Risk (m)	Utilization (%)	Distance (m)
<b>MHD</b>	685.6±23.6	0.19±0.083	4801.8±213.5
<b>NDE</b>	612.1±15.2	0.19±0.083	5948.1±36.0
<b>RANDOM</b>	958.4±13.9	0.19±0.083	4546.3±42.1
<b>SPSA:</b> $W_R/W_U/W_D$			
1/0/0	413.5±11.6	0.19±0.0083	3944.5±82.0
5/0/1	489.2±13.1	0.19±0.0083	2170.9±37.2
1/0/1	500.8±12.9	0.19±0.0083	2139.7±36.4
1/0/5	502.1±12.5	0.19±0.0083	2135.4±36.8
0/0/1	523.3±13.4	0.19±0.0083	2092.1±35.4

Table 5: Comparison of algorithms for busy synthetic anchorage.

Algorithm	Risk (m)	Utilization (%)	Distance (m)
<b>MHD</b>	1190.2±15.0	0.48±0.0147	4093.4±28.7
<b>NDE</b>	1200.1±15.6	0.47±0.0147	4505.9±32.9
<b>RANDOM</b>	1231.2±15.0	0.48±0.0157	4134.8±25.3
<b>SPSA:</b> $W_R/W_U/W_D$			
1/0/0	931.6±14.8	0.46±0.0134	3780.0±32.9
5/0/1	938.9±15.9	0.46±0.0141	3606.4±34.5
1/0/1	968.2±16.5	0.47±0.0147	3555.5±35.4
1/0/5	973.7±14.4	0.47±0.0143	3552.3±33.7
0/0/1	998.1±16.4	0.47±0.0147	3518.8±35.4

Table 6: Comparison of algorithms for idle synthetic anchorage.

Algorithm	Risk (m)	Utilization (%)	Distance (m)
<b>MHD</b>	385.6±23.1	0.03±0.0029	6391.3±68.3
<b>NDE</b>	252.1±9.2	0.03±0.0029	6881.4±19.6
<b>RANDOM</b>	884.8±18.9	0.03±0.0029	5092.5±38.5
<b>SPSA:</b> $W_R/W_U/W_D$			
1/0/0	152.3±5.8	0.03±0.0029	6017.7±50.0
5/0/1	202.6±7.6	0.03±0.0029	1215.9±20.0
1/0/1	210.1±7.7	0.03±0.0029	1187.7±20.1
1/0/5	222.1±7.9	0.03±0.0029	1181.4±19.2
0/0/1	244.4±9.0	0.03±0.0029	1174.6±19.5



Table 7: Optimal planning metric coefficients for the Ahırkapı Anchorage.

$W$		$\mathbf{x}^*$					
$W_R/W_U/W_D$	$x_1^*$	$x_2^*$	$x_3^*$	$x_4^*$	$x_5^*$	$x_6^*$	$x_7^*$
1/0/0	0.053	0.325	0.117	-0.287	0.087	-0.121	-0.219
5/0/1	0.019	0.525	0.150	-0.729	-0.559	0.733	-0.389
1/0/1	-0.100	0.614	-0.020	-0.134	-0.406	-0.274	-0.304
1/0/5	-0.066	0.580	-0.002	-0.372	0.240	0.712	-0.882
0/0/1	-0.185	0.155	-0.393	0.189	-0.219	-0.291	-0.559

From the comparison tables, we observe that when the priority is risk or distance, SPSA outperforms all the other algorithms. Even when  $W_R = W_D = 1$ , SPSA outperforms all competing algorithms in both risk and distance. On the other hand, the numbers for utilization are indicative of an interesting notion; when the anchorage does not reach its full capacity, utilization, as it is defined in this work, would be the same regardless of any criteria for choosing among corner points and, since we use CRN for sampling, the numbers in the utilization columns are exactly the same in this case. That is why we only present results when  $W_U = 0$ . As expected, setting different values for  $W_U$  does not make any difference in the optimal solution; even considerably large values for  $W_U$  will yield the same results as zero in this case. However, there is one case where utilization could differ among algorithms. As indicated in Table 5, the numbers in the utilization column slightly vary, but there are two key issues that need to be taken into account while pondering on the results. First, with a trivial margin, the highest utilization in the busy anchorage case belongs to MHD that only focuses on utilization, and yet, the Random method has the same performance. This gives rise to the claim that the notion of corner points may suffice for optimizing utilization.

In order to make a definitive judgment, we need to determine whether the differences between the scenarios are statistically significant or not. There are sizable overlaps between utilization intervals for all the algorithms, meaning the differences in utilization are not statistically significant (per paired t-tests conducted at a 95% significance level). On the other hand, the differences in risk and distance are significant in most cases. Considering these results, a crucial observation is that our algorithm is commendably sensitive to changes in weights in objective function, making it a reliable multi-objective optimization algorithm.

Although in some cases the differences are not statistically significant, SPSA algorithm almost entirely dominates competing algorithms. Specifically, in the objective that it is aimed to optimize,

it statistically dominates all other algorithms in all cases and instances. For instance, for the Ahırkapı Anchorage, regarding the risk objective, SPSA yields an average value of 223.7 meters whereas NDE, the closest of the other three algorithms, yields an average of 389 meters, which is a 42% reduction. Likewise, regarding the distance metric, SPSA results in an average of 2199 meters while the closest MHD method yields an average of 4031 meters, which corresponds to a 45% reduction in fuel costs. In addition, regarding the distance performance metric for the idle synthetic anchorage, SPSA gives an average of 1174 meters whereas the closest Random method yields an average of 5092 meters. Such results underline the superior performance of our SPSA-based approach against the current state-of-the art methods for anchorage planning in general.

## 8 Summary and Conclusions

As maritime transportation gains momentum, anchorage planning and related problems call for closer attention and dealing with them demand appropriate strategies. So far, the research in this area mostly have been case studies focusing on one or two objectives while ignoring the time dimension. In this research, we embark on developing a more general methodology that can be of assistance for decision makers when facing dynamic multi-objective optimization problems in this particular field.

For this purpose, we introduce performance metrics aimed at assessing anchorage planning performance. Next, we present effective planning metrics associated with one or more of the objectives that can be employed for optimization. Then, we use the SPSA stochastic optimization algorithm to identify the best planning metric coefficients for a given instance of the problem. With the aid of a custom simulation tool, we benchmark our algorithm against current best practices and we showcase the power of our approach in four different settings we generate using historical data gathered from Ahırkapı Anchorage. It is worth mentioning our study is the first in this field that (1) accounts for the time dimension of the anchorage planning problem and (2) attempts to simultaneously optimize the triple objectives of risk, utilization, and average distance traveled (in lieu of fuel consumption and environmental impacts).

Our results indicate that our SPSA-based methodology predominantly outperforms competing algorithms in risk and distance. For Istanbul’s Ahırkapı Anchorage, for instance, which is one of the busiest anchorages in the world, reduction in risk of an accident alone was 42% whereas reduction in distance alone (in lieu of fuel costs) was 45% when compared the best of the current

state-of-the-art methods. As far as utilization is concerned, we argue the concept of corner point placement seems to be sufficient for optimizing utilization and further considerations would not lead to statistically significant differences, at least under the conditions and assumptions in our study. Should there be any possibility for significantly different results under different conditions in the future, our approach, with appropriate alterations, could be employed to optimize utilization as well due to its flexible design for accounting for any number of desired performance and planning metrics.

Our methodology has a number of strengths and desirable features. In terms of technical aspects, our research method accounts for the time dimension in daily anchorage planning by simultaneously modeling vessel arrivals and departures. Our methodology also allows for any number of performance metrics as part of the objective function together with any number of real-time planning metrics. In terms of practical aspects, our methodology facilitates a trade-off analysis for anchorage planners via specification of weights for each one of the performance metrics comprising the objective function.

Regarding limitations of our methodology, we would like to point out that we do not consider any environmental conditions in our work such as waves, winds, or sea currents. In addition, we model vessel arrivals and departures as straight lines, which is not quite realistic. Furthermore, our methodology assumes that probability distributions of vessel inter-arrival and dwell times are known in advance, which is not unreasonable, yet an assumption nonetheless. One other limitation is that we assume the anchorage area is of uniform-depth, which is also not very realistic. On the other hand, the methodology presented in Malekipirbazari et al. (2015) for safe anchor circle calculations in non-uniform depth anchorages can be incorporated into our approach in a relatively straightforward manner.

As for future research, one direction is to incorporate environmental conditions such as waves, winds, and sea currents into the problem and modify the methodology presented herein to account for these conditions. Moreover, considering more realistic arrival and departure paths instead of straight lines can potentially make a difference in increasing the accuracy and effectiveness of the current model, thereby bringing the anchorage planning model one step closer to reality. In this work, we experimented with a limited number of planning metric weight combinations, which do not fully reveal the interactions and trade-offs between the risk, utilization, and environmental impact/ fuel cost objectives. Future research might investigate these relationships in detail for a

pareto-optimal approach to the multi-objective optimization problem at hand.

## Acknowledgements

The authors are grateful to the editor and the two anonymous reviewers for their thoughtful comments and suggestions that significantly improved the overall quality of this article. This research was partially supported by The Scientific and Technological Research Council of Turkey (TUBITAK), Grant No. 113M489. Some portions of this article are based on the M.Sc. thesis of Bahman Madadi [1] while at Istanbul Sehir University. The authors thank Istanbul Vessel Traffic Services (VTS) Authority for providing the Ahırkapı Anchorage historical data and also for a very helpful interview on maritime policies governing Istanbul Strait anchorages. The custom simulation tool that was developed for this study can be made available upon request as a Java software package with a graphical user interface.

## References

- Akeb, H., Hifi, M., 2008. Algorithms for the circular two-dimensional open dimension problem. *International Transactions in Operational Research* 15 (6), 685–704.
- Aksakalli, V., Malekipirbazari, M., 2016. Feature selection via binary simultaneous perturbation stochastic approximation. *Pattern Recognition Letters* 75, 41–47.
- Aydogdu, V., Kum, S., Yurturen, C., Pitirlioglu, E., Sanal, T., 2012. Marine accident analysis at Ahirkapi Anchorage Area in southern entrance of the Istanbul Strait. In: *Proceedings of Asia Navigation Conference*, Kobe, Japan.
- Bugaric, U., Petrovic, D., 2007. Increasing the capacity of terminal for bulk cargo unloading. *Simulation Modelling Practice and Theory* 15 (10), 1366—1381.
- Danton, G., 1996. *The theory and practice of seamanship*. Routledge & Kegan Paul, London, UK.
- Disser, Y., Klimm, M., Lübbecke, E., 2015. Scheduling bidirectional traffic on a path. In: *Proceedings of International Colloquium on Automata, Languages, and Programming*, Kyoto, Japan. Springer, pp. 406–418.

- Fan, H., Cao, J., 2000. Sea space capacity and operation strategy analysis system. *Transportation Planning and Technology* 24 (1), 49–63.
- Huang, S., Hsu, W., He, Y., 2011. Assessing capacity and improving utilization of anchorages. *Transportation Research Part E Logistics and Transportation Review* 47 (2), 216–227.
- Huang, S., Hsu, W., He, Y., Song, T., 2013. A marine traffic simulation system for hub ports. In: *Proceedings of ACM SIGSIM Conference on Principles of Advanced Discrete Simulation*. pp. 295–304.
- Huang, W., Li, Y., Akeb, H., Li, C., 2005. Greedy algorithms for packing unequal circles into a rectangular container. *Journal of the Operational Research Society* 56 (5), 539–548.
- Jajac, N., Kilic, J., Rogulj, K., 2018. An integral approach to sustainable decision-making within maritime spatial planning—a DSC for the planning of anchorages on the Island of Solta, Croatia. *Sustainability* 11 (1).
- Lalla-Ruiz, E., Shi, X., Voß, S., 2018. The waterway ship scheduling problem. *Transportation Research Part D: Transport and Environment* 60, 191–209.
- Li, F., Yang, D., Wang, S., Weng, J., 2019. Ship routing and scheduling problem for steel plants cluster alongside the yangtze river. *Transportation Research Part E: Logistics and Transportation Review* 122, 198–210.
- Malekipirbazari, M., Oz, D., Aksakalli, V., Alkaya, A. F., Aydogdu, V., 2015. Capacity planning in non-uniform depth anchorages. In: *Proceedings of Intelligent Decision Technologies*. Springer, pp. 21–30.
- Olba, X. B., Daamen, W., Vellinga, T., Hoogendoorn, S. P., 2017. Network capacity estimation of vessel traffic: An approach for port planning. *Journal of Waterway, Port, Coastal, and Ocean Engineering* 143 (5), 1–9.
- Oz, D., Aksakalli, V., Alkaya, A. F., Aydogdu, V., 2015. An anchorage planning strategy with safety and utilization considerations. *Computers & Operations Research* 62 (1), 12–22.
- Schmalhofer, F., 2001. Expert systems in cognitive science. *International Encyclopedia of the Social and Behavioral Sciences*, 5128–5135.

- Shyshou, A., Gribkovskaia, I., Barceló, J., 2010. A simulation study of the fleet sizing problem arising in offshore anchor handling operations. *European Journal of Operational Research* 203 (1), 230–240.
- Spall, J. C., 1992. Multivariate stochastic approximation using a simultaneous perturbation gradient approximation. *IEEE Transactions on Automatic Control* 37 (3), 332–341.
- Spall, J. C., 1998. Implementation of simultaneous perturbation algorithm for stochastic optimization. *IEEE Transactions on Aerospace and Electronic Systems* 34 (3), 817–823.
- Zhang, X., Lin, J., Guo, Z., Liu, T., 2016. Vessel transportation scheduling optimization based on channel–berth coordination. *Ocean Engineering* 112, 145–152.